Review of Accounting Studies, 10, 185–221, 2005

Information Uncertainty and Expected Returns

GUOHUA JIANG
Guanghua School of Management, Peking University

CHARLES M. C. LEE* charles.lee@barclaysglobal.com
Johnson Graduate School of Management, Cornell University

YI ZHANG
Barclays Global Investors, 45 Fremont Street, San Francisco, CA, 94105

Abstract. This study examines the role of information uncertainty (IU) in predicting cross-sectional stock returns. We define IU in terms of "value ambiguity," or the precision with which firm value can be estimated by knowledgeable investors at reasonable cost. Using several different proxies for IU, we show that (1) on average, high-IU firms earn lower future returns (the "mean" effect), and (2) price and earnings momentum effects are much stronger among high-IU firms (the "interaction" effect). These findings are consistent with analytical models in which high IU exacerbates investor overconfidence and limits rational arbitrage.

Keywords: behavioral finance, cross-sectional returns, information uncertainty, risk

JEL Classification: G12, G14, M41

This study examines the relation between information uncertainty (IU) and cross-sectional stock returns. By information uncertainty, we do not mean information asymmetry, such that some agents know more about a firm's value than others. Rather, we define IU in terms of "value ambiguity," or the degree to which a firm's value can be reasonably estimated by even the most knowledgeable investors at reasonable costs. By this definition, high-IU firms are companies whose expected cash flows are less "knowable," perhaps due to the nature of their business or operating environment. These firms are associated with higher information acquisition costs, and estimates of their fundamental value are inherently less reliable and more volatile.

Information uncertainty (IU), as we define it, is at the heart of a number of curiously consistent findings in empirical finance that are difficult to reconcile with traditional asset pricing models. Specifically, prior studies have found that firms with higher volatility, higher volume (i.e., turnover), greater expected growth, higher price-to-book (PB) ratios, wider dispersion in analyst earnings forecasts, and longer implied duration in their future cash flows, all earn lower subsequent returns.[1] Although various explanations have been proposed for these phenomena, it is also true

*Corresponding author.

that in each instance, firms operating in higher IU environments are observed to earn lower future returns.

These empirical results are puzzling because in standard CAPM or multi-factor asset pricing models, non-systematic risk is not priced, and various IU proxies should have no ability to predict future returns. More recently, some analytical papers have argued in favor of a role for information risk in asset pricing (e.g., Easley and O'Hara, 2003). But even in these models, the directional prediction is that higher IU should be associated with higher information risk or greater information acquisition costs, and therefore higher (not lower) expected returns.

In this study, we present and empirically evaluate a theory of information uncertainty that not only predicts a negative relation between IU and average expected returns (the "mean" effect), but also predicts a relation between IU and the magnitude of the price and earnings momentum phenomena (an "interaction" effect). Specifically, this theory predicts that high-IU firms will exhibit stronger momentum effects—that is, a strategy of buying recent winners and selling recent losers will yield higher trading profits among high-IU firms.

Our analysis is rooted in recent theoretical work in behavioral finance. According to behavioral finance theory, market mispricings arise when two conditions are met: (1) an uninformed demand shock, and (2) a limit on arbitrage.[2] Our two-part thesis is that the level of information uncertainty is positively correlated with a particular form of decision bias (investor overconfidence), and that it is also positively correlated with arbitrage costs. Collectively, these two effects conspire to produce lower mean returns and greater momentum profits among high-IU firms.

In the overconfidence literature (e.g., Odean, 1998; Daniel et al., 1998, 2001), otherwise rational investors overestimate the precision of their information signals. DHS (1998), in particular, features a model in which investors overweight the value of their private signals, and place inadequate weight on the information content of important public events, such as earnings releases and past stock returns. Their model, therefore, nominates investor overconfidence as a driving force behind market anomalies that feature post-event continuation of stock returns—e.g., the post-earnings announcement drift (Bernard and Thomas, 1990).

Building on this concept, we argue that the overconfidence bias is accentuated in high-IU settings, where firm values are nebulous even to the most knowledgeable investors. With greater value ambiguity, investors will trade more aggressively on their private signals. More importantly, if pessimistic investors are kept out of the market, even partially, by asymmetric costs associated with short-selling (Miller, 1977), the prices of high-IU firms will reflect the excess optimism of the investors with the highest private valuations. As the excess optimism incorporated in the price of high-IU firms are corrected over time, these firms will earn lower returns in future periods.[3]

Our premise is that the degree to which the overconfidence bias affects returns will vary in a predictable manner across stocks with differing degrees of information uncertainty. In higher IU firms, investors' private valuations are more diffused and solid feedback on the quality of their private signal is more difficult to obtain. Thus emboldened, investors in high-IU firms tend to overweight their private signals, and place too little weight on public news and news about firm fundamentals. As a result, two empirical phenomena emerge: (1) high-IU firms tend to be over-priced, thus earning lower future returns; and (2) high-IU firms will exhibit greater price and earnings momentum effects.

Another important feature of a high-IU environment is that informational arbitrage will be more difficult to implement among these firms. The literature on limits to arbitrage identifies three types of costs facing would-be arbitrageurs: (1) information costs, (2) trading costs, and (3) holding costs.[4] With greater IU, rational traders face elevated information acquisition and processing costs, as well as higher risks associated with noisier value estimates.[5] At the same time, trading costs (associated with entering and exiting a position) and holding costs (associated with risk exposure while holding a position) are also generally higher for high-IU firms. We argue that increased arbitrage costs also contribute to greater price and earnings momentum effects among higher IU-firms.

Our empirical analyses examine the two main predictions of this theory: that is, the ''mean'' and ''interaction'' effects of IU on future returns. Specifically, we use four broadly available variables to proxy for information uncertainty: the age of the firm (*Firm Age*), return volatility (*Volatility*), average daily turnover (*Volume*), and the duration of its future cash flows (*Duration*).[6] Based on the preceding discussion, we expect younger firms, firms with higher returns volatility, greater trading volume, and longer duration cash flows, to have higher IU. We also combine these variables to create composite portfolios that feature two, three, or all four of these IU characteristics.

Consistent with prior studies, we find that younger firms, firms with higher volatility, firms with higher turnover, and firms with higher cash flow duration, all earn lower returns. Interestingly, we show that the ''mean'' effect is not typically monotonic across the IU portfolios. Firms in the highest IU deciles (young firms, volatile firms, firms with high turnover, and firms with long duration cash flows) earn sharply lower returns, while firms in the other nine IU portfolios tend to have fairly similar returns. In particular, low-IU firms do not generally earn significantly higher future returns.[7] In fact, we show that the average underperformance of young, volatile, and high-volume firms reported in earlier studies is concentrated almost entirely in the most extreme high-IU decile. These results are strikingly consistent with the Miller (1977) argument that short-sell related factors play an important role in the lower returns earned by high-IU firms. In low-IU portfolios, where short-selling arguments do not apply, firms earn normal returns.

We also document a strong ''interaction'' effect between IU and the profitability of momentum strategies. In these tests, we define price momentum in terms of recent returns, and earnings momentum in terms of average monthly revisions in analysts' earnings forecasts over the past quarter. For all four IU proxies, we find that returns on hedge (winner–loser) portfolios are much higher for high-IU firms. The results are even sharper when we use composite measures of IU that combine two, three, or all four IU proxies.

We find similar results for both price momentum and earnings momentum strategies. Among low-IU firms, price momentum strategies based on extreme quintiles earn average monthly returns that range from −0.10 to 0.27%. Among high-IU firms, the same momentum strategies produce average monthly returns of 1.26 to 1.82%. Similarly, when firms are sorted on the basis of recent changes in analyst forecast revisions, a strategy of buying positive revision stocks and shorting negative revision stocks yields average monthly returns of 0.77–1.30% for low-IU firms, and 1.94–2.66% for high-IU firms. Unlike the ''mean'' effect, this ''interaction'' effect is quite symmetrical—that is, momentum profits are sharply lower in low-IU firms, and are sharply higher in high-IU firms.

Risk-based explanations do not appear to account for these findings. The standard risk adjustments based on time-series (Fama and French, 1993) and cross-sectional (Fama and MacBeth, 1973) methodologies have little effect on these results. Moreover, a substantial portion of the returns earned by momentum strategies in high-IU firms is realized in short-windows around subsequent earnings announcements. This pattern is not observed among low-IU firms.

Further analysis shows that the concentration of high (and low) IU firms varies by industry. In general, the following industries have a large proportion of firms in the high-IU category (2-digit SIC code in parentheses): Business Services (73), Health Services (80), Electronic Equipment (36), Engineering, Research and Consulting Services (87), Home Furnishings Stores (57), Automotive Repairs (75), Industrial Machinery and Computer Equipment (35), Eateries (58), Educational Services (82), and Recreational Services (79). In short, service providers and technology-oriented firms are heavily represented in the high-IU category.

In the other extreme, the following industries have relatively few firms in the high-IU category: Tobacco Products (21), Utilities (49), Railroads (40), Furniture Makers (25), Banks (60), Food Stores (54), Nonmetal Minerals (14), Stone, Clay, Glass and Concrete Products (32), Paper Products (26), and Food Products (20). In short, utilities, transportation-related, basic materials and capital goods companies tend to be under-represented in the high-IU category.

Collectively, our findings support the view that market pricing dynamics, and therefore the cross-section of expected returns, vary systematically according to the level of information uncertainty. On average, high-IU firms earn lower returns. Moreover, in high-IU environments, with greater value ambiguity, stocks exhibit stronger positive serial correlation in returns (i.e., price momentum), and the sluggish price adjustment to the release of earnings news (i.e., earning momentum) is much more pronounced.

1. Hypotheses Development

Our two-part thesis is that the level of information uncertainty is positively correlated with a particular form of decision bias (investor overconfidence), and that it is also positively correlated with arbitrage costs. In this section, we develop these hypotheses and link our work to prior studies.

1.1. Overconfidence and Information Uncertainty

Overconfidence is arguably the single most universal and well-documented behavioral bias in cognitive psychology. A large body of experimental evidence supports the view that individuals are overconfident about the precision of their own information (see Odean, 1998 and references therein). Psychologists also find that people systematically overweight some types of information (e.g., more salient, less reliable) and underweight others (e.g., more abstract, statistical evidence).[8] More recently, several theoretical models of investor behavior nominate overconfidence as the driving force behind a host of empirical market anomalies, such as excessive volatility and trading volume, sluggish price adjustment to public news events, and predictable patterns in cross-sectional returns (see Odean, 1998; DHS, 1998, 2001). None of these models, however, discusses explicitly the probable effect of information uncertainty on investor overconfidence.

We argue that investor overconfidence is accentuated in high-IU settings. We base this argument on three observations. First, with greater value ambiguity, we expect a greater difference between subjective and actual distributions of firm value estimates. Figure 1 illustrates this phenomenon. Figure 1a presents the standard statistical representation of overconfidence, where the distribution of individuals' subjective value estimates is too narrow compared to the actual underlying distribution. In high-IU settings, the true distribution of value estimates is more diffused, with wider variance (Figure 1b). Based on prior experimental evidence, we posit that investors do not adjust sufficiently for systematic changes in the IU environment across firms. Consequently, we expect investors to exhibit behavior consistent with greater overconfidence in high-IU settings.

Second, with higher IU, the quality of investor's private signals is more difficult to assess, and *solid feedback is more difficult to obtain*, thus minimizing the disciplining benefits of trading experience. In other words, learning is a more difficult and protracted exercise in high-IU settings.[9] Finally, high-IU firms tend to be "story stocks," in which public signals about firm value are noisy, and by comparison *private signals appear more plausible*. In these stocks, investors' propensity to speculate is fueled by rumors and innuendos that have the cloak of legitimacy. Thus, extending the arguments in DHS (1998), we expect investors in higher-IU settings to overweight their own private (more salient) signals and underweight the (more abstract and statistical) public information contained in past returns and earnings news.[10]

In an early study, Miller (1977) predicts that firms with a greater divergence of opinions will earn lower returns. Miller based his argument on a combination of overconfidence bias and market frictions. Noting that private valuations are more diverse in high-IU firms, Miller reasons that if pessimistic investors are kept out of the market, even partially, by asymmetric costs associated with short-selling, the prices of high-IU firms will reflect the excess optimism of the investors with the highest private valuations. As the excess optimism incorporated in the price of high-IU firms is corrected over time, these firms will earn lower returns in future periods.[11] Our argument is an extension of the Miller (1977) proposition that predicts an "interaction" effect with the momentum phenomenon.

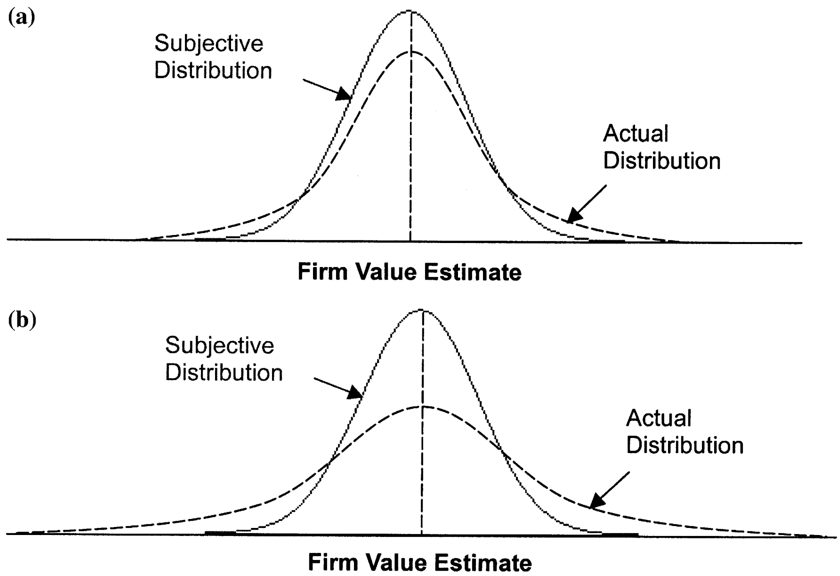

Figure 1. (a) Overconfidence in firm valuation estimation. This figure depicts the general phenomenon of investor overconfidence in firm value estimation—i.e., when investors' distribution of subjective estimates are too narrow relative to the actual underlying distribution. (b) Overconfidence in high information uncertainty (IU) firms. We posit that the overconfidence bias is exacerbated by increased information uncertainty (IU). In high-IU settings, the actual underlying distribution of firm value estimates is more diffused. To the extent that investors' subjective assessment of probabilities do not fully adjust for the increased variance in the underlying distribution, investors behavior will exhibit patterns consistent with elevated levels of overconfidence.

In sum, we expect the degree of investor overconfidence to be higher in high-IU firms. Investor overconfidence, *per se*, is not observable. However, as we argue below, this line of reasoning leads to testable hypotheses regarding differences in the pattern of expected returns across high-IU and low-IU portfolios.

1.2. Arbitrage Costs and Information Uncertainty

The second part of our argument is that informational arbitrage will be more difficult to implement in high-IU settings. When firm values are more nebulous, fully rational (well-calibrated) traders will face greater costs in their effort to implement arbitrage strategies against overconfident investors. These higher costs come in the form of increased information risk (arising from the low reliability estimates), greater information acquisition costs, longer holding periods before price:value convergence, and the increased likelihood of informational cascades.

The arguments for higher information acquisition costs and greater information risk derive directly from the literature on the limits of arbitrage (e.g., Shleifer and

Vishny, 1997; Mitchel et al., 2002; Barberis and Thaler, 2003). In high-IU settings rational arbitrageurs face higher information acquisition and analysis costs and their eventual value estimates are less reliable, rendering their strategies more risky. In addition, when fundamental value is uncertain, the process of price convergence to value is more likely to be protracted, adding to the costs of maintaining the arbitrage position.[12]

The arguments associated with informational cascades merit further elaboration. In their classic analysis of these cascades, Bikchandani et al. (1992) show that when each individual receives a noisy private signal, it is often optimal to follow the behavior of the preceding traders without regard to his or her own information. In their model, the likelihood of an incorrect cascade is a function of the precision of each individual's private signal—i.e., incorrect cascades are much more frequent when individuals receive noisy (low precision) signals. Therefore, their model suggests that in high-IU settings, incorrect pricing due to informational cascades is much more likely to occur.

We assert that adaptive behavior by rational arbitrageurs can contribute to the momentum effect in high-IU settings. When valuation is uncertain, rational arbitrageurs will reduce the weight they place on their private fundamental signals, and update more quickly in the direction of other traders. In other words, in high-IU firms, rational arbitrageurs will engage in a form of positive feedback trading (Delong et al., 1990) to compensate for the noisy nature of their own signals.[13] As a result, rather than helping to correct mispricings, the actions of rational investors can in fact cause prices to diverge even further from fundamental values. The greater frequency of cascades is another source of increased arbitrage cost for high-IU firms.[14]

In sum, we argue that when firm value is highly uncertain (i.e., when estimates of firm value are susceptible to wide swings over time), future returns will be characterized by two important empirical regularities: (1) lower average returns (the "mean" effect); and (2) increased momentum profits (the "interaction" effect). These predictions derive from elevated levels of investor confidence, as well as from increased costs associated with rational arbitrage. Our empirical analysis tests both predictions.

After we completed our work, we became aware of a study by Zhang (2004), which also examines the role of information uncertainty and its effects on stock return. Much of the motivation for his paper, and most of his results, are similar to ours. However, there are several interesting differences in research design and empirical findings.

In terms of research design differences, Zhang uses a slightly different set of IU proxies—specifically, he uses firm size, analyst coverage, the dispersion in analyst forecasts, and cash flow volatility; but he does not use cash flow duration or trading volume. Some of Zhang's IU measures are arguably more closely aligned with the underlying economic construct. However, a potential disadvantage of these measures is that they are only available for firms that have analyst coverage. As a result, his sample is smaller and more confined than ours (i.e. it reflects larger firms, and is limited to more recent time periods).

In terms of empirical results, Zhang (2004) also finds greater IU produces relatively lower future returns following bad news, and relatively higher future returns following good news. In other words, his results show that momentum strategies work better among high-IU stocks. His study also documents a "mean" effect, but the difference in returns between high-IU firms and low-IU firms in that study is not statistically significant. Comparing his study to ours, Zhang attributes this difference to the shorter sample period in his study, and his focus on near-term returns.

Overall, the results in Zhang (2004) complement the results in this paper; together, the two studies present a consistent set of empirical facts that link information uncertainty to cross-sectional returns.[15]

2. Sample and Methodology

Our sample consists of all firms listed on the NYSE, the AMEX and the NASDAQ during the period January 1965 through December 2001 with at least one year of data prior to the portfolio formation date. We exclude all closed-end funds, REIT, ADR, and foreign companies. To mitigate illiquidity concerns, we also eliminate any firm-month where the company's market capitalization as of the portfolio formation date is less than 150 million in year 2001 dollars (adjusted for inflation).

At the beginning of each event month t, we compute four information uncertainty (IU) proxies as follows. *Firm Age* is defined as the number of months between event month t and the first month that a stock appears in CRSP (Zhang, 2004 uses the same proxy).[16] Return volatility (*Volatility*) is defined as the standard deviation of daily returns of past 25 trading days.[17] Trading volume (*Volume*) is defined as the average daily turnover in percentage over the past six months, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day.[18] *Duration* is a measure of implied equity duration derived from financial statement data and the current stock price, using the methodology and estimation procedures developed in Dechow et al. (2004)—see Appendix A for details.

To compute the *Duration* measure, we also require firms to have several financial variables available from COMPUSTAT. Specifically, we require book value of equity (Compustat Data Item 60), Earnings (Item 18), Sales (Item 12) and Market Capitalization (Item 199 $\times$ Item 25). We use financial data from the most recent fiscal year end that ended at least four months before the portfolio formation date to ensure this information is publicly available at the beginning of event month t.

We also compute two momentum variables using data publicly available at the beginning of each event month. Our price momentum measure is simply the raw returns for each firm over the past J months ($J = 3$, 6, 9, 12). To avoid potential microstructure biases, we impose a one-week lag between the end of the portfolio formation period (J) and the beginning of the performance measurement period (K

months, $K=3, 6, 9, 12$). Because our results are robust to different time horizons, we only report a subset of these findings (for $J=6$, and $K=6, 12$).

Our measure of earnings momentum is the average revision in the analysts' consensus forecast over the past three months, each scaled by end-of-month price. Specifically, we compute our earnings momentum measure for firm i in month t as

$$\mathrm{REV}_{i,t} = \sum_{j=0}^{3} \frac{\mathrm{rev}_{i,t-j}}{p_{i,t-j-1}}$$

where $\mathrm{rev}_{i,t}$ is the change in the consensus FY1 earnings forecasts in month t for firm i. Our results are quite similar if we use revisions computed over the past one or six months, rather than the 3-month horizon.[19]

From January 1965 to December 2001, we rank stocks independently at the beginning of the month using each of these four IU characteristics (Firm Age, Volatility, Volume, and Duration), as well as on the two momentum variables. The intersections resulting from these two-way independent sorts give rise to our portfolios of interest. Most of our analysis focuses on the monthly returns of the extreme winner and loser portfolios over the next K months ($K=6, 12$).

Similar to Jegadeesh and Titman (1993), the monthly return for a K-month holding period is based on an equal-weighted average of portfolio returns from strategies implemented in the current month and the previous $K-1$ months. For example, the monthly return for a three-month holding period is based on an equal-weighted average of portfolio returns from this month's strategy, last month's strategy, and the strategy from two months ago. This is equivalent to revising the weights of (approximately) one-third of the portfolio each month and carrying over the rest from the previous month. The technique allows us to use simple t-statistics for monthly returns.

Table 1 presents summary statistics for the four information uncertainty variables, as well as the pairwise correlations between them. Panel A reports that the mean (median) age of the firms in our sample is 224 (159) months, the mean (median) volatility is 0.023 (0.020), the mean (median) average daily turnover is 0.382 (0.206), and the mean (median) duration is 15.54 (15.92) years. The number of firm-month observations for the first three IU variables ranges between 757,638 and 791,250. As expected, the number of firm-month observations drops (to 580,375) for the *Duration* variable, reflecting its more stringent data requirements.

Panel B shows that the four IU variables are correlated in the expected directions. Younger firms tend to have higher volatility, greater turnover, and longer duration cash flows. However, the correlation between Age and the other three variables is not overwhelming—i.e., range between −0.160 and −0.282. Volume and volatility are more highly correlated (0.455 and 0.480), but generally these levels of pairwise correlation indicate that each IU measure is capable of providing independent information relative to the others.

Table 1. Summary statistics.

Panel A: Summary statistics for Information Uncertainty (IU) variables

	Number of firm-months	Mean	10%	Lower quartile	Median	Upper quartile	90%	Standard deviation
Firm Age	791,250	224	33	69	159	317	534	198
Volatility	791,250	0.023	0.010	0.014	0.020	0.028	0.040	0.016
Volume	757,638	0.382	0.050	0.097	0.206	0.421	0.854	0.633
Duration	580,375	15.541	11.969	14.189	15.917	17.204	18.234	3.076

Panel B: Pairwise correlations between Information Uncertainty (IU) cariables

	Firm age	Volatility	Trading volume	Duration
Firm Age	–	−0.229	−0.181	−0.160
Volatility	−0.282	–	0.455	0.272
Volume	−0.196	0.480	–	0.271
Duration	−0.221	0.315	0.339	–

This table presents summary statistics for the key variables used in this paper. Our sample consists of all firms listed on NYSE/AMEX/NASDAQ between 1965 and 2001, excluding closed-end funds, REIT, ADR, and foreign companies. In addition, we exclude any firm whose market capitalization as of the portfolio formation date is less than \$150 million in year 2001 dollars (adjusting for inflation), as well as any firm with less than 12 months of past returns data on CRSP. At the beginning of each event month t, we compute the following information uncertainty (IU) variables for each firm: *Firm Age* is defined as the number of months between event month t and the first month that a stock appears in CRSP; *Volatility* is defined as the standard deviation of daily returns for the past 25 trading days; and *Volume* is defined as the average daily turnover in percentage over the past six months, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day. *Duration* is a measure of how long in years it takes for the price of a stock to be repaid by its internal cash flows (see Appendix A for details). In Panel B, Pearson correlation coefficients are shown above the diagonal, while Spearman correlation coefficients are shown below the diagonal. All correlation coefficients are significant at 1% level.

3. Empirical Results

3.1. The Mean Effect of Information Uncertainty

Table 2 reports the average monthly return to portfolios formed on each of the four information uncertainty proxies. To construct this table, we calculate these variables for each sample firm at the beginning of every month. Starting in January 1965, each month we sort all stocks using one of the four IU proxies into 10 equal-weighted portfolios. Table values represent the average monthly return for each portfolio over the next K months, where $K = 6$ or 12. The numbers in parentheses represent simple time-series t-statistics for the average monthly returns.

Table 2 shows that high-IU firms generally earn lower average returns over the next six to twelve months. For example, panel A shows that firms in the youngest decile earn average monthly returns of 0.89% over the next six months. This is significantly (−0.23%) lower than the average monthly returns earned by the oldest

Table 2. Returns to Information Uncertainty Portfolios.

Panel A: Monthly Returns to Firm Age Portfolios	V1 (Oldest)	V2	V3	V4	V5	V6	V7	V8	V9	V10 (Youngest)	V10–V1
$K=6$	1.11 (15.90)	1.25 (16.66)	1.11 (14.72)	1.18 (14.97)	1.22 (14.63)	1.19 (13.77)	1.14 (11.42)	1.20 (11.82)	0.99 (9.94)	0.89 (8.17)	−0.23 (−3.46)
$K=12$	1.11 (24.88)	1.25 (25.21)	1.10 (23.23)	1.17 (23.59)	1.22 (23.41)	1.21 (21.88)	1.12 (17.10)	1.12 (17.87)	0.98 (15.26)	0.80 (15.02)	−0.31 (−6.38)
Panel B: Monthly Returns to Volatility Portfolios	V1 (Lowest)	V2	V3	V4	V5	V6	V7	V8	V9	V10 (Highest)	V10–V1
$K=6$	1.09 (16.73)	1.16 (16.87)	1.20 (16.69)	1.23 (16.55)	1.24 (15.67)	1.25 (14.92)	1.23 (13.30)	1.16 (11.36)	1.02 (8.76)	0.62 (4.65)	−0.47 (−4.36)
$K=12$	1.10 (23.94)	1.15 (25.12)	1.17 (24.61)	1.20 (24.88)	1.21 (23.88)	1.21 (22.59)	1.18 (20.31)	1.12 (17.22)	1.01 (13.60)	0.67 (7.96)	−0.43 (−5.62)
Panel C: Monthly Returns to Trading Volume Portfolios	V1 (Lowest)	V2	V3	V4	V5	V6	V7	V8	V9	V10 (Highest)	V10–V1
$K=6$	1.20 (17.80)	1.19 (17.04)	1.18 (16.55)	1.19 (16.10)	1.18 (15.26)	1.17 (13.99)	1.15 (12.55)	1.14 (11.55)	1.10 (9.87)	0.83 (6.58)	−0.37 (−3.87)
$K=12$	1.21 (26.60)	1.16 (24.99)	1.17 (25.68)	1.17 (25.26)	1.16 (23.46)	1.16 (21.75)	1.12 (19.06)	1.12 (17.19)	1.06 (14.43)	0.82 (10.15)	−0.39 (−5.95)
Panel D: Monthly Returns to Duration Portfolios	V1 (Lowest)	V2	V3	V4	V5	V6	V7	V8	V9	V10 (Highest)	V10–V1
$K=6$	1.57 (17.66)	1.42 (17.83)	1.31 (17.43)	1.25 (17.05)	1.20 (15.11)	1.16 (14.52)	1.12 (13.29)	1.11 (12.76)	1.04 (11.18)	0.96 (8.27)	−0.61 (−6.98)
$K=12$	1.53 (26.09)	1.40 (27.00)	1.31 (26.93)	1.23 (25.92)	1.18 (23.50)	1.13 (21.80)	1.11 (20.25)	1.05 (18.92)	0.97 (16.22)	0.90 (12.16)	−0.63 (−10.28)

This table presents average monthly returns to portfolios formed on four information uncertainty (IU) proxies. See Table 1 for a description of the sample and for definitions of the four IU variables. Starting in January of 1965, each month we sort all stocks using one of the four IU proxies into 10 equal-weighted portfolios, and document the average monthly returns over the next K months, where $K=6$ or 12. To avoid serial-correlation problems in computing test statistics, monthly holding period returns are defined as the equal-weighted average of returns from strategies initiated at the beginning of this month and the past $K-1$ months. The numbers in parentheses represent simple time-series t-statistics for the average monthly returns.

Table 3. Average monthly returns to portfolios based on Information Uncertainty (IU) and price momentum.

Portfolio	Average monthly returns				Average number of observations		
	V1	V2	V3	V3–V1	V1	V2	V3
Panel A: Portfolios based on firm age and past price momentum							
R1	0.85 (8.10)	0.57 (5.18)	0.19 (1.63)	−0.66 (−11.48)	44	58	76
R5	1.15 (16.12)	1.18 (14.88)	1.00 (11.26)	−0.15 (−3.66)	70	58	50
R10	1.43 (15.75)	1.63 (14.80)	1.80 (14.40)	0.36 (6.32)	35	60	83
R10–R1	**0.58 (7.50)**	**1.06 (13.42)**	**1.60 (18.94)**	**1.02 (16.57)**			
Panel B: Portfolios based on volatility and past price momentum							
R1	0.95 (10.23)	0.80 (7.97)	0.21 (1.69)	−0.74 (−10.63)	23	47	107
R5	1.17 (16.45)	1.22 (14.90)	0.86 (7.99)	−0.31 (−4.36)	80	60	37
R10	1.46 (19.59)	1.79 (18.54)	1.64 (12.38)	0.17 (2.05)	25	46	106
R10–R1	**0.51 (8.38)**	**0.99 (16.00)**	**1.43 (17.94)**	**0.92 (15.04)**			
Panel C: Portfolios based on trading volume and past price momentum							
R1	0.74 (7.89)	0.51 (4.86)	0.27 (2.20)	−0.48 (−9.11)	33	48	90
R5	1.19 (17.29)	1.15 (14.61)	0.98 (9.40)	−0.21 (−2.24)	74	59	38
R10	1.58 (17.17)	1.72 (16.59)	1.66 (13.38)	0.08 (1.01)	25	44	100
R10–R1	**0.84 (10.58)**	**1.20 (14.97)**	**1.40 (17.36)**	**0.56 (8.60)**			
Panel D: Portfolios based on duration and past price momentum							
R1	1.04 (9.12)	1.13 (10.57)	0.53 (4.78)	−0.50 (−8.60)	27	35	59
R5	1.40 (18.24)	1.10 (14.50)	0.92 (10.50)	−0.49 (−8.35)	51	48	36
R10	1.81 (18.67)	1.74 (15.83)	1.88 (14.78)	0.08 (1.12)	35	34	54
R10–R1	**0.77 (9.95)**	**0.61 (6.97)**	**1.35 (15.79)**	**0.58 (9.24)**			

This table presents average monthly returns to portfolios formed by independent two-way sorts on information uncertainty proxies and past returns. See Table 1 for a description of the sample and for definitions of the four IU variables. At the beginning of each month, stocks are sorted based on an IU proxy into three equal-weighted portfolios, and independently sorted on past six-month returns into 10 portfolios. To avoid potential microstructure biases, we compute past returns after imposing a one-week lag. V3 represents the highest IU portfolio (young, high volatility, high volume or high duration), while V1 represents the lowest IU portfolio (old, low volatility, low volume or low duration). R1 represents the loser portfolio and R10 represents the winner portfolio. Table values are the average monthly return for each portfolio over the next six months. The portfolio returns for each month is computed as an equal-weighted average of returns from strategies initiated at the end of each of the past *six* months. The *t*-statistics in parentheses are simple *t*-statistics for monthly returns. The three columns on the right report the average number of firms per month in each sub-portfolio.

decile firms. However, the relation between Firm Age and returns is not monotonic across the 10 portfolios. The most striking pattern is that the youngest firms (i.e. deciles 9 and 10) tend to underperform all other firms.

A similar pattern is observed when firms are sorted on Volatility or Volume. High volatility firms earn lower returns than low volatility firms (panel B). Similarly, high turnover firms earn lower returns than low turnover firms (panel C). These differences (V10–V1) range from −0.37% to −0.47% per month, and appear both statistically and economically significant. Interestingly, the effect is again asymmetric. In each case, the returns for the highest IU (high volatility or high volume) decile is distinctly lower than the returns for the other deciles; but we do not find a symmetrical increase in the returns of the low-IU portfolios. These findings are strikingly consistent with the Miller (1977) argument that short-selling constraints play an important role in the lower returns earned by firms with divergent private valuations.

Like the first three IU measures, the mean effect for *Duration* is in the expected direction. Specifically, panel D shows high duration fines underperform low duration firms by an average of 0.61–0.63% per month. This mean effect is stronger than the effect observed for the other three variables. However, average returns across the *Duration* deciles are monotonic, and do not fit the pattern predicted by the IU hypothesis. One possible explanation is that duration is not a pure IU proxy—i.e., high duration firms are also ‘‘glamour’’ stocks and low duration firms are also ‘‘value’’ stocks. Thus, part of the higher returns to low duration stocks might be due to general under-pricing of value firms.

3.2. Interaction with Price Momentum

Table 3 presents average monthly returns to portfolios formed by independent two-way sorts on information uncertainty proxies and past returns. To construct this table, stocks are sorted at the beginning of each month on each IU variable, and divided into three equal-weighted portfolios; we also independently sort stocks on past six-month returns into 10 portfolios (after imposing a one-week lag). V3 represents the highest IU portfolio (young, high volatility, high volume, or long duration), while V1 represents the lowest IU portfolio (old, low volatility, low volume, or short duration). R1 represents the loser portfolio and R10 represents the winner portfolio. Table values are the average monthly return for each portfolio over the next six months (results are similar for 3, 9, and 12 month holding periods). The portfolio return for each month is computed as an equal-weighted average of returns from strategies initiated at the end of each of the past *six* months. The *t*-statistics in parentheses are simple *t*-statistics for monthly returns. The columns on the right report the average number of firms per month in each sub-portfolio.

This table reveals two striking patterns. First, the mean effect of IU is largely driven by losers (R1–R5 stocks). This is evident by examining the V3–V1 column. The underperformance of young, volatile, high turnover, and long duration firms is significant for R1 and R5, but is not evident in R10. Thus, consistent with Miller (1977), the mean effect associated with IU variables is only exploitable by either shorting or underweighting high-IU stocks. Little can be gained by buying low-IU firms. Indeed, among winners (R10 stocks), we find that high-IU firms actually outperform low-IU firms in all four panels.

Second, this table shows that the momentum effect (R10–R1) is much stronger for high-IU firms. Among younger firms (V3 by Age), losers earn 0.19% per month and winners earn 1.80%, resulting in a momentum hedge return of 1.60% per month. Among older firms (V1 by Age), the return to the R10–R1 portfolio is only 0.58% per month. Thus, the momentum effect is almost three times as large among young firms. A similar pattern is observed for volatility, volume, and duration. In each case, returns to a momentum strategy are significantly larger for high-IU firms. The difference appears economically significant, and ranges from 0.56% to 1.02% per month.

Because these sorts are conducted independently, a possible concern is that the results are based on insufficient number of firms in the extreme cells. The right-hand-side columns address this issue. These table values represent the average number of firms per month in each sub-portfolio. For example, a strategy of buying young winners and shorting young losers would involve an average of 76 firms on the short side and 83 firms on the long side. A similar high-IU momentum strategy would involve 106 firms long and 107 firms short for volatility; 100 longs and 90 shorts for volume; and 54 long and 59 shorts for duration. These seem to be reasonable portfolio sizes, suggesting that our results are not due to a few unusual firms.

Recognizing that each of the four IU proxies is unlikely to fully capture the theoretical construct we have in mind, Table 4 reports results using *combined* measures of IU—i.e., IU portfolios formed on the basis of two or more of the four IU proxies. In panel A, membership in the high-IU (low-IU) portfolio is defined using two IU variables. For example, in the first row, we report results when IU = f(Firm Age and Volatility). In other words, a firm is deemed to be high-IU (low-IU) if it is in the upper-(lower-) third by both Age and Volatility. The second row repeats the procedure with IU defined by Age and Volume.

In panel B, we report results when membership in High and Low IU portfolios is based on three IU variables—i.e., a firm must be in the upper (or lower) tertile by three IU measures. In panel C, we define IU in terms of all four variables. To ensure a sufficient number of firms for each sub-portfolio, we sort stocks into just *five* momentum portfolios, with R1 representing the loser portfolio and R5 representing the winner. Table values represent average monthly returns for price momentum strategies (R5–R1), with simple time-series *t*-statistics reported in parentheses. The average number of firms in each extreme sub-portfolio (R1 or R5) is reported in the right side of each panel.

Table 4 results show that the patterns observed using single IU measures simply become stronger when we define IU using more than one proxy. In all three panels, the momentum effect (R5–R1) is much stronger for high-IU portfolios. In fact, a high-IU momentum strategy yields average monthly returns that range from 1.26% (panel A: IU = volume + duration) to 1.82% (panel C: IU = age + volume + volatility + duration). The difference in momentum profits between high-IU and low-IU firms range between 1.05% and 1.92% per month—results that are two to three times larger than when IU was defined using only one empirical measure. The average number of firms per high-IU portfolio range from 27 to 107, suggesting that these are reasonably sized portfolios.

Table 4. Average Monthly Returns to Portfolios formed using *Combined* Measures of Information Uncertainty (IU) and Past Price Momentum.

	Average monthly returns for price momentum strategy winners minus losers (R5–R1)			Number of observations			
	Low IU	High IU	High-Low	High IU		Low IU	
				R1	R5	R1	R5
Panel A: IU is based on two variables							
IU = f (two variables)							
Age and Volatility	0.14 (2.78)	1.51 (19.46)	1.37 (20.47)	83	87	34	27
Age and Volume	0.21 (3.13)	1.56 (19.19)	1.35 (19.42)	58	70	28	19
Age and Duration	0.20 (2.83)	1.36 (17.84)	1.16 (15.03)	49	50	27	27
Volatility and Volume	0.25 (4.28)	1.30 (17.55)	1.05 (15.34)	97	107	34	27
Volatility and Duration	0.22 (3.85)	1.34 (15.73)	1.11 (14.31)	65	58	21	25
Volume and Duration	0.20 (3.51)	1.26 (14.55)	1.06 (12.96)	53	55	20	22
Panel B: IU is based on three variables							
IU = f (three variables)							
Age, Volatility and Volume	0.04 (0.63)	1.71 (17.96)	1.67 (16.63)	47	54	15	10
Age, Volatility and Duration	0.27 (4.28)	1.52 (15.68)	1.24 (12.65)	37	35	11	11
Age, Volume and Duration	0.05 (0.49)	1.55 (14.96)	1.50 (12.90)	28	30	9	8
Volatility, Volume and Duration	0.14 (1.87)	1.33 (13.88)	1.19 (10.81)	42	41	10	10
Panel C: IU is based on four variables							
IU = f (four variables)							
Age, Volatility, Volume and Duration	−0.10 (−1.00)	1.82 (13.42)	1.92 (10.59)	27	27	6	5

This table presents average monthly returns to portfolios formed on independent two-way sorting on information uncertainty (IU) proxies and past returns. See Table 1 for a description of the sample and for definitions of the four IU variables. At the beginning of each month, stocks are sorted monthly based on an IU proxy into three equal-weighted portfolios, and independently sorted on past six-month returns into *five* portfolios. To avoid potential microstructure biases, we compute past returns after imposing a one-week lag. For each panel, we define high-IU and low-IU firms differently, using combinations of each of the four IU proxies. In each case, a stock must be in the highest (lowest) IU tertile by all the IU variables to be included in the high (low) IU portfolio. We also sort firms into quintiles based on returns over the past six months, with R1 represents the loser portfolio and R5 represents the winner portfolio. Table values are the average monthly return for the R5-R1 portfolio over the next six months. The portfolio return for each month is computed as an equal-weighted average of returns from strategies initiated at the end of each of the past six months. The *t*-statistics in parentheses are simple *t*-statistics for monthly returns. The three columns on the right report the average number of firms per month in each sub-portfolio.

3.3. *Interaction with Earning Momentum*

Thus far, our results show a strong interaction effect between IU and price momentum. One possible concern with price momentum is that it reflects changes in risk or investor sentiment, rather than fundamental news about a company. We

Table 5. Average monthly returns to portfolios gormed using *combined* measures of information uncertainty (IU) and past earnings momentum.

	Average monthly returns for darnings momentum strategy: winners minus losers (R5–R1)			Number of observations			
	Low IU	High IU	High-Low	High IU		Low IU	
				R1	R5	R1	R5
Panel A: IU is based on two variables							
IU = f (two variables)							
Age and Volatility	0.99 (22.21)	2.36 (35.52)	1.37 (17.91)	61	51	32	35
Age and Volume	1.02 (18.64)	2.55 (32.52)	1.53 (18.52)	42	40	25	26
Age and Duration	0.84 (15.38)	2.15 (28.53)	1.31 (15.10)	31	31	37	35
Volatility and Volume	1.30 (34.99)	2.19 (31.70)	0.89 (12.21)	77	63	28	38
Volatility and Duration	1.03 (25.71)	1.94 (29.65)	0.91 (12.80)	44	37	29	38
Volume and Duration	1.22 (23.90)	2.10 (26.66)	0.88 (10.40)	36	34	28	35
Panel B: IU is based on three variables							
IU = f (three variables)							
Age, Volatility and Volume	0.99 (18.89)	2.66 (26.96)	1.67 (16.16)	33	28	13	14
Age, Volatility and Duration	0.79 (14.97)	2.21 (24.59)	1.42 (13.01)	23	21	15	16
Age, Volume and Duration	0.81 (10.98)	2.55 (23.11)	1.74 (14.84)	17	16	11	12
Volatility Volume and Duration	1.14 (24.51)	2.23 (23.60)	1.08 (10.68)	27	23	13	18
Panel C: IU is based on four variables							
IU = f (four variables)							
Age, Volatility, Volume and Duration	0.77 (11.97)	2.51 (19.74)	1.74 (12.82)	15	13	6	8

This table presents average monthly returns to portfolios formed on independent two-way sorting on information uncertainty (IU) proxies and earnings momentum. We define earnings momentum in terms of the average monthly revision in the analysts' consensus FY1 earnings forecast over the past three months, each scaled by the end-of-month price. See Table 1 for a description of the sample and for definitions of the four IU variables. In addition, the firm must have analysts' consensus FY1 earnings forecasts in past *three* months on I/B/E/S. At the beginning of each month, stocks are sorted monthly based on an IU proxy into three equal-weighted portfolios, and independently sorted on cumulative price-deflated revisions in the past three months into *five* portfolios. For each panel, we define high-IU and low-IU firms differently, using combinations of each of the time IU proxies. In each case, a stock must be in the highest (lowest) IU portfolio by all the IU variables to be included in the high (low) IU portfolio. We also sort firms into quintiles based on earnings momentum, with R1 representing the loser portfolio and R5 represents the winner portfolio. Table values are the average monthly return for the R5–R1 portfolio over the next six months, The portfolio returns for each month is computed as an equal-weighted average of returns from strategies initiated at the end of each of the past *six* months. The *t*-statistics in parentheses are simple *t*-statistics for monthly returns.

address this issue by examining the interaction between IU and earnings momentum (defined by recent changes in the consensus FY1 forecast).

Table 5 reports average monthly returns to combined measures of IU and portfolios formed on earnings momentum. The construction of this table is analogous to that of Table 4, except we form momentum quintile portfolios using the analyst

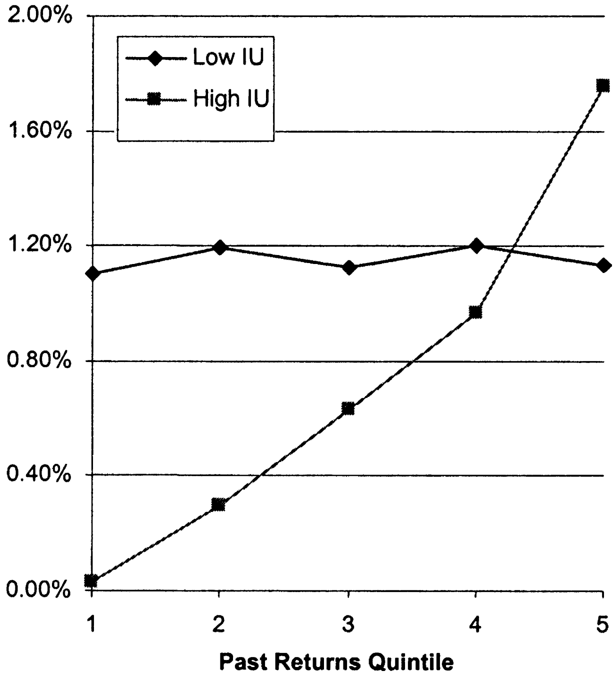

Figure 2. Average monthly returns to portfolios formed using combined measures of information uncertainty (IU) and past price momentum. This figure depicts average monthly returns to portfolios formed by independent two-way sorting on information uncertainty (IU) proxies and past returns. At the beginning of each month, we compute the following information uncertainty (IU) variables for each firm: *Firm Age*, *Volatility*, and *Volume*, as defined in Table 1, At the beginning of each month, stocks are sorted based on an IU proxy into three equal-weighted portfolios, and independently sorted on past six-month returns into *five* portfolios. A stock must be in the highest (lowest) IU portfolio by all the IU variables to be included in the high (low) IU portfolio. R1 represents the loser portfolio and R5 represents the winner portfolio. We compute the average monthly return for each portfolio over the next six months. The portfolio returns for each month is computed as an equal-weighted average of returns from strategies initiated at the end of each of the past *six* months.

revision variable, rev_{it}, defined earlier. In this table, R5 (winners) are firms with the most positive revisions over the past three months, and R1 (losers) are firms with the most negative revisions over the past three months. Table values represent the average monthly returns to earnings momentum strategies (R5–Rl) in different IU sub-portfolios.

Table 5 results show that IU variables also have a strong interaction effect with earnings momentum—i.e., hedge returns to analyst revision strategies are much stronger for high-IU firms than for low-IU firms. Overall, earnings momentum strategies seem to produce higher returns than price momentum strategies in our sample (this result holds for both high and low-IU firms). The returns to earnings momentum strategies (R5–R1) in high-IU firms are particularly striking, ranging from 1.94% per month to 2.66% per month. Returns to earnings momentum strategies in low-IU firms, while also significant, are much more muted at 0.77–1.30% per

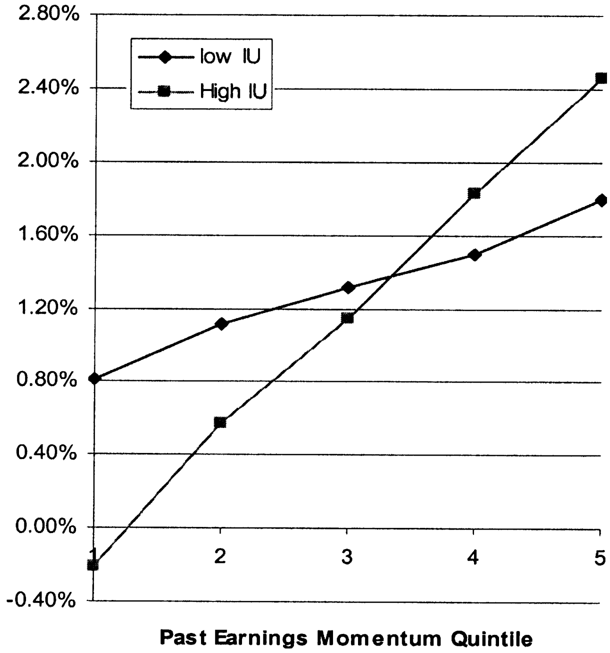

Figure 3. Average monthly returns to portfolios formed using combined measures of information uncertainty (IU) and earnings momentum. This figure depicts average monthly returns to portfolios formed by independent two-way sorting on information uncertainty (IU) proxies and past analysts' earnings forecast revisions. At the beginning of each month, we compute the following information uncertainty (IU) variables for each firm: *Firm Age*, *Volatility*, and *Volume*, as defined in Table 1. At the beginning of each month, stocks are sorted based on an IU proxy into three equal-weighted portfolios, and independently sorted on cumulative price-deflated revision in the past three months *into five* portfolios. A stock must be in the highest (lowest) IU portfolio by all the IU variables to be included in the high (low) IU portfolio. R1 represents the loser portfolio and R5 represents the winner portfolio. We compute the average monthly return for each portfolio over the next six months. The portfolio returns for each month is computed as an equal-weighted average of returns from strategies initiated at the end of each of the past *six* months.

month. The difference in profitability between high and low-IU firms is highly significant in every partition. The number of firms in each sub-portfolio is much smaller, due to the requirement that all firms have analyst coverage. Nevertheless, even in the most constrained sample (panel D: IU = f (four variables)), the long portfolio averaged 13 stocks per month and the short portfolio averaged 15 stocks.

Figures 2 and 3 provide a graphical summary of these results. These figures present the average monthly returns to portfolios formed by independent two-way sorts on IU and momentum. We use a combined measure of information uncertainty that incorporates three of the four IU proxies (IU = V + V + A).[20] Each IU variable is used to sort firms into three tertiles, and high-IU firms are defined as those in the top tertile of each IU proxy. We also independently sort firms into quintiles by either price momentum (Figure 2) or earnings momentum (Figure 3). In both figures R5 represents winner portfolios and R1 represents loser portfolios.

Table 6. Industry Distribution of Sample.

SIC	Industry name	Overall sample	High IU (V + V)	% of overall sample	High IU (V + V + A)	% of overall sample
73	Business Services	38,592	15,116	39.2%	10,557	27.4%
80	Health Services	9,720	3,534	36.4%	2,360	24.3%
36	Electronic/Electrical Equip and Component (Except Computer Equip)	44,537	17,188	38.6%	7,987	17.9%
87	Engineering, Accounting, Research, Management and Related Services	6,733	1,849	27.5%	1,142	17.0%
57	Home Furniture, Furnishing and Equipment Stores	2,989	1,221	40.8%	476	15.9%
75	Automotive Repair, Services and Parking	1,897	494	26.0%	292	15.4%
35	Industrial and Commercial Machinery and Computer Equipment	47,375	14,789	31.2%	7,250	15.3%
58	Eating and Drinking Places	8,185	2,111	25.8%	1,224	15.0%
82	Educational Services	1,475	344	23.3%	217	14.7%
79	Amusement and Recreation Services	3,481	819	23.5%	506	14.5%
78	Motion Pictures	3,436	1,271	37.0%	418	12.2%
56	Apparel and Accessory Stores	6,730	1,836	27.3%	812	12.1%
70	Hotels, Rooming Houses, Camps and Other Lodging Places	5,197	1,771	34.1%	621	11.9%
50	Wholesale Trade—Durable Goods	10,773	2,309	21.4%	1,277	11.9%
38	Measuring/Analyzing/Controlling Instru/Photo/Medical/Optical Goods	24,970	7,357	29.5%	2,863	11.5%
59	Miscellaneous Retail	10,768	2,071	19.2%	1,233	11.5%
61	Non-depository Institutions	7,142	1,770	24.8%	807	11.3%
52	Building Materials, Hardware, Garden Supply and Mobile Home Dealers	2,235	468	20.9%	244	10.9%
89	Service, not Elsewhere Classified	1,176	161	13.7%	127	10.8%
45	Transportation by Air	8,546	3,839	44.9%	890	10.4%
13	Oil and Gas Extraction	25,203	6,357	25.2%	2,562	10.2%
48	Communications	21,044	3,492	16.6%	2,066	9.8%
15	Building Construction—General Contractors and Operative Builders	3,098	736	23.8%	298	9.6%
62	Security and Commodity Brokers, Dealers, Exchanges and Services	6,657	1,069	16.1%	596	9.0%
39	Miscellaneous Manufacturing Industries	6,437	1,391	21.6%	553	8.6%
17	Construction Special Trades Contractors	1,166	285	24.4%	98	8.4%
01	Agriculture Production-Crops	1,006	158	15.7%	84	8.3%
28	Chemicals and Allied Products	50,913	8,928	17.5%	4,057	8.0%
72	Personal Services	1,998	274	13.7%	157	7.9%
31	Leather and Leather Products	2,366	579	24.5%	184	7.8%
23	Apparel/Other Finished Prod Made From Fabrics and Similar Materials	5,943	1,082	18.2%	450	7.6%

Table 6. Continued.

SIC	Industry name	Overall sample	High IU (V + V)	% of overall sample	High IU (V + V + A)	% of overall sample
55	Automotive Dealers and Gasoline Service Stations	1,225	253	20.7%	88	7.2%
65	Real Estate	4,086	479	11.7%	264	6.5%
12	Coal Mining Services	1,461	371	25.4%	93	6.4%
30	Rubber and Miscellaneous Plastics Products	7,869	1,090	13.9%	495	6.3%
10	Metal Mining	7,824	1,911	24.4%	488	6.2%
53	General Merchandise	11,143	1,530	13.7%	650	5.8%
44	Water Transportation	2,495	488	19.6%	145	5.8%
24	Lumber and Wood Products (Except Furniture)	4,302	784	18.2%	234	5.4%
47	Transportation Services	1,649	134	8.1%	81	4.9%
16	Heavy Construction (Except Building Construction Contractors)	2,946	552	18.7%	143	4.9%
33	Primary Metal Industries	18,599	3,323	17.9%	879	4.7%
51	Wholesale Trade—Non-durable Goods	9,689	1,088	11.2%	447	4.6%
63	Insurance Carriers	23,408	2,006	8.6%	969	4.1%
22	Textile Mill Products	6,932	899	13.0%	286	4.1%
42	Motor Freight Transportation and Warehousing	3,594	361	10.0%	134	3.7%
67	Holding and Other Investment Offices	41,202	3,436	8.3%	1,456	3.5%
34	Fabricated Metal Products (Except Machine and Transport Equipment)	15,856	1,837	11.6%	560	3.5%
37	Transportation Equipment	21,475	3,912	18.2%	752	3.5%
64	Insurance Agents, Brokers and Service	2,543	147	5.8%	88	3.5%
27	Printing, Publishing and Allied Industries	14,692	1,248	8.5%	468	3.2%
29	Petroleum, Refining and Related Industries	12,289	1,364	11.1%	330	2.7%
20	Food and Kindred Products	24,968	2,080	8.3%	607	2.4%
26	Paper and Allied Products	13,767	1,135	8.2%	329	2.4%
32	Stone, Clay, Glass and Concrete Products	9,381	866	9.2%	218	2.3%
14	Nonmetallic Minerals	1,848	345	18.7%	41	2.2%
54	Food Stores	7,952	475	6.0%	168	2.1%
60	Depository Institutions	37,711	1,505	4.0%	722	1.9%
25	Furniture and Fixtures	3,523	226	6.4%	67	1.9%
40	Railroad Transportation	5,347	559	10.5%	74	1.4%
49	Electric, Gas and Sanitary Services	59,859	1,570	2.6%	652	1.1%
21	Tobacco Products	1,739	98	5.6%	11	0.6%
	Miscellaneous	3,184	341	10.7%	261	8.2%
		756,346	141,082	18.7%	64,608	8.5%

This table presents the number and the percentage of firm-months represented by high-IU stocks for each industry, defined by two-digit SIC code. Information uncertainty (IU) proxies (*Firm Age*, *Volatility* and *Volume*) are defined as in Table 1. At the beginning of each month starting January of 1965, all stocks are independently sorted into *three* equal-weighted portfolios using each IU variable. We identify two groups of high-IU firms: (V + V) firms are firms that in the high-IU portfolio as measured by both volume and volatility, and (V + V + A) firms are firms that are in the high-IU portfolio as measured by three IU measures: firm age, volatility and volume. We report the proportion of high-IU firms-months by industry, starting with the highest IU percentage industries as defined using (V + V + A). Our sample consists of all firms listed on NYSE/AMEX/NASDAQ between 1965 and 2001. We exclude all closed-end funds, REIT, ADR, and foreign companies. We also exclude firms with a market capitalization of less than 150 million in year 2001 dollars (after adjusted for inflation) as of the portfolio formation date, as well as any firm with less than 12 months of past returns. Industry groups with less than 1,000 firm-months are reported in the Miscellaneous category.

These two figures illustrate: (1) the mean effect, that is, high-IU firms generally earn lower returns than low-IU firms; and (2) the interaction effect, that is, the return difference (spread) between R5 and R1 portfolios is much larger for high-IU firms. In the case of price momentum (Figure 2), hedge returns to the momentum strategy are non-existent for low-IU firms (i.e., returns for all five momentum quintiles are essentially the same). In contrast, for the high-IU firms, the effect results in a return spread of more than 1.70% per month between R5 and R1 firms.

In the case of earnings momentum (Figure 3), the post-revision price drift is also much smaller for low-IU firms than for high-IU firms. In low-IU firms, the post-revision price drift yields an average return spread of 0.99% per month over the next six months. For high-IU firms, the same post-revision strategy produces an average return spread of 2.66% per month.

3.4. Industry Distribution by Information Uncertainty

Table 6 provides additional information on the industries that have the highest and lowest concentration of high-IU firms. This table groups all the firm-months in our sample by two-digit SIC codes, and reports the proportion of firm-months in each industry that falls into the category of "high-IU". We define "high-IU" in two ways: first, using just volume and volatility (IU = V + V), so that high-IU firms are those in the upper third by both volume and volatility each month; and second, by three IU proxies (IU = V+ V + A), so that high-IU firms are those in the upper third by volume and volatility, and the lower third by age.[21] The results for each industry are presented in descending order according to the concentration of high-IU firms, where high IU is defined using the latter definition (IU = V + V + A).

The results show that the concentration of high (and low) IU firms varies quite widely by industry. In general, the following industries have a large proportion of firms in the high-IU category (2-digit SIC code in parentheses): Business Services

(73), Health Services (80), Electronic Equipment (36), Engineering, Research and Consulting Services (87), Home Furnishings Stores (57), Automotive Repairs (75), Industrial Machinery and Computer Equipment (35), Eateries (58), Educational Services (82), and Recreational Services (79). In short, service providers and technology-oriented firms are more heavily represented in the high-IU category. Using the most stringent definition for high IU (IU = V + V + A), the proportion of high-IU firm-months in these industries range from 14.5% to 27.4%. In terms of importance to the overall sample based on total number of observations, Business Services (73), Electronics (36) and Industrial and Computer Equipment (35) stand out among the high-IU industries.

In the other extreme, the following industries have relatively few firms in the high-IU category: Tobacco Products (21), Utilities (49), Railroads (40), Furniture Makers (25), Banks (60), Food Stores (54), Nonmetal Minerals (14), Stone, Clay, Glass and Concrete Products (32), Paper Products (26), and Food Products (20). In short, utilities, transportation-related, basic materials and capital goods companies tend to be under-represented in the high-IU category. In terms of importance to the overall sample, Utilities (49) and Banks (60) stand out among the low-IU industries.

Collectively, these results suggest that some industries are more momentum-oriented than others. In industries characterized by high-IU firms, rational arbitrage may call for a greater emphasis on momentum-related signals.

3.5. Risk-Adjustments and Robustness Checks

Thus far the results we have reported do not incorporate additional risk adjustments. In fact, prior studies have demonstrated the resilience of the price momentum phenomenon to the standard multi-factor risk adjustments (e.g., Fama, 1991; Jegadeesh and Titman, 1993; Grundy and Martin, 2001). However, we now turn to this issue to ensure our results are not driven by difference in risk in the long and short portfolios. We also seek to better understand the risk characteristics of the resulting hedge portfolios.

Table 7 reports the result of three-factor (Fama-French, 1993) time-series regressions of monthly excess returns for various price momentum and IU portfolios. For these regressions, we define firms in the high-IU portfolios as firms in the highest tertile by three measures (young, high volatility, and high volume); low-IU portfolios are firms in the lowest tertile by these measures (old, low volatility, and low volume). We use returns from the past six months ($J=6$) to form five momentum portfolios, where R1 represents the loser portfolio and R5 represents the winner portfolio.

For each portfolio, we estimate the following three-factor time-series regression:

$$r_i - r_f = a_i + b_i(r_m - r_f) + s_i\mathrm{SMB} + h_i\mathrm{HML} + e_i \tag{1}$$

where r_i is the return for portfolio i, r_m is the return on the NYSE/AMEX/NASDAQ value-weighted market index, SMB is the small firm factor, and HML is the

Table 7. Three-factor regressions of monthly excess returns on price momentum-information uncertainty portfolios.

	Low IU	High IU	High–low	Low IU	High IU	High–low	Low IU	High IU	High–low	Low IU	High IU	High–low	Low IU	High IU	High–low
	a			*b*			*s*			*h*			Adj. R^2 (%)		
Panel A: Full Sample (1965–2001)															
R1	0.432	−0.693	−1.125	0.141	0.235	0.094	0.065	0.245	0.180	0.132	−0.055	−0.187	15.62	27.54	21.17
	(5.81)	(−5.48)	(−10.15)	(7.60)	(7.43)	(3.39)	(2.73)	(6.01)	(5.04)	(4.72)	(−1.17)	(−4.50)			
R3	0.477	−0.049	−0.526	0.143	0.209	0.066	0.034	0.233	0.200	0.111	−0.127	−0.239	18.87	25.34	22.18
	(7.60)	(−0.37)	(−4.54)	(9.13)	(6.26)	(2.26)	(1.67)	(5.43)	(5.35)	(4.74)	(−2.55)	(−5.51)			
R5	0.510	1.102	0.593	0.127	0.184	0.057	0.055	0.249	0.194	0.042	−0.191	−0.233	12.43	23.64	16.54
	(6.61)	(7.56)	(4.47)	(6.56)	(5.04)	(1.73)	(2.21)	(5.29)	(4.53)	(1.47)	(−3.49)	(−4.69)			
R5–R1	0.077	1.796	1.718	−0.015	−0.051	−0.036	−0.011	0.003	0.014	−0.089	−0.136	−0.046	2.65	2.96	0.08
	(1.20)	(18.62)	(16.66)	(−0.92)	(−2.13)	(−1.41)	(−0.51)	(0.11)	(0.42)	(−3.68)	(−3.76)	(−1.20)			
Panel B: First Sub-Period (1965–1983)															
R1	0.230	−0.714	−0.933	0.148	0.266	0.119	0.064	0.365	0.301	0.031	−0.125	−0.155	17.26	33.76	29.81
	(2.05)	(−3.52)	(−6.28)	(5.11)	(5.11)	(3.08)	(1.64)	(5.19)	(5.78)	(0.73)	(−1.64)	(−2.75)			
R3	0.205	−0.270	−0.475	0.155	0.247	0.092	0.054	0.381	0.326	0.052	−0.190	−0.242	22.29	31.80	28.22
	(2.10)	(−1.25)	(−2.83)	(6.17)	(4.46)	(2.13)	(1.61)	(5.09)	(5.61)	(1.40)	(−2.35)	(−3.85)			
R5	0.361	0.771	0.409	0.147	0.200	0.053	0.084	0.402	0.318	−0.061	−0.176	−0.114	16.43	28.19	18.12
	(2.72)	(3.51)	(2.33)	(4.31)	(3.54)	(1.17)	(1.82)	(5.27)	(5.21)	(−1.23)	(−2.13)	(−1.73)			
R5 − R1	0.131	1.485	1.353	−0.001	−0.066	−0.066	0.020	0.037	0.017	−0.092	−0.051	−0.041	1.94	0.12	0.70
	(1.29)	(10.00)	(8.71)	(−0.02)	(−1.74)	(−1.65)	(0.56)	(0.71)	(0.31)	(−2.42)	(−0.91)	(0.70)			
Panel C: Second Sub-Period (1984–2001)															
R1	0.644	−0.681	−1.326	0.151	0.172	0.020	0.124	0.134	0.010	0.249	−0.099	−0.348	21.77	22.24	20.97
	(6.90)	(−4.45)	(−8.59)	(6.32)	(4.37)	(0.51)	(4.01)	(2.63)	(0.19)	(6.54)	(−1.59)	(−5.53)			
R3	0.741	0.142	−0.599	0.134	0.128	−0.006	0.057	0.107	0.050	0.172	−0.186	−0.358	20.43	21.54	21.88
	(9.88)	(0.90)	(−3.84)	(6.96)	(3.19)	(−0.14)	(2.27)	(2.04)	(0.96)	(5.61)	(−2.91)	(−5.63)			
R5	0.670	1.368	0.697	0.112	0.112	0.001	0.071	0.105	0.034	0.124	−0.309	−0.433	13.86	22.38	20.24
	(8.45)	(7.16)	(3.61)	(5.49)	(2.29)	(0.01)	(2.69)	(1.66)	(0.54)	(3.84)	(−3.97)	(−5.49)			

Table 7. Continued.

	Low IU	High IU	High–low	Low IU	High IU	High–low	Low IU	High IU	High–low	Low IU	High IU	High–low	Low IU	High IU	High–low
	a			*b*			*s*			*h*			Adj. R^2 (%)		
R5–R1	0.026	2.049	2.023	−0.040	−0.059	−0.020	−0.053	−0.029	0.025	−0.125	−0.210	−0.085	5.05	7.27	0.75
	(0.31)	(16.57)	(15.09)	(−1.87)	(−1.87)	(−0.57)	(−1.95)	(−0.70)	(0.56)	(−3.71)	(−4.17)	(−1.56)			

This table summarizes three-factor regression results for monthly returns on price momentum and information uncertainty (IU) portfolios for ($J=6$, $K=6$) portfolio strategies between January 1965 and December 2001. We report results for the whole sample period and two sub-periods. The three IU variables are defined as in Table 1. Low IU firms are in the lowest IU portfolio by three measures (old, low volatility, and low volume) while high-IU represent the firms in the highest IU portfolio (young, high volatility, and high volume). We use returns from the past six months ($J=6$) to form *five* momentum portfolios, where R1 represents the loser portfolio and R5 represents the winner portfolio. The three-factor regression is as follows: $r_i - r_f = a_i + b_i(r_m - r_f) + s_i\mathrm{SMB} + h_i\mathrm{HML} + e_i$ where r_m is the return on the NYSE/AMEX/NASDAQ value-weighted market index, SMB is the small firm factor, and HML is the value factor. The numbers within parentheses represent White heteroskedasticity corrected t-statistics.

value factor. The numbers in parentheses represent White heteroskedasticity corrected t-statistics.

Panel A reports results for the full sample period (1965–2001). These results show that high-IU portfolios have slightly higher Betas (see results for b), and are somewhat more sensitive to the SMB factor (see results for s). Also, high-IU stocks tend to behave like glamour stocks (i.e., they load negatively on the HML factor), while low-IU stocks tend to behave like value stocks (i.e., they have positive HML loadings). However, the estimated coefficients on the intercept variable (a) show that these risk adjustments do little to change the earlier results.

Like prior studies (e.g., Grundy and Martin, 2001), we find that price momentum profits are generally sharper (strong in magnitude with larger t-statistics) after controlling for other risk factors. We show that the mean negative performance of high-IU firms is largely in the loser (R1–R3) portfolios, and that the effect actually reverses for winners. Also, the interaction effects we find earlier between IU and momentum is clearly evident in this table. Momentum profits (R5–R1) for high-IU firms average 1.796% per month, while they are an insignificant 0.077% per month for low-IU firms.

Panels B and C report test results for the two sub-periods (1965–1983 and 1984–2001). These tables show that the same pattern holds in both halves of our sample. In fact, the mean effect and the interaction effect of IU are both stronger in the second half of the sample period. For the period 1984–2001, momentum profits in high-IU firms average 2.049% per month, compared to 0.026% per month for low-IU firms. The difference in momentum profits between high and low-IU firms is, in fact, over 2% per month.

Table 8 reports results of the same three-factor regressions using earnings momentum to form winner and loser portfolios. Compared to Table 7, these results show that the IU-hedge (high IU minus low IU) portfolios have no significant market (b) or size (s) exposure. However, these portfolios do tend to load negatively on the book-to-market factor (h). More importantly, these risk adjustments actually increase the abnormal returns (a) earned by earnings momentum strategies in high-IU firms to an average of 2.754% per month. Once again, the results are stronger in the second sub-period.

As a further test, we also conduct cross-sectional (Fam-MacBeth, 1973 type) regressions of stock returns on various firm characteristics. For this test, Size is defined as market capitalization at the beginning of the month; book-to-market ratio (BM) is book value of equity of the previous fiscal year divided by beginning-of-month market capitalization; price momentum (J6) is the average monthly returns in the six months before the beginning of the current month and earnings momentum (REV3) is the average forecast revision in the analyst consensus over the past three months.

In these tests, IU is a dummy variable denoting information uncertainty, which is defined differently for each set of regressions. In the first set of regressions for each panel, high-IU and low-IU firms are defined in terms of both volume and volatility (IU = volatility + volume). For the second set of regressions in each panel,

Table 8. Three-Factor Regressions of Monthly Excess Returns on Earnings Momentum–Information Uncertainty Portfolios.

	Low IU	High IU	High –low	Low IU	High IU	High –low	Low IU	High IU	High –low	Low IU	High IU	High –low	Low IU	High IU	High –low
	a			*b*			*s*			*h*			Adj. R^2 (%)		
Panel A: Full Sample (1977–2001)															
R1	0.099	−0.855	−0.955	0.151	0.175	0.025	0.094	0.138	0.044	0.175	−0.087	−0.261	17.45	21.39	18.08
	(1.20)	(−6.35)	(−7.82)	(7.27)	(5.19)	(0.80)	(3.51)	(3.17)	(1.12)	(5.57)	(−1.69)	(−5.64)			
R3	0.637	0.574	−0.063	0.116	0.131	0.015	0.023	0.113	0.090	0.97	−0.225	−0.322	14.65	21.01	18.67
	(10.03)	(3.74)	(−0.42)	(7.26)	(3.41)	(0.41)	(1.140)	(2.28)	(1.83)	(4.01)	(−3.86)	(−5.61)			
R5	1.138	1.898	0.760	0.116	0.157	0.041	0.053	0.053	−0.000	0.122	−0.276	−0.398	16.93	21.43	20.89
	(18.37)	(11.37)	(4.77)	(7.50)	(3.75)	(1.02)	(2.63)	(0.98)	(−0.00)	(5.17)	(−4.35)	(−6.58)			
R5–R1	1.038	2.754	1.715	−0.034	−0.018	0.016	−0.041	−0.085	−0.044	−0.053	−0.190	−0.136	3.07	8.40	5.14
	(19.40)	(28.11)	(16.43)	(−2.54)	(−0.73)	(0.61)	(−2.37)	(−2.69)	(−1.31)	(−2.62)	(−5.09)	(−3.44)			
Panel B: First Sub-Period (1977–1989)															
R1	0.140	−0.852	−0.992	0.136	0.139	0.003	0.051	0.167	0.116	0.033	−0.150	−0.183	14.61	21.73	10.43
	(1.21)	(−4.93)	(−7.03)	(4.48)	(3.31)	(0.10)	(1.02)	(2.40)	(2.03)	(0.62)	(−2.01)	(−3.00)			
R3	0.664	0.534	−0.130	0.112	0.107	−0.005	0.007	0.250	0.243	0.001	−0.326	−0.326	16.46	25.85	20.70
	(6.85)	(2.57)	(−0.72)	(4.77)	(2.12)	(−0.12)	(0.19)	(3.00)	(3.340)	(0.01)	(−3.64)	(−4.19)			
R5	1.228	1.870	0.642	0.099	0.138	0.039	0.044	0.177	0.133	−0.012	−0.335	−0.323	17.99	24.64	20.97
	(13.58)	(8.59)	(3.75)	(4.49)	(2.60)	(0.94)	(1.21)	(2.02)	(1.94)	(−0.36)	(−3.57)	(−4.37)			
R5–R1	1.088	2.722	1.634	−0.037	−0.001	0.036	−0.007	0.011	0.018	−0.045	−0.185	−0.140	0.89	6.13	3.92
	(14.07)	(19.30)	(9.70)	(−1.97)	(−0.04)	(0.87)	(−0.23)	(0.19)	(−0.26)	(−1.35)	(−3.05)	(−1.93)			
Panel C: Second Sub-Period (1990–2001)															
R1	0.111	−0.854	−0.965	0.163	0.213	0.049	0.149	0.143	−0.006	0.276	−0.041	−0.317	30.25	20.44	22.61
	(1.08)	(−4.05)	(−4.76)	(5.88)	(3.72)	(0.90)	(5.06)	(2.35)	(−0.11)	(7.50)	(−0.55)	(−4.35)			
R3	0.648	0.634	−0.013	0.110	0.116	0.006	0.053	0.066	0.013	0.156	−0.205	−0.361	19.66	17.53	18.16
	(8.27)	(2.79)	(−0.05)	(5.21)	(1.88)	(0.08)	(2.33)	(1.00)	(0.18)	(5.56)	(−2.52)	(−4.09)			
R5	1.089	1.932	0.843	0.126	0.145	0.019	0.087	0.002	−0.085	0.205	−0.278	−0.483	28.22	18.70	21.34
	(13.85)	(7.50)	(3.07)	(5.90)	(2.07)	(0.26)	(3.83)	(0.03)	(−1.07)	(7.28)	(−3.00)	(−4.90)			

Table 8. Continued.

	Low IU	High IU	High –low	Low IU	High IU	High –low	Low IU	High IU	High –low	Low IU	High IU	High –low	Low IU	High IU	High –low
	a			*b*			*s*			*h*			Adj. R^2 (%)		
R5–R1	0.978	2.786	1.808	−0.038	−0.068	−0.030	−0.063	−0.141	−0.078	−0.071	−0.236	−0.166	5.43	13.99	8.66
	(13.15)	(20.67)	(14.97)	(−1.87)	(−1.86)	(−0.93)	(−2.93)	(−3.63)	(−2.25)	(−2.64)	(−4.89)	(−3.82)			

This table summarizes three-factor regression results for monthly returns on earnings momentum and information uncertainty (IU) portfolios for portfolio strategies between January 1977 and December 2001. We report results for the whole sample period and two sub-periods. The three IU variables are defined as in Table 1. Low IU firms are in the lowest IU portfolio by three measures (old, low volatility, and low volume) while high IU represents the firms in the highest IU portfolio (young, high volatility, and high volume). We use cumulative price-deflated revisions in the past three months to form *five* earnings momentum portfolios, where R1 represents the loser portfolio and R5 represents the winner portfolio. The three-factor regression is as follows: $r_i - r_f = a_i + b_i (r_m - r_f) + s_i\text{SMB} + h_i\text{HML} + e_i$ where r_m is the return on the NYSE/AMEX/NASDAQ value-weighted market index, SMB is the small firm factor, and HML is the value factor. The numbers within parentheses represent White heteroskedasticity corrected t-statistics.

high-IU and low-IU firms are defined in terms of volatility, volume, as well as age (IU = Volatility + Volume + Age).

We then estimate the following cross-sectional regression each month:

$$\begin{aligned} R_i = a + b\ \mathrm{Size}_i + c\,\mathrm{BM}_i + d\ \mathrm{IU}(L)_i + e\ \mathrm{IU}(H)_i \\ + f\ J6_i + g\ J6_i^{*}\mathrm{IU}(L)_i + h\ J6_i^{*}\mathrm{IU}(H)_i + e_i \end{aligned} \tag{2}$$

where R_i is the average monthly return over the next six months. The independent variables are the decile ranks for Size, BM, and *J*, all scaled to have a value between zero and one. This scaling allows us to interpret the coefficient estimates as the average month return to a hedge portfolio that buys the top decile and sells the bottom decile of stocks with a particular characteristic. IU(H) is a dummy variable that assumes a value of one for firms belonging to the IU(H) group, and zero otherwise. IU(L) is a dummy variable that assumes a value of one for firms belonging to the IU(L) group, and zero otherwise. Table values are the time-series means of the estimated coefficients from the monthly regressions, with autocorrelation-corrected *t*-statistics reported in parenthesis (Table 9).

The results for panel A show that both the mean and interaction effects reported earlier survive in this cross-sectional test. As in prior studies, we find a small negative Size effect and a positive BM effect. We also find a mean effect in this test, such that IU(L) exhibits a modest, but significant, positive correlation with future returns. IU(H) exhibits a strongly negative correlation with future returns. The coefficients on $J6^{*}\mathrm{IU}(L)$ and $J6^{*}IU(H)$ show that momentum effects are sharply higher for high-IU firms and sharply lower for low-IU firms. These results hold when IU is defined using just volume and volatility, and becomes stronger when using three IU variables.

Panel B reports an analogous test using the earnings momentum variable (REV3) rather than the price momentum variable (*J6*). Once again, the variable we used in the regression is the decile rank of REV3, scaled to have a value between zero and one. The results in this panel confirm our previous findings—the mean effect is primarily in the high-IU firms (IU(H)). Moreover, even after controlling for REV3, we document a sharp interaction effect between REV3 and IU. This effect holds when IU is defined using just volume and volatility, and becomes stronger when using three IU variables.

Finally, we also examine the abnormal returns around quarterly earnings announcements for various momentum and IU portfolios. These tests are motivated by two concerns. First, we wish to address the critique that the abnormal returns we documented are due to a misspecified risk model. By focusing on short-windows around earnings announcements, we reduce the potential that the returns are due to inadequate risk controls. Second, if information cascades and other IU-related effects collapse with the release of public news about earnings, we should observe a concentration of abnormal returns around subsequent earnings release dates.

Table 10 reports four-day (day −2 to +1) cumulative abnormal returns (CAR) in percentages around quarterly earnings announcement dates for various momentum and IU portfolios. We use the value-weighted NYSE/AMEX/NASDAQ index as benchmark to compute CAR. High and low IU firms are defined using three proxies:

Table 9. Monthly Cross-Sectional Regression of Returns on Size, Book-to-Market, Price (Earnings) Momentum and Information Uncertainty (IU) Proxies.

Panel A: Results for Extreme IU Firms (Both High and Low IU): Price Momentum

$K=$	$J=$	IU =	Intercept	Size	BM	IU(L)	IU(H)	$J6$	$J6$*IU(L)	$J6$*IU(H)
6	6	Volatility + Volume	0.007 (2.29)	−0.003 (−2.01)	0.005 (2.73)	0.002 (2.92)	−0.006 (−4.50)	0.008 (5.91)	−0.005 (−5.12)	0.005 (4.52)
6	6	Volatility + Volume + Age	0.007 (2.25)	−0.003 (−1.93)	0.005 (2.74)	0.002 (2.34)	−0.009 (−5.16)	0.008 (5.32)	−0.005 (−3.56)	0.010 (6.15)

Panel B: Results for Extreme IU Firms (Both High and Low IU): Earnings Momentum

$K=$	$J=$	IU =	Intercept	Size	BM	IU(L)	IU(H)	REV3	REV3*IU(L)	REV3*IU(H)
6	6	Volatility + Volume	0.005 (1.75)	−0.004 (−2.51)	0.005 (1.80)	0.001 (0.54)	−0.004 (−3.29)	0.017 (15.19)	−0.003 (−3.40)	0.007 (3.87)
6	6	Volatility + Volume + Age	0.005 (1.68)	−0.004 (−2.58)	0.005 (1.78)	0.002 (1.89)	−0.008 (−4.94)	0.017 (15.99)	−0.006 (−6.42)	0.013 (5.39)

Each month from January 1965 to December 2001, we regress monthly individual stock returns on size, book-to-market ratio (BM), price momentum ($J6$), and three information uncertainty (IU) proxies: *Firm Age*, *Volatility*, and *Volume* as in Table 1. Each month from January 1977 to December 2001, we run the same regression with earnings momentum (REV3) replacing price momentum (J6). Size is market capitalization at the beginning of the month. BM is book value of equity as of the previous fiscal year divided by beginning-of-month market capitalization. Price momentum, $J6$, is the average monthly returns in the six months before the beginning of the current month, computed with a 1-week lag. Earnings momentum, REV3, is the cumulative price-deflated revisions in the past three months. At the beginning of each month from January 1965 (or January 1977), we independently rank firms on Size, BM, and $J6$ (or REV3) into 10 portfolios. The independent variables used in the regression are the decile ranks of Size, BM and $J6$ (or REV3), all scaled to have a value between zero and one. At the beginning of each month, we also independently sort stocks into *three* portfolios by Firm Age, Volatility and Volume. IU is a dummy variable that is defined differently for each set of regressions. For the first set of regressions in each panel, high-IU and low-IU firms are defined in terms of both volume and volatility (IU = volatility + volume). For the second set of regressions in each panel, high-IU and low-IU firms are defined in terms of volatility, volume, as well as age (IU = Volatility + Volume + Age). In Panel A, we compare results for the high-IU firms (IU (H)), low-IU firms (IU(L)), and the benchmark firms where price momentum (J6) is used. In Panel B, we compare results for the high-IU firms (IU(H)), low-IU firms (IU(L)), and the benchmark firms where earnings momentum (REV3) is used. Table values are the time-series means of the estimated coefficients from the monthly regressions. Autocorrelation corrected t-statistics are in parenthesis.

Firm Age, Volatility, and Volume. We report results for both price momentum (panels A and B) and earnings momentum (panels C and D). R5 represent winners and R1 represent losers. Quarter 0 is the most recent quarterly earnings announcement prior to the portfolio formation date. The sample is monthly observations from 1/1985 to 12/2001, representing the period during which we have I/B/E/S earnings announcement dates. The numbers in parentheses are Hansen-Hodrick *t*-statistics with six moving average lags.

Panel A results show that returns around subsequent earnings announcements of high-IU firms exhibit the predicted pattern. The aggregate high-IU sample does not earn abnormal returns around future quarterly earnings announcements (see top row; high-IU firms). However, high-IU winners (high IU R5) earn positive returns over the next three quarterly announcement periods, while high-IU losers (high IU R1) earn negative or insignificant positive returns. The difference (high IU R5–high IU R1) is significant for the next two quarters, and shows some sign of a reversal by the fourth quarter—a pattern reminiscent of the Bernard and Thomas (1990) result for post-earnings announcement drifts.

Panel B shows that, for low-IU firms, we find no abnormal return patterns around subsequent earnings announcements. For these firms, earnings announcement event window returns are not significantly different from zero (see top row; low-IU firms). Moreover, among low-IU firms, price momentum has no predictive power for event window returns—neither R1 nor R5 firms earn reliable returns around future earnings dates. In conjunction with the evidence in panel A, these results suggest that a significant portion of the returns to price momentum strategies in high-IU firms is due to investor misperceptions about future earnings.

Panels C and D repeat these tests for earnings momentum portfolios. Once again, we find that the IU proxy itself has no directional value in predicting future abnormal returns around quarterly earnings announcements (see top row of panels C and D). However, we find that the direction of past analyst forecast revisions has powerful ability to predict these short-window returns, especially among high-IU firms. Panel C shows that for high-IU firms, winner portfolios earn 2.95% more than loser portfolios around the next quarterly earnings announcement. This effect is smaller for low-IU firms, but is still quite significant at 1.43%. In both panels, we find that the predictive power of the earnings momentum variable decays quickly, suggesting that the information in past analyst revisions relates largely to the next quarterly announcement. Comparing the two panels, we find that the difference in momentum returns between high and low-IU firms (the last row in the table) is positive over the next three quarters, and turns negative in the fourth.

Overall, Table 10 findings indicate that the results we documented earlier are, at least in part, due to investor misperceptions about earnings news. We find that a substantial portion of the mispricing is corrected at the next quarterly announcement date. Perhaps more importantly, we show that this effect is significantly more pronounced for high-IU firms. These findings are suggestive of the fact that future earnings announcements play a more important role in resolving information uncertainty among high-IU firms.

Table 10. Abnormal Returns around Quarterly Earnings Announcements for Price/Earnings Momentum and Information Uncertainty Portfolios.

	Quarters								
Strategy	−4	−3	−2	−1	0	1	2	3	4
Panel A: High IU Price Momentum Portfolios									
High IU	1.40	1.36	1.16	0.88	0.59	0.22	0.14	0.11	0.16
	(5.26)	(5.30)	(4.76)	(4.08)	(2.49)	(1.11)	(0.84)	(0.56)	(0.70)
High IU R1	1.37	0.87	0.17	−2.48	−2.40	−0.35	−0.05	0.09	0.64
	(4.52)	(2.63)	(0.58)	(−8.90)	(−8.56)	(−1.28)	(−0.22)	(0.41)	(2.46)
High IU R5	1.58	1.74	2.25	3.93	3.45	0.72	0.63	0.25	0.11
	(6.83)	(7.68)	(7.92)	(13.87)	(11.93)	(2.90)	(2.51)	(1.06)	(0.35)
Difference	0.21	0.87	2.08	6.42	5.85	1.07	0.67	0.16	−0.53
(high IU R5–High IU R1)	(0.84)	(3.58)	(7.04)	(16.02)	(15.74)	(3.41)	(2.12)	(0.63)	(−1.84)
Panel B: Low IU Price Momentum Portfolios									
Low IU	−0.06	−0.04	−0.05	0.04	0.06	0.02	0.01	0.12	0.07
	(−0.83)	(−0.69)	(−0.81)	(0.57)	(0.82)	(0.22)	(0.17)	(1.66)	(0.87)
Low IU R1	0.04	−0.36	−0.02	−1.07	−1.22	0.25	0.16	0.10	0.13
	(0.19)	(−2.22)	(−0.11)	(−6.00)	(−6.55)	(1.01)	(0.77)	(0.48)	(0.60)
Low IU R5	0.05	0.17	0.06	1.61	1.48	0.09	0.23	0.00	0.28
	(0.23)	(0.89)	(0.28)	(7.42)	(6.44)	(0.43)	(0.75)	(0.01)	(1.43)
Difference	0.00	0.54	0.07	2.68	2.70	−0.16	0.07	−0.10	0.15
(low IU R5–low IU R1)	(0.01)	(1.88)	(0.29)	(10.33)	(8.94)	(−0.51)	(0.19)	(−0.25)	(0.56)
High IU difference–low IU difference	0.21	0.33	2.01	3.74	3.16	1.23	0.60	0.26	−0.68
	(0.49)	(0.91)	(5.17)	(7.81)	(9.91)	(3.59)	(1.31)	(0.56)	(−1.94)
Panel C: High IU Earnings Momentum Portfolios									
High IU	1.41	1.36	1.15	0.89	0.58	0.23	0.16	0.11	0.14
	(5.27)	(5.29)	(4.74)	(4.07)	(2.45)	(1.13)	(0.95)	(0.56)	(0.59)
High IU R1	0.67	0.18	−0.47	−1.38	−2.99	−1.14	−0.06	−0.14	0.38
	(1.92)	(0.57)	(−1.48)	(−5.32)	(−8.25)	(−4.38)	(−0.25)	(−0.56)	(1.32)
High IU R5	1.64	2.02	2.28	2.52	4.20	1.81	0.40	0.23	−0.01
	(4.86)	(6.56)	(8.41)	(10.23)	(12.93)	(6.20)	(1.41)	(0.99)	(−0.03)
Difference	0.97	1.84	2.75	3.90	7.19	2.95	0.47	0.38	−0.39
(high IU R5–high IU R1)	(2.94)	(6.01)	(9.73)	(13.07)	(15.11)	(8.97)	(1.21)	(1.54)	(−1.24)

Table 10. Continued.

Strategy	Quarters								
	−4	−3	−2	−1	0	1	2	3	4
Panel D: Low IU Earnings Momentum Portfolios									
Low IU	−0.06	−0.04	−0.04	0.04	0.06	0.01	0.01	0.12	0.07
	(−0.81)	(−0.60)	(−0.74)	(0.52)	(0.85)	(0.15)	(0.09)	(1.60)	(0.85)
Low IU R1	−0.20	−0.57	−0.48	−0.46	−0.80	−0.73	0.04	0.09	0.22
	(−1.68)	(−3.90)	(−3.36)	(−3.72)	(−6.36)	(−4.52)	(0.25)	(0.53)	(1.05)
Low IU R5	0.10	0.28	0.15	0.56	1.14	0.70	0.19	−0.16	0.14
	(0.79)	(1.67)	(1.34)	(3.53)	(6.84)	(4.80)	(1.68)	(−1.28)	(0.87)
Difference	0.30	0.85	0.63	1.02	1.94	1.43	0.15	−0.25	−0.08
(low IU R5–low IU R1)	(1.73)	(3.59)	(3.51)	(4.42)	(8.16)	(6.66)	(0.77)	(−1.45)	(−0.32)
High IU difference–low IU difference	0.67	0.99	2.11	2.88	5.26	1.52	0.32	0.63	−0.31
	(1.87)	(3.06)	(6.93)	(8.19)	(11.17)	(5.08)	(0.76)	(2.16)	(−0.89)

This table reports four-day (from day −2 to day +1) cumulative abnormal returns (CAR) in percentage around quarterly earnings announcement dates for various momentum and IU portfolios. The sample is monthly observations from 1/1985 to 12/2001. At the beginning of each month, we rank firms on price momentum (panels A and B) or earnings momentum (panels C and D) into *five* portfolios. R1 represents losers and R5 represents winners. Then we independently sort firms into *three* portfolios by Firm Age, Volatility and Volume. High-IU and low-IU firms are defined in terms of these three variables. Quarter 0 is the most recent earnings announcement prior to the portfolio formation date. Prior quarters are represented by $-k$, and subsequent quarters are represented by $+k$, where $k = 1$–4. To be included, we require firms to have announcement period CAR in all nine quarters. The NYSE/AMEX/NASDAQ value-weighted index is used as the benchmark in computing the CAR. The numbers in parentheses are Hansen-Hodrick t-statistics with six moving average lags.

4. Conclusion

In this study, we have explored the role of information uncertainty (IU) in the prediction of cross-sectional stock returns. We define IU in terms of "value ambiguity," or the precision with which a firm's value can be estimated by knowledgeable investors at reasonable cost. Using several different proxies for IU, we show that: (1) on average, high-IU firms earn lower future returns than low-IU firms (the "mean" effect), and (2) price and earnings momentum effects are much stronger among high-IU firms than among low-IU firms (the "interaction" effect).

The fact that IU is negatively correlated with future returns is difficult to reconcile with traditional asset pricing models, which either predict no role for IU in returns prediction, or a positive relation between IU and subsequent returns. We argue that this finding can be understood in terms of generally elevated levels of investor overconfidence in high-IU firms (DHS, 1998), in conjunction with market friction associated with short-selling constraints (Miller, 1977).

In support of this argument, we show that the lower returns earned by high-IU firms is generally concentrated in the highest-IU stocks, where short-sell constraints are likely to be a significant factor. Our analysis certainly does not preclude other explanations for these pricing anomalies. However, our findings suggest that IU might be an important dimension of the puzzle that deserves more attention from researchers.

We also introduce a behavioral-based framework for understanding how IU might affect price and earnings momentum. Behavioral finance theory asserts that market mispricings arise when two conditions are met: (1) an uninformed demand shock, and (2) a limit on arbitrage. Our two-part thesis is that the level of information uncertainty is positively correlated with a pervasive form of decision bias (investor overconfidence), and that it is also positively correlated with arbitrage costs (in particular, the prevalence of informational cascades). Collectively, these two effects conspire to produce greater momentum effects among high-IU firms.

Using a variety of IU proxies, and two measures of momentum, we find strong evidence in support of this prediction. During our sample period, monthly hedge returns to quintile-based price momentum strategies averaged 1.80% for high-IU firms, and only 0.08% for low-IU firms—after adjusting for the three Fama-French (1993) factors. Earnings momentum (based on recent analyst FY1 forecast revisions) produced average monthly hedge returns of 2.75% for high-IU firms, and 1.04% for low-IU firms. These results are robust to various risk adjustments, and are even stronger in the most recent sub-sample period.

Our findings have interesting implications for investment managers. Prior studies show that value-related and momentum-related signals both have predictive power for returns. However, because these two types of signals are negatively correlated (Asness, 1997; Lee and Swaminathan, 2000), sorting out the appropriate weights for each type of signal is a substantial challenge. Our findings suggest that IU is a potential arbiter in such decisions. Specifically, it is rational to place more weight on momentum-related signals in high-IU settings, and more weight on value-related signals in low-IU settings.

Our results also nominate information uncertainty as a natural partitioning variable when conducting contextual financial analysis. High-IU firms (and industries populated by a greater proportion of such firms) call for a different investment approach than low-IU firms. In fact, our results may help to explain why the investment industry is broadly grouped into style categories, with some portfolio managers focusing on "value" (low-IU) stocks while others specializing in "growth" (high-IU) stocks. These groupings seem to arise quite naturally given our analyses.

In sum, we believe IU is a central concept in understanding market pricing dynamics. Our study does not explain the existence of momentum *per se*. However, our work helps to shed light on how IU can alter the price discovery process, and thus the magnitude of the momentum effect. We also introduce an alternative explanation for a series of puzzling empirical regularities in the asset pricing literature. Our hope is that future work will extend this line of inquiry to provide a more complete picture of how the level of IU can affect capital markets.

Appendix A: Definition and Empirical Implementation of Implied Equity Duration

Duration is a measure of implied equity duration introduced by Dechow et al. (2004). Intuitively, it is analogous to the Macaulay measure of duration in bond pricing, and measures how long in years it takes for the price of a stock to be repaid by its internal cash flows. Dechow et al. (2004) nominate this variable as a measure of information uncertainty, and show that it differentiates return co-movements better than the more traditional book-to-market ratio. We follow their methodology and estimation procedure in computing this variable.

An attractive feature of the Dechow et al. (2004) procedure is that it relies on only a few financial variables, and no analyst-based data. Specifically, their procedure calls for four financial variables and four forecasting parameters. We follow their implementation procedures, and use the following key inputs and forecasting parameters, as reported in Table 1 of their paper:

Financial Variables	
Financial variables	Compustat Data
Book value of equity (BV)	Item 60
Earnings (E)	Item 18 = Income before extraordinary items
Sales (S)	Item 12
Market capitalization	Item 199 × Item 25
Forecasting Parameters	
Autocorrelation Coefficient for ROE	0.57
Cost of equity capital	0.12
Autocorrelation Coefficient for Growth in sales	0.24
Long-run growth rate in sales	0.06

Acknowledgments

We thank two anonymous referees, Peter Easton (the editor), Ilia Dichev, David Hirshleifer, Paul Schultz (the discussant) as well as workshop participants at Cornell University, Barclays Global Investors' Advanced Strategies and Research Group, and 2004 RAST conference at University of Notre Dame for helpful comments and discussions. We also gratefully acknowledge the contribution of Thomson Financial in providing earnings forecast data, made available through I/B/E/S International, Inc.

Notes

1. A representative, non-exhaustive, list of references for these results includes: Volatility (Ang et al., 2003); Volume (Datar et al., 1998; Lee and Swaminathan, 2000); Expected growth (LaPorta, 1996); PB (Fama and French, 1992); Analyst dispersion (Diether et al., 2002); Duration of future cash flows (DeChow et al., 2004). Our work is also closely related to Zhang (2004), discussed in more detail later.
2. See Shleifer (2000), Hirshleifer (2001), and Barberis and Thaler (2003) for surveys of this literature.
3. As we discuss in more detail later, Diether et al. (2002) makes the same point in motivating their study on differences of opinion and future returns.
4. See Lee (2001), Shleifer and Vishny (1997), Mitchel et al. (2002), Barberis and Thaler (2003).
5. Bushman and Smith (2001) discuss the link between the quality of accounting data and information risk.
6. To exclude recent IPOs, we require past 12-month returns. To mitigate the effect of illiquid stocks, we also limit our analysis to firms with a market capitalization as of the portfolio formation date of at least 150 million in year 2001 dollars (inflation-adjusted).
7. The result holds for all the IU proxies except the Duration variable (which orders returns monotonically).
8. For example, see Griffin and Tversky (1992).
9. Nelson et al. (2003) provide experimental evidence that timely feedback mitigates, but does not eliminate, trader overconfidence.
10. A concrete example would be a value investor who is reluctant to forego the results of a careful discounted cash flow analysis (DCF) even though the firm in question has highly uncertain cash flows. More generally, the DCF process as taught in most financial analysis classes typically produces point estimates of value, and does not provide systematic feedback on the confidence band of these estimates. Thus value investors with a theoretically sound investment approach can also place too much reliance on their own private signals.
11. Diether et al. (2002) makes the same point in motivating their study on differences of opinion and future returns. As they observe, explicit constraints on short-selling is not the only reason firms with greater divergence of opinion (or in our case high-IU firms) might become over-priced. More generally, any friction that prevents the revelation of negative opinions will produce an upward bias in the prices of these stocks. For example, the documented reluctance of financial analysts to issue negative (sell) recommendations could contribute an upward bias that is most pronounced among high-IU firms. Rules that prohibit many large institutional investors from taking short positions can have a similar effect.
12. Using a residual-income model estimate of firm value, Frankel and Lee (1998) provide evidence that price convergence to value is a protracted process that takes place over extended periods of time, averaging 3–5 years.
13. Brunnermeier and Nagel (2003) offer an interesting case study of this phenomenon. In their study, the authors show that hedge fund managers initially resisted increasing their technology holdings as valuation for these stocks soared in the late 1990s. However, toward the end of the bubble, most fund managers capitulated and engaged in positive-feedback trading, increasing their exposure to technology stocks.

14. In the original Bikchandani et al. (1992) paper, informational cascades collapse with the introduction of endogenous price, because as people buy stocks, they drive up the price, making further purchases less attractive. However, subsequent studies show that noise in the information aggregation process can limit the inference individuals make from price, thus allowing cascades to persist even in the presence of price (e.g., Avery and Zemsky, 1998). See Hirshleifer and Teoh (2003) for a good synthesis of herding behavior and cascading studies in capital market settings.
15. In a less related study, Francis et al. (2003) also explore the empirical relation between accounting anomalies and information uncertainty. However, their economic construct and empirical measure of uncertainty bear little relation to ours, and their results do not address the issues we examine.
16. As a proxy for IU, firm age comes with some baggage. In particular, the addition of NASDAQ stocks in 1972 could potentially taint our results. To partially address this problem, we exclude small firms (firms with less than 150 million in market capitalization using 2001 dollars) and firms with less than 12-months of trading history. Further, we check our findings using composite IU measures that exclude Firm Age (see Tables 4, 5, and 9). Finally, we find that using only NYSE firms also yields similar results.
17. We use different time horizons in measuring past volume and past volatility in an attempt to derive two signals that are less correlated. In fact, using the standard deviation of weekly returns over the past six months produces very similar results.
18. In ranking firms into volume portfolios, we separately sort stocks listed on the NYSE/AMEX and stocks on NASDAQ, because trading volume on NASDAQ is inflated relative to NYSE/AMEX stocks due to double counting of dealer trades (Lee and Swaminathan, 2000).
19. In most months, rev_t is the mean *FY1* estimate in month t minus the mean *FY1* estimate in month $t-1$. However, in the month when a firm announces its fiscal earnings, analysts' earnings forecasts switch to the new fiscal years after the announcement. To ensure consistency in the month of the announcement, if the announcement date is before the I/B/E/S compilation date, rev_t is defined as the mean *FY1* estimate in month t minus the mean *FY2* estimate in month $t-1$. If the announcement occurs after the I/B/E/S compilation date, rev_t is defined as the difference between month t and $t-1$'s mean *FY1* estimates, but rev_{t+1} is defined as the mean *FY1* estimate in month $t+1$ minus the mean *FY2* estimate in month t.
20. We exclude *Duration* because of its more stringent data requirements and because the results are similar whether we include it or not.
21. Once again, we exclude *Duration* in the definition of IU for this and the ensuing tables, because of its more stringent data requirements and because results are qualitatively the same using just three variables to proxy for IU.

References

Ang, A., R. Hodrick, Y. Xing, and X. Zhang. (2003). "The Cross-section of Volatility and Expected Returns." Working paper, Columbia University.

Asness, C. (1997). "The Interaction of Value and Momentum Strategies." *Financial Analysts Journal* 53, 29–36.

Avery, C. and P. Zemsky. (1998). "Multi-dimensional Uncertainty and Herd Behavior in Financial Markets." *American Economic Review* 88, 724–748.

Barberis, N. and R. Thaler. (2003). "A Survey of Behavioral Finance." *Handbook of the Economics of Finance*, Chapter 18, edited by G. M. Constantinides, M. Harris, and R. Stulz. Elsevier/North-Holland.

Bernard, V. L. and J. K. Thomas. (1990). "Evidence that Stock Prices do not Fully Reflect the Implications of Current Earnings for Future Earnings." *Journal of Accounting and Economics* 13, 305–341.

Bikhchandani, S., D. Hirshleifer and I. Welch. (1992). "A Theory of Fads, Fashion, Custom and Cultural Change as Information Cascades." *Journal of Political Economy* 100, 992–1026.

Brunnermeier, M. K. and S. Nagel. (2003). "Hedge Funds and the Technology Bubble." *Journal of Finance*, forthcoming.

Bushman, R. and A. Smith. (2001). "Financial Accounting Information and Corporate Governance." *Journal of Accounting and Economics* 32, 237–333.

Daniel, K., D. Hirshleifer and A. Subrahmanyam. (1998). "Investor Psychology and Security Market Under- and Over-reaction." *Journal of Finance* 53, 1839–1886.

Daniel, K., D. Hirshleifer and A. Subrahmanyam. (2001). "Overconfidence, Arbitrage, and Equilibrium Asset Pricing." *Journal of Finance* 56, 921–965.

Datar, V., N. Naik and R. Radcliffe. (1998). "Liquidity and Asset Returns: an Alternative Test." *Journal of Financial Markets* 1, 203–220.

Dechow, P., R. Sloan and M. Soliman. (2004). "Implied Equity Duration: A New Measure of Equity Security Risk." *Review of Accounting Studies* 9, 197–228.

De Long, J. B., A. Shleifer, L. H. Summers and R. J. Waldmann. (1990). "Positive Feedback Investment Strategies and Destabilizing Rational Speculation." *Journal of Finance* 45, 379–395.

Diether, K., C. Malloy and A. Scherbina. (2002). "Differences of Opinion and the Cross-Section of Stock Returns." *Journal of Finance* 57, 2113–2141.

Easley, D. and M. O'Hara. (2003). "Information and the Cost of Capital." *Journal of Finance*, forthcoming.

Fama, E. F. (1991). "Efficient Capital Markets: II." *Journal of Finance* 46, 1575–1617.

Fama, E. F. and K. R. French. (1992). "The Cross-section of Expected Stock Returns." *Journal of Finance* 47, 427–465.

Fama, E. F. and K. R. French. (1993). "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33, 3–56.

Fama, E. F. and J. MacBeth. (1973). "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81, 607–636.

Francis, J., R. LaFond, P. Olsson and K. Schipper. (2003). "Accounting Anomalies and Information Uncertainty." Working Paper, Duke University, Wisconsin University, and the Financial Accounting Standards Board.

Frankel, R. and C. M. C. Lee. (1998). "Accounting Valuation, Market Expectation, and Cross-sectional Stock Returns." *Journal of Accounting and Economics* 25, 283–319.

Griffin, D. and A. Tversky. (1992). "The Weighing of Evidence and the Determinants of Confidence." *Cognitive Psychology* 24, 411–443.

Grundy, B. and J. S. Martin. (2001). "Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing." *Review of Financial Studies* 14, 29–78.

Hirshleifer, D. (2001). "Investor Psychology and Asset Pricing." *Journal of Finance* 56, 1533–1597.

Hirshleifer, D. and S. Hong Teoh. (2003). "Herding Behavior and Cascading in Capital Markets: A Review and Synthesis." *European Financial Management* 9, 25–66.

Jegadeesh, N. and S. Titman. (1993). "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48, 65–91.

La Porta, R. (1996). "Expectations and the Cross-section of Stock Returns." *Journal of Finance* 51, 1715–42.

Lee, C. M. C.. (2001). "Market Efficiency and Accounting Research: A Discussion of 'Capital Market Research' by S.P. Kothari." *Journal of Accounting and Economics* 31, 233–253.

Lee, C. M. C. and B. Swaminathan. (2000). "Price Momentum and Trading Volume." *Journal of Finance* 55, 2017–2069.

Miller, E. M. (1977). "Risk, Uncertainty, and Divergence of Opinion." *Journal of Finance* 32, 1151–1168.

Mitchell, M., T. Pulvino and E. Stafford. (2002). "Limited Arbitrage in Equity Markets." *Journal of Finance* 57, 551–584.

Nelson, M. W., S. D. Krische and R. J. Bloomfield. (2003). "Confidence and Investors' Reliance on Disciplined Trading Strategies." *Journal of Accounting Research* 41, 503–523.

Odean, T. (1998). "Volume, Volatility, Price, and Profit when all Traders are Above Average." *Journal of Finance* 53, 1887–1934.

Shleifer, A. (2000). *Inefficient Markets: An Introduction to Behavioral Finance*. Oxford, UK: Oxford University Press.

Shleifer, A. and R. W. Vishny. (1997). "The Limits of Arbitrage." *Journal of Finance* 52, 35–55.

Zhang, F. (2004). "Information Uncertainty and Stock Returns." Working paper, University of Chicago.