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Information Uncertainty and Stock Returns

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ABSTRACT

There is substantial evidence of short-term stock price continuation, which the prior literature often attributes to investor behavioral biases such as underreaction to new information. This paper investigates the role of information uncertainty in price continuation anomalies and cross-sectional variations in stock returns. If short-term price continuation is due to investor behavioral biases, we should observe greater price drift when there is greater information uncertainty. As a result, greater information uncertainty should produce relatively higher expected returns following good news and relatively lower expected returns following bad news. My evidence supports this hypothesis.

THERE IS SUBSTANTIAL EVIDENCE OF SHORT-TERM stock price continuation, which the prior literature often attributes to investor underreaction to new information. Examples include the positive serial correlation of returns at 3- to 12-month horizons (Jegadeesh and Titman (1993)), post-earnings announcement stock price drift in the direction indicated by the earnings surprise, and post-event return drift in the direction of the announcement date return.[1]

In this paper I investigate how information uncertainty contributes to this phenomenon. By information uncertainty, I mean ambiguity with respect to the implications of new information for a firm's value, which potentially stems from two sources: the volatility of a firm's underlying fundamentals and poor information.[2] My main hypothesis is that if investors underreact to public

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[1] See the appendix of Daniel, Hirshleifer, and Subrahmanyam (1998) for a thorough review of this evidence.

[2] Theoretically, an observed signal (s) is characterized as a firm's fundamental value (v), such as future cash flow or dividend, plus a noise term (e), that is, $s = v + e$. The variance of the signal measures information uncertainty: $var(s) = var(v) + var(e)$, where $var(v)$ is a firm's underlying fundamental volatility and $var(e)$ reflects the quality of information. I do not distinguish a firm's underlying fundamental volatility from information quality because both effects contribute to the uncertainty of a firm's value and because it is hard to empirically disentangle one from the other as observed stock volatility and other empirical constructs capture both effects. This definition parallels the argument in Hirshleifer (2001).

information, they will underreact even more in cases of greater information uncertainty. The testable implication is that greater information uncertainty about the impact of news on stock value leads to higher expected stock returns following good news but lower expected stock returns following bad news relative to the returns of stocks about which there is less information uncertainty. A distinct feature of the analysis is the focus on how price continuation following the release of public information varies with information uncertainty.

My hypothesis is motivated by two results from the behavioral finance literature. Several papers including Chan, Jegadeesh, and Lakonishok (1996) attribute price continuation to a gradual market response to information. Hirshleifer (2001) and Daniel, Hirshleifer, and Subrahmanyam (1998, 2001) posit that psychological biases are increased when there is more uncertainty. This study combines these two ideas and tests the following joint hypothesis: If the slow market response to information is due to psychological biases such as overconfidence, these psychological biases will be larger and, hence, the price response will be slower when there is more ambiguity about the implications of the information for a firm's value.

Specifically, I study two price continuation anomalies: post-analyst forecast revision price drift and price momentum. I focus on these two anomalies because the new information is public, easily categorized as good or bad, and occurs fairly frequently. For the first anomaly, the new information is the current month's earnings forecast revision. For the second, the new information is the average monthly stock returns over the past 11 months. I classify upward forecast revisions or past winners as good news and downward revisions or past losers as bad news.

Using ex post returns as a proxy for expected returns, I find consistent results across six proxies for information uncertainty: firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility, and cash flow volatility.[3] For each of the six proxies, I find that greater information uncertainty leads to relatively lower future stock returns following bad news and relatively higher future returns following good news, suggesting that uncertainty delays the flow of information into stock prices.[4] In other words, the market reaction to

[3] In all analyses, I construct the proxies in such a way that a higher value corresponds to greater information uncertainty. Specifically, I use the reciprocals of firm size, firm age, and analyst coverage. To ensure that all information is available before the portfolio formation date, I use all sorting variables as of the current month and predict 1-month-ahead stock returns.

[4] The paper studies both the mean and interaction effects of information uncertainty. By the mean effect, I refer to the effect of information uncertainty on future stock returns unconditional on the nature of news. I investigate whether high-uncertainty stocks earn relatively higher future returns than low-uncertainty stocks. By the interaction effect, I mean the interaction between information uncertainty and the nature of news. I predict that high-uncertainty stocks have relatively higher (lower) future returns than low-uncertainty stocks following good (bad) news, that is, $RET_H^G > RET_L^G$ and $RET_H^B < RET_L^B$, where RET_H^G and RET_L^G (RET_H^B and RET_B^L) are returns for high- and low-uncertainty stocks following good (bad) news, respectively. I also study how the performance of certain trading strategies varies with information uncertainty. I predict that the momentum strategy works better for high-uncertainty stocks, that is, $RET_H^G - RET_H^B > RET_L^G - RET_L^B$. It can easily be shown that the effect of information uncertainty conditional on the nature of news, as hypothesized in the paper, is a sufficient but not a necessary condition for the stronger momentum effect for high-uncertainty stocks.

new information is relatively complete for low-uncertainty stocks, and there is little news-based return predictability. For high-uncertainty stocks, on the other hand, the market reaction is far from complete. Good news predicts relatively higher future returns and bad news predicts relatively lower future returns. This relation between information uncertainty and future returns remains after I control for common factors used in prior empirical studies. I provide further assurance that missing risk factors do not drive the results by documenting a similar return pattern around subsequent earnings announcement dates.

The opposite effects of information uncertainty on stock returns following good versus bad news amplify the results of previously documented trading strategies. As a result, trading strategies that buy good-news stocks and short bad-news stocks work particularly well when limited to high-uncertainty stocks.[5] For example, a momentum strategy (buying past winners and shorting past losers) on stocks in the bottom stock volatility quintile (low uncertainty) generates a 0.63% monthly return, but a similar strategy based on stocks in the top stock volatility quintile (high uncertainty) yields a 2.63% monthly return. Other uncertainty proxies produce similar returns.

My main prediction is related to the theoretical work of Daniel et al. (1998, 2001), but has broader implications.[6] Daniel et al. (1998) develop a model in which investors are overconfident about their private information, and therefore overweight their private information and underreact to public signals (e.g., analyst forecast revisions). As a result, future returns are predictable. Daniel et al. (1998, 2001) further argue that the return predictability should be stronger in firms with greater uncertainty because investors tend to be more overconfident when firms' businesses are hard to value. This argument implies that greater uncertainty is related to relatively higher (lower) stock returns following good (bad) news. Because I do not incorporate measures of private information or overconfidence in my empirical analysis, my evidence leaves the door open for other behavioral models. For example, my results are also consistent with a behavioral model in which investors overweight their priors relative to new information due to the anchoring/conservatism bias and overweight their priors more when there is greater information uncertainty.

This study contributes to the accounting and finance literature in several ways. First, the paper provides evidence in support of the hypothesis that price continuation following public signals increases with proxies for the ambiguity of the signals with respect to the implications for a firm's value. The fact that proxies for information uncertainty, such as cash flow and stock return volatility, are associated with both higher returns following good news and lower returns following bad news but are not significantly related to unconditional expected returns suggests that momentum effects are more likely to

[5] Prior literature finds that the momentum strategy works better for small firms, growth firms, firms with low analyst following, and firms with high abnormal trading volume (see Daniel and Titman (1999), Hong, Lim, and Stein (2000) Lee and Swaminathan (2000)). Such evidence is in general accordance with my prediction on the interaction effect between information uncertainty and momentum.

[6] Also see Jiang, Lee, and Zhang (2004) for the argument supporting the position that the information uncertainty effect is associated with investor overconfidence and arbitrage costs.

reflect slow absorption of ambiguous information into stock price than to reflect missing risk factors.

Second, the evidence presented here sheds new light on the role of accounting disclosure in capital market settings. In the prior literature, information uncertainty is often modeled as the information asymmetry component of the cost of capital (e.g., Diamond and Verrecchia (1991), Easley and O'Hara (2001), Verrecchia (2001)) or estimation risk (e.g., Barry and Brown (1985), Coles and Loewenstein (1988), Klein and Bawa (1976)) and therefore increases expected stock returns. The theoretical argument that accounting disclosure can reduce information uncertainty and cost of capital is appealing, but the overall empirical evidence is mixed.[7] My evidence that the effects of information uncertainty on future returns following good and bad news offset each other in unsigned analysis might explain why previous studies often find an insignificant effect of accounting disclosure (see the review by Verrecchia (2001)). My evidence also suggests a potential additional role for accounting disclosure: More transparent disclosure might reduce information uncertainty and speed the absorption of new information into the stock prices.

Finally, the evidence also questions the underlying cause of the size effect. The prior literature finds that small stocks historically earned higher returns than large stocks, but that this effect has disappeared in the last 20 years. As shown in this paper, the opposite effects of size on stock returns following good and bad news suggest that firm size behaves more like a proxy for information uncertainty than a common risk factor in the cross section of stock returns. The positive (negative) size premium following good (bad) news is also persistent over time. These results also have implications for studies using firm size or other variables related to information uncertainty as control variables in unsigned cross-section analysis.

The remainder of the paper is organized as follows. The next section discusses related literature and outlines my main prediction. Section II describes the sample data and provides descriptive statistics. Section III examines the role of information uncertainty from a portfolio approach. Section IV uses a four-factor model to control for some common factors. Section V examines stock price reactions to earnings announcements following the portfolio formation date. Section VI conducts some robustness checks, and Section VII concludes.

I. Related Literature and Hypothesis Development

There is substantial evidence of short-term stock price continuation. For example, Stickel (1991), Chan et al. (1996), and Gleason and Lee (2003) document that stock prices exhibit a drift after analyst forecast revisions. Forming

[7] For example, Botosan (1997) finds a negative association between a self-constructed disclosure index and the cost of capital but only for firms followed by few analysts. Using AIMR scores as a proxy for disclosure level, Botosan and Plumlee (2002) find that the cost of capital is negatively related to annual report disclosure level but positively related to quarterly report disclosure level. Finally, Cohen (2003) reports that the negative relation between disclosure and the cost of capital disappears once he controls for the endogeneity associated with the reporting quality choice.

portfolios based on past intermediate-horizon stock returns, Jegadeesh and Titman (1993) show that past winners on average continue to outperform past losers over the next 3 to 12 months. Several papers including Bernard and Thomas (1990) demonstrate that stock prices continue to drift in the direction of quarterly earnings surprises for at least 120 trading days following the earnings announcement.

Short-term stock price continuation is often attributed to investor behavioral biases such as investor underreaction to new information. Chan et al. (1996) show that the post-analyst revision drift is part of a general class of "momentum" strategies, in which the market response to recently released information is gradual so that prices exhibit predictable drift patterns. Chan et al. (1996) and Barberis, Shleifer, and Vishny (1998), among others, argue that the intermediate-horizon price momentum effect is due to investor underreaction to some information.[8] Daniel et al. (1998) develop a model in which investors are overconfident with their private information and therefore underreact to public signals. This model provides a potential explanation for the underlying cause of post-analyst revision drift or momentum.[9]

Hirshleifer (2001) posits that greater uncertainty about a set of stocks and a lack of accurate feedback about their fundamentals leave more room for psychological biases. Therefore, the misvaluation effects of almost any mistaken-beliefs model should be strongest among firms about which there is high uncertainty and poor information. For example, Daniel et al. (1998, 2001) show that return predictability should be stronger in firms with greater uncertainty because investors tend to be more overconfident when firms' businesses are hard to value.

I combine these two ideas and test the following joint hypothesis: If post-analyst revision drift, momentum, and other short-term anomalies are due to investor psychological biases such as overconfidence, we should observe greater investor behavioral biases and stronger price drifts when there is greater information uncertainty. The testable implication is that greater information uncertainty produces relatively higher (lower) stock returns following good (bad) news. The opposite effects of information uncertainty on future stock returns following good and bad news also amplify the profitability of certain trading strategies. As a result, the momentum trading strategy works particularly well when limited to high-uncertainty stocks.

I use two measures of news. First, I use analyst forecast revisions for the current month. An upward revision means good news, and a downward revision means bad news. Although this measure may be noisy since analysts may suffer from behavioral biases or have incentives to bias their forecasts,

[8] It seems safe to classify momentum as an underreaction story in my setting, as I focus on a short return window (1 month) and Lee and Swaminathan (2000) and Jegadeesh and Titman (2001) find that the price momentum effect only partially reverses over long horizons (5 years).

[9] While momentum in the correction phase and virtually all postevent price drifts are classified as investor underreaction to public signals in Daniel et al. (1998), they offer a different mechanism for momentum in the overreaction phase. Namely, investors keep overreacting to their priors because of biased self-attribution, which contributes positively to short-term momentum.

it is relevant as long as analysts on average react in the same direction as the news suggests. Measurement error in my variables works against finding any significant results. My second measure is past stock returns. If investors follow the direction of new information, a partition based on price momentum (the past 11-month stock returns) is another way to distinguish good news from bad.

I also need a proxy for information uncertainty. One natural variable is firm size (MV), measured as the market capitalization at the portfolio formation date. It seems plausible that small firms are less diversified and have less information available for the market than large firms. Small firms may also have fewer customers, suppliers, and shareholders, and may not bear high disclosure preparation costs. Investors might have fixed costs of information acquisition, which makes small firms' stocks unattractive. Unfortunately, even if firm size is, in fact, a useful measure of uncertainty, it is likely to capture other things as well, potentially confounding any inferences. I therefore use five alternative proxies for information uncertainty: firm age, analyst coverage, dispersion in analyst forecasts, stock volatility, and cash flow volatility. Although each proxy might also capture other effects, the common element is their ability to quantify information uncertainty.

Firms with a long history have more information available to the market (Barry and Brown (1985)). To the extent that older firms are more likely to be in more mature industries, firm age also captures the underlying volatility at the industry level. I use firm age (AGE) as my second proxy, measured as the number of years since the firm was first covered by the Center for Research in Securities Prices (CRSP). To my knowledge, the role of firm age in predicting future returns has not been empirically documented in the prior literature.

A third proxy is analyst coverage (COV), measured as the number of analysts following the firm in the previous year. Analysts collect, digest, and distribute information about a firm's performance. There is evidence that larger analyst coverage is likely to correspond to more information available about the firm, which implies less uncertainty. Lang and Lundholm (1996) find that analyst coverage is positively associated with disclosure scores. Hong, Lim, and Stein (2000) use larger analyst coverage as an indicator of less information asymmetry. Gleason and Lee (2003) show that the post-revision price drift is more pronounced in firms with smaller analyst coverage.

The fourth proxy is dispersion in analyst earnings forecasts (DISP). In the prior literature, forecast dispersion is widely used to proxy for the uncertainty about future earnings or the degree of consensus among analysts or market participants (e.g., Barron et al. (1998), Barron and Stuerke (1998), Diether, Malloy, and Scherbina (2002), Imhoff and Lobo (1992), Lang and Lundholm (1996)). I measure forecast dispersion as the standard deviation of analyst forecasts scaled by the prior year-end stock price to mitigate heteroskedasticity.

The fifth proxy is stock volatility (SIGMA), which is measured by the standard deviation of weekly market excess returns over the year ending at the portfolio formation date. Following Lim (2001), I measure weekly returns from Thursday to Wednesday to mitigate nonsynchronous trading or bid-ask bounce effects in daily prices. A 1-year estimation period is chosen to provide a reasonable number of observations.

The final proxy is cash flow volatility (CVOL), measured as the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years). I treat CVOL as missing if there are only 1 or 2 years' data available. Cash flow from operations is earnings before extraordinary items (Compustat #18) minus total accruals, scaled by average total assets (Compustat #6), where total accruals are equal to changes in current assets (Compustat #4) minus changes in cash (Compustat #1), changes in current liabilities (Compustat #5), and depreciation expense (Compustat #14) plus changes in short-term debt (Compustat #34).[10] Although the cash flow measure is indirectly calculated from financial statements and therefore is affected by a firm's information system, it is more likely to capture the underlying volatility.

II. Sample Data and Descriptive Statistics

The sample data come from three sources. Returns are from the CRSP Monthly Stocks Combine File, which includes NYSE, AMEX, and Nasdaq stocks. Book value and other financial data are from Compustat. Analyst forecast revisions are from I/B/E/S.[11] The sample period spans from January 1983 to December 2001.

I delete observations for which the absolute value of earnings forecast revision exceeds 100% of the prior year-end stock price, because these observations are likely to be erroneous. Following Jegadeesh and Titman (2001), I exclude stocks with a share price below $5 at the portfolio formation date to make sure that the results are not driven by small, illiquid stocks or by the bid–ask bounce. To avoid any potential confounding effect of recent IPOs, I also exclude firms with less than 12 months of past return data on CRSP.

Table I presents descriptive statistics for variables of interest. The mean monthly return is 1.15% and the median is 0.74%, indicating a slight right skewness in the distribution. Although I/B/E/S tends to cover large firms, there is a large variation in firm size in my sample. The market value ranges from

[10] This balance sheet approach to estimate accruals may be subject to the measurement error problem (see Hribar and Collins (2002)), but it is unavoidable as cash flow statements are not available until 1987. The results are robust in the post-1987 period using accruals from the cash flow approach.

[11] There are two problems with the standard-issue I/B/E/S summary data set. First, I/B/E/S uses all existing analyst forecasts to calculate summary statistics, and some of these forecasts are stale. These stale forecasts tend to increase the dispersion in analyst forecasts. Second, there is a rounding error problem with stock splits because I/B/E/S adjusts all data for stock splits and only rounds the estimate to the nearest cent (Baber and Kang (2002)). For example, the adjustment factor for Dell during the 1988 to 1991 period is 96, which renders virtually all forecast revisions to be zero in the I/B/E/S-adjusted Detail History File. Dell had $1.35 actual earnings per share in 1990. Any forecast between $0.48 and $1.44 would have the same adjusted $0.02 earnings per share in the I/B/E/S database. The rounding error problem tends to reduce both forecast revisions and forecast dispersion. To avoid these issues, I follow Diether et al. (2002) and Zhang (2005) and calculate forecast revisions and other variables based on the raw detail forecast data unadjusted for stock splits. However, the results are robust to the standard-issue I/B/E/S data set.

Table I

Descriptive Statistics

Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Book-to-market (BM) is the book value of equity divided by its market value at the end of the last fiscal year. $\mathrm{RET}_{t-11,t-1}$ is accumulated returns from months $t-11$ to $t-1$. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals estimated from the balance sheet approach, scaled by average total assets. Stocks with a price less than $5 are excluded from the sample. The sample period is from January 1983 to December 2001.

Panel A: Descriptive Statistics

	N	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
RET_{t+1}	490,396	1.15%	13.72%	−98.13%	−5.56%	0.74%	7.32%	556%
MV_t	490,396	2,378	11,033	0	130	382	1,286	602,433
BM_t	490,396	0.642	0.462	0.000	0.326	0.550	0.849	20.941
$\mathrm{RET}_{t-11,t-1}$	483,213	22.65%	68.21%	−98.16%	−10.42%	12.49%	39.49%	4608%
AGE_t	490,396	18	16	1	6	13	24	77
COV_t	458,263	11	10	1	4	7	15	67
DISP_t	420,499	0.72%	2.67%	0.00%	0.12%	0.29%	0.71%	638%
SIGMA_t	487,675	5.54%	2.96%	1.03%	3.48%	4.82%	6.78%	82.47%
CVOL_t	351,417	0.074	0.094	0.001	0.031	0.053	0.089	6.940

Panel B. Correlation Matrix (Pearson Correlations Are Shown above the Diagonal with Spearman Below)

	RET_{t+1}	MV_t	BM_t	$\mathrm{RET}_{t-11,t-1}$	AGE_t	COV_t	DISP_t	SIGMA_t	CVOL_t
RET_{t+1}	1	−0.006	0.014	0.017	0.005	0.005	−0.002	−0.026	−0.008
MV_t	0.014	1	−0.096	0.028	0.232	0.350	−0.034	−0.081	−0.057
BM_t	0.025	−0.180	1	−0.069	0.163	−0.006	0.185	−0.174	−0.153
$\mathrm{RET}_{t-11,t-1}$	0.025	0.147	−0.050	1	−0.063	−0.058	−0.009	0.160	0.080
AGE_t	0.026	0.409	0.252	0.003	1	0.428	0.008	−0.378	−0.209
COV_t	0.023	0.725	−0.025	−0.033	0.404	1	0.000	−0.252	−0.144
DISP_t	−0.006	−0.204	0.416	−0.076	0.070	0.045	1	0.011	0.042
SIGMA_t	−0.054	−0.332	−0.280	−0.087	−0.491	−0.293	0.033	1	0.359
CVOL_t	−0.030	−0.294	−0.239	−0.013	−0.349	−0.245	0.059	0.492	1

$70,000 to $602 billion. Firm age ranges from 1 to 77 years. Young firms account for a considerable portion of the sample, which is partly due to the fact that after 1973, CRSP includes Nasdaq firms. Stock returns are volatile, as suggested by a mean SIGMA of 5.54% per week and a median of 4.82% per week.

Panel B shows the correlation matrix. The Pearson (Spearman) correlation between returns and book-to-market is 0.014 (0.025), which confirms the value premium in univariate tests. The size effect is negative in the Pearson measure but positive in the Spearman measure. Firm size, firm age, and analyst coverage are positively correlated with each other and negatively correlated with stock volatility and cash flow volatility, supporting the idea that these proxies capture the same phenomenon. One exception is analyst dispersion, which is negatively correlated with firm size but not with firm age and analyst coverage. Firm size is highly correlated with analyst coverage (Pearson = 0.35 and Spearman = 0.725), but the correlation between firm size and firm age is only moderate (Pearson = 0.232 and Spearman = 0.409). Stock volatility is highly correlated with cash flow volatility (Pearson = 0.359 and Spearman = 0.492) but not with dispersion in analyst forecasts or any other proxy for information uncertainty, suggesting that these proxies might capture different aspects of information uncertainty.

III. Portfolio Effects of Information Uncertainty

In this section I assign stocks to portfolios based on the nature of news and the level of information uncertainty in order to draw conclusions about the average returns for these classes of stocks. This is a standard approach in asset pricing, which reduces the variability in returns.

A. Portfolio Returns by Information Uncertainty Proxy

The first set of empirical tests examines the cross-sectional variation in stock returns by information uncertainty level (the mean effect) and verifies the existence of the momentum effect and the post-analyst revision drift for my sample. In Table II, Panel A, each month I sort stocks into 10 deciles using a proxy for information uncertainty. I find that high-uncertainty stocks tend to have lower future returns than do low-uncertainty stocks. However, none of the trading strategies with a long position in high-uncertainty stocks and a short position in low-uncertainty stocks yields statistically negative returns.[12] The evidence of lower returns for high-uncertainty stocks than for low-uncertainty stocks does not support the notion that information uncertainty is a cross-sectional risk factor and compensated by higher stock returns.

The last column in Table II, Panel A verifies the existence of the momentum effect for my sample. I sort stocks based on past 11-month stock returns and find that past winners on average outperform past losers by 2.22% (t = 5.38)

[12] In a more recent, complementary study, Jiang, Lee, and Zhang (2004) find a significant negative mean effect in a similar setting. The insignificant mean effect here might be partly due to my choice of a 1-month holding period. Because the literature usually measures the monthly return for a K-month holding period as the simple average of portfolio returns from strategies implemented in the current month and the previous $K - 1$ months, the monthly return tends to be less volatile when K is larger. I focus on the 1-month holding period in order to pick up the strong information uncertainty effect in the first month following public signals, as the effect of information uncertainty quickly goes away following good news (see footnote 14 and Figure 1). My short sample period might also play a role. When I test the mean effect of information uncertainty using the expanded 1964 to 2003 sample period, I find that the size effect is significantly negative, the stock volatility effect is marginally negative, and the effect of firm age is insignificant.

Table II

Portfolio Returns by Information Uncertainty Proxy, Past Returns, and Analyst Forecast Revision

This table reports average monthly portfolio returns sorted by each information uncertainty proxy and verifies the existence of the momentum effect and the postrevision drift for my sample. In Panel A, each month I sort stocks into 10 deciles based on an information uncertainty proxy in month t or the past 11-month stock returns. In Panel B, I sort stocks into three news categories based on analyst forecast revisions in month t. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. 1/MV, 1/AGE, and 1/COV are the reciprocals of MV, AGE, and COV, respectively. Stocks with a price less than $5 at the portfolio formation date are excluded from the sample. Stocks are held for 1 month, and portfolio returns are equally weighted. The sample period is from January 1983 to December 2001; t-statistics in parentheses are adjusted for autocorrelation.

Panel A: 10 Decile Returns Sorted by Information Uncertainty Level or Momentum

	Sorted by 1/MV	Sorted by 1/AGE	Sorted by 1/COV	Sorted by DISP	Sorted by SIGMA	Sorted by CVOL	Sorted by $RET_{t-11,t-1}$
D1 (low)	1.18%	1.22%	1.18%	1.21%	1.40%	1.33%	0.13%
D2	1.28%	1.38%	1.20%	1.28%	1.44%	1.37%	0.87%
D3	1.21%	1.25%	1.18%	1.33%	1.40%	1.25%	1.03%
D4	1.23%	1.33%	1.19%	1.31%	1.39%	1.22%	1.15%
D5	1.29%	1.42%	1.22%	1.40%	1.35%	1.28%	1.18%
D6	1.30%	1.38%	1.17%	1.40%	1.29%	1.26%	1.34%
D7	1.42%	1.16%	1.12%	1.28%	1.34%	1.28%	1.47%
D8	1.40%	1.20%	1.08%	1.17%	1.24%	1.32%	1.47%
D9	1.23%	1.13%	1.26%	1.30%	1.05%	1.24%	1.76%
D10 (high)	1.15%	0.96%	1.09%	1.15%	0.72%	0.94%	2.35%
D10-D1	−0.02%	−0.26%	−0.09%	−0.06%	−0.68%	−0.38%	2.22%
	(−0.10)	(−0.61)	(−0.66)	(−0.25)	(−1.04)	(−0.91)	(5.38)

Panel B: Portfolio Returns Based on Analyst Forecast Revision

	Sample	RET_t	RET_{t+1}
Bad news ($REV_t < 0$)	30.3	−0.20	0.72
		(−0.53)	(1.99)
No news ($REV_t = 0$)	46.5%	1.92%	1.29%
		(5.71)	(3.80)
Good news ($REV_t > 0$)	23.2%	3.55%	1.84%
		(9.78)	(5.31)
Good – bad			1.13%
			(9.32)

in the first month after portfolio formation, which is consistent with the prior literature.

In Table II, Panel B, I sort stocks based on analyst forecast revisions to verify the existence of post-revision drift. An upward forecast revision means good news, and a downward revision means bad news. If a revision is zero, I assign it to a separate category. On average, negative, zero, and positive revisions account for 30.3%, 46.5%, and 23.2% of the sample data, respectively. Panel B shows that bad news corresponds to lower future returns and good news is followed by higher future returns, confirming the post-revision price drift documented in the prior literature. On average, bad-news firms gain 0.72% (t = 1.99) in the following month, compared to 1.84% (t = 5.31) for good-news firms. The return of 1.29% (t = 3.80) for no-news firms falls in the middle. The returns for bad-, no-, and good-news firms are −0.20%, 1.92%, and 3.55%, respectively, in the month in which the revision news comes out. This pattern of future returns is consistent with the underreaction argument in the sense that investors underreact to new information and, as a result, future stock price movements are in the same direction as in the month in which the news occurs.

B. Portfolio Returns by Analyst Forecast Revision and Information Uncertainty Proxy

To test the relation between the nature of news and the effect of information uncertainty on future returns, in Table III I sort stocks by information uncertainty proxy for different news categories. Stocks are first classified into one of three categories based on their forecast revision in the current month. Within each revision category, stocks are sorted into 10 deciles by information uncertainty proxy. For the resulting 30 portfolios, there are an average of 66, 101, and 51 stocks each month for each portfolio in the bad-, no-, and good-news categories, respectively. To make sure that investors have all information available when forming portfolios, I use sorting variables as of the current month and predict 1-month-ahead stock returns.

Table III confirms my hypothesis. For each proxy, I observe that greater information uncertainty produces relatively lower future returns following bad news and relatively higher future returns following good news. For example, for the COV proxy, the mean portfolio return decreases from 0.94% in decile 1 (low uncertainty) to 0.10% in decile 10 (high uncertainty) in the bad-news category. A trading strategy with a long position in D10 stocks and a short position in D1 stocks (D10 − D1) yields a −0.84% (t = −2.96) monthly return. For the good-news category, the mean portfolio return increases sharply from 1.63% in D1 to 2.28% in D10. The D10 − D1 strategy yields a 0.65% monthly return (t = 2.27).[13] For the no-news category, high-uncertainty stocks have slightly

[13] Unreported results show that analyst coverage for the bad-news category closely matches that of the good-news category, which excludes analyst coverage per se as a possible explanation for the difference in future returns for these two categories. Other uncertainty proxies in the bad-news category closely match those in the good-news category in each decile too.

Table III

Portfolio Returns by Analyst Forecast Revision and Information Uncertainty Proxy

This table reports average monthly portfolio returns sorted by analyst forecast revision and information uncertainty proxy. Each month I sort stocks into three categories depending on whether the forecast revision is negative, zero, or positive. The forecast revision is the average of individual revisions by analysts who covered the firm in both months $t-1$ and t. For each category, I further sort stocks into 10 deciles based on information uncertainty proxy. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. 1/MV, 1/AGE, and 1/COV are the reciprocals of MV, AGE, and COV, respectively. Stocks with a price less than \$5 at the portfolio formation date are excluded from the sample. Stocks are held for 1 month, and portfolio returns are equally weighted. The sample period is from January 1983 to December 2001; t-statistics in parentheses are adjusted for autocorrelation.

	Sorted by 1/MV			Sorted by 1/AGE			Sorted by 1/COV		
	REV < 0	REV = 0	REV > 0	REV < 0	REV = 0	REV > 0	REV < 0	REV = 0	REV > 0
D1 (low)	1.00%	1.17%	1.41%	1.03%	1.13%	1.49%	0.94%	1.28%	1.63%
D2	0.82%	1.19%	1.60%	1.08%	1.26%	1.70%	0.97%	1.34%	1.64%
D3	1.04%	1.33%	1.69%	1.11%	1.56%	1.71%	0.99%	1.25%	1.71%
D4	0.96%	1.28%	1.60%	0.92%	1.33%	1.82%	0.78%	1.20%	1.59%
D5	0.82%	1.34%	1.62%	0.92%	1.65%	1.74%	0.74%	1.06%	1.72%
D6	0.72%	1.35%	1.83%	0.49%	1.34%	2.10%	0.58%	1.21%	2.08%
D7	0.61%	1.26%	2.02%	0.79%	1.00%	2.03%	0.69%	1.19%	1.83%
D8	0.55%	1.44%	2.13%	0.44%	1.18%	2.15%	0.56%	1.09%	1.93%
D9	0.30%	1.24%	2.52%	0.18%	1.21%	1.92%	0.31%	1.17%	2.05%
D10 (high)	0.12%	1.23%	2.36%	−0.16%	0.96%	1.97%	0.10%	1.10%	2.28%
D10 − D1	−0.87%	0.06%	0.96%	−1.19%	−0.17%	0.48%	−0.84%	−0.17%	0.65%
	(−3.02)	(0.23)	(2.88)	(−2.55)	(−0.38)	(1.03)	(−2.96)	(−1.05)	(2.27)

	Sorted by DISP			Sorted by SIGMA			Sorted by CVOL		
	REV < 0	REV = 0	REV > 0	REV < 0	REV = 0	REV > 0	REV < 0	REV = 0	REV > 0
D1 (low)	0.71%	1.29%	1.48%	1.25%	1.41%	1.71%	1.01%	1.25%	1.73%
D2	0.72%	1.26%	1.70%	1.12%	1.54%	1.73%	1.04%	1.42%	1.64%
D3	0.99%	1.34%	1.67%	1.04%	1.34%	1.81%	1.00%	1.19%	1.59%
D4	0.83%	1.28%	1.94%	0.91%	1.46%	1.75%	0.82%	1.24%	1.78%
D5	0.88%	1.38%	1.97%	0.79%	1.42%	1.77%	0.84%	1.44%	1.74%
D6	0.59%	1.44%	1.91%	0.63%	1.42%	1.76%	0.68%	1.18%	1.88%
D7	0.82%	1.31%	1.96%	0.54%	1.49%	1.94%	0.66%	1.43%	1.82%
D8	0.59%	1.20%	1.76%	0.53%	1.31%	1.90%	0.62%	1.19%	1.99%
D9	0.63%	1.28%	2.00%	0.37%	0.88%	2.24%	0.62%	1.00%	2.13%
D10 (high)	0.48%	1.08%	2.04%	−0.23%	0.51%	2.16%	0.05%	0.79%	2.27%
D10 − D1	−0.23%	−0.21%	0.56%	−1.47%	−0.90%	0.44%	−0.97%	−0.46%	0.54%
	(−0.77)	(−0.95)	(1.82)	(−2.23)	(−1.36)	(0.64)	(−2.10)	(−1.04)	(1.07)

lower returns than low-uncertainty stocks, but the difference is insignificant.[14] Other proxies for information uncertainty produce qualitatively similar patterns for future returns. The bad-news D10-D1 strategy produces significantly negative returns for all proxies except for DISP. For the good-news strategy, only the SIZE and COV proxies produce significantly positive returns. Information uncertainty has a slightly greater effect following bad news than following good news.[15] Such asymmetry between good and bad news might be partly explained by short-sale restrictions.

Another interesting observation is that firm size works well as a proxy for information uncertainty. Market participants underreact more to new information for small firms than for large firms. As a result, small firms have relatively lower future returns following bad news and relatively higher future returns following good news. In other words, the size premium (SMB), which is defined as the return differential between five small-size deciles and five big-size deciles in each news category, is positive following good news but negative following bad news. The positive premium following good news offsets the negative premium following bad news, resulting in a positive premium overall. The negative (positive) SMB following bad (good) news is also persistent over time. Following bad news (REV < 0), SMB is negative in 17 out of 19 years, with an average annual return of -5.56% and a t-statistic of -2.41 (results untabulated). Following good news, SMB is positive for 15 years, with an average annual return of 7.41% and a t-statistic of 3.09. For the whole sample, SMB is 0.05% and is indistinguishable from zero in the 1983 to 2001 sample period, which is consistent with previous evidence. This evidence might provide an alternative explanation to the well-known size anomaly. Certainly, it is interesting to see whether this approach can fully explain the size anomaly both by examining bad/good news for small firms versus large firms during different market conditions, and by examining whether there is more bad news for small firms in the late 1980s due to competition and globalization.[16] A full investigation of this issue is beyond the scope of this paper.

The opposite effects of information uncertainty on future returns following good and bad news have a big impact on the performance of a trading strategy

[14] In untabulated results, I find that the predictability of stock returns based on information uncertainty lasts for at least 6 months for the bad-news category but only 1 or 2 months for the good-news category. The asymmetry of results between good and bad news might be partially due to short-sale restrictions, especially for high-uncertainty firms. The fact that the predictability of stock returns is much more short-lived for good news than for bad news explains why high-uncertainty firms have slightly lower returns than low-uncertainty firms in the no-news category. The no-news category is actually a combination of good news and bad news from previous months. Given that the information effect lasts longer for bad news, the no-news category exhibits a pattern more similar to the bad-news category than to the good-news category. In this sense, the no-news category is mislabeled.

[15] The asymmetry of results following good versus bad news is relatively big for SIGMA, which is consistent with the results of Ang et al. (2003), who find that idiosyncratic stock volatility is negatively priced in the overall market.

[16] The evidence in Fama and French (1995) that the recession in 1981 and 1982 turns into a prolonged earnings depression for small stocks but not for large stocks supports this argument.

based on analyst forecast revisions. For low-uncertainty firms the initial market reaction is largely complete. For example, a trading strategy of buying good-news stocks and shorting bad-news stocks yields a small 0.46% monthly return when I focus on low-volatility stocks (SIGMA D1, Table III). On the other hand, the initial market response is far from complete for high-uncertainty firms. A similar strategy using high-volatility stocks (SIGMA D10, Table III) generates a 2.39% monthly return. To make a comparison, a simple trading strategy with a short position in all downward-revision stocks and a long position in all upward-revision stocks yields a 1.13% monthly return (Table II, Panel B).

C. Portfolio Returns by Price Momentum and Information Uncertainty Proxy

Intermediate-horizon stock returns offer another measure of the nature of news. Past winners imply good news and past losers imply bad news. Therefore, my prediction is that greater information uncertainty predicts relatively lower future returns for past losers and relatively higher future returns for past winners.

Table IV shows the returns when momentum interacts with information uncertainty. Each month I sort stocks into five quintiles based on past returns from $t - 11$ to $t - 1$.[17] For each momentum quintile, I further sort stocks into five groups by information uncertainty level. As shown in Table IV, information uncertainty is highly negatively correlated with 1-month-ahead stock returns for past losers. For example, the youngest firm (AGE) quintile earns an average -0.47% monthly return, compared to 1.20% for the oldest firm quintile. The return differential between these two quintiles (U5-U1) is -1.67% ($t = -4.42$). On the other hand, information uncertainty is strongly positively correlated with 1-month-ahead returns for past winners. The youngest firm quintile gains 2.43% per month, but the oldest firm quintile gains only 1.60% per month. The return differential between these two quintiles is 0.83% ($t = 2.64$). Other information uncertainty proxies produce similar results. This evidence clearly supports my hypothesis.

Table IV also shows that because of a strong interaction effect between momentum and information uncertainty, the momentum effect is much stronger for high-uncertainty firms than for low-uncertainty firms.[18] The return from a trading strategy with a long position in past winners and a short position in past losers increases monotonically as information uncertainty increases. For example, using the AGE proxy, the momentum trading strategy produces an average monthly return as high as 2.90% ($t = 7.21$) for the youngest firm

[17] I allow a 1-month lag between the momentum measure and the portfolio formation date, consistent with Fama and French (1996) and Diether et al. (2002).

[18] This two-way nonindependent sort by momentum and then by information uncertainty accurately measures the information uncertainty effect within each momentum group but not the momentum effect within each uncertainty group. I replicate the results when first sorting stocks by information uncertainty and then by momentum. In this way, the hedge portfolio returns accurately reflect the momentum profit within each uncertainty group. I also find similar results using independent sorts by momentum and information uncertainty.

Table IV

Portfolio Returns by Price Momentum and Information Uncertainty Proxy

This table reports average monthly portfolio returns sorted by price momentum and information uncertainty proxy. Each month I first sort stocks into five quintiles based on returns from months $t-11$ to $t-1$. For each momentum quintile, I further sort stocks into five groups based on information uncertainty proxy. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. 1/MV, 1/AGE, and 1/COV are the reciprocals of MV, AGE, and COV, respectively. Stocks with a price less than $5 at the portfolio formation date are excluded from the sample. Stocks are held for 1 month, and portfolio returns are equally weighted. The sample period is from January 1983 to December 2001; t-statistics in parentheses are adjusted for autocorrelation.

	Momentum Quintile					
	M1 (Losers)	M2	M3	M4	M5 (Winners)	M5 − M1
	Uncertainty Proxied by 1/MV					
U1 (low)	0.75%	1.09%	1.09%	1.21%	1.53%	0.78%
						(1.74)
U2	0.50%	1.04%	1.14%	1.36%	1.88%	1.38%
						(3.53)
U3	0.66%	1.08%	1.23%	1.37%	1.96%	1.30%
						(3.55)
U4	0.23%	1.15%	1.46%	1.71%	2.33%	2.09%
						(6.07)
U5 (high)	0.35%	1.11%	1.40%	1.69%	2.58%	2.23%
						(6.45)
U5 − U1	−0.40%	0.02%	0.31%	0.48%	1.05%	1.45%
	(−1.30)	(0.08)	(1.23)	(1.94)	(3.96)	(4.43)
	Uncertainty Proxied by 1/AGE					
U1 (low)	1.20%	1.26%	1.19%	1.32%	1.60%	0.40%
						(1.08)
U2	0.89%	1.21%	1.37%	1.40%	1.90%	1.01%
						(2.71)
U3	0.52%	1.08%	1.44%	1.57%	2.04%	1.52%
						(4.03)
U4	0.32%	1.00%	1.24%	1.58%	2.24%	1.92%
						(5.08)
U5 (high)	−0.47%	0.86%	1.05%	1.47%	2.43%	2.90%
						(7.21)
U5 − U1	−1.67%	−0.41%	−0.14%	0.15%	0.83%	2.50%
	(−4.42)	(−1.55)	(−0.53)	(0.54)	(2.64)	(7.98)
	Uncertainty Proxied by 1/COV					
U1 (low)	0.72%	1.08%	1.09%	1.17%	1.64%	0.92%
						(2.13)
U2	0.74%	0.98%	1.19%	1.28%	1.88%	1.13%
						(2.85)

(*continued*)

Table IV—*Continued*

	Momentum Quintile					
	M1 (Losers)	M2	M3	M4	M5 (Winners)	M5 − M1
U3	0.31%	1.05%	1.15%	1.46%	1.93%	1.63%
						(4.69)
U4	0.21%	0.75%	1.13%	1.29%	2.24%	2.03%
						(5.31)
U5 (high)	−0.12%	0.96%	1.14%	1.34%	2.02%	2.14%
						(5.85)
U5 − U1	−0.84%	−0.12%	0.05%	0.17%	0.38%	1.22%
	(−3.00)	(−0.57)	(0.25)	(0.50)	(1.44)	(4.17)
Uncertainty Proxied by DISP						
U1 (low)	0.65%	1.00%	1.22%	1.42%	1.76%	1.11%
						(2.62)
U2	0.95%	1.08%	1.18%	1.35%	2.00%	1.05%
						(2.90)
U3	0.66%	1.29%	1.30%	1.50%	1.92%	1.26%
						(3.31)
U4	0.39%	1.12%	1.26%	1.46%	2.09%	1.70%
						(4.51)
U5 (high)	0.15%	1.03%	1.41%	1.63%	2.45%	2.30%
						(6.76)
U5 − U1	−0.50%	0.02%	0.18%	0.22%	0.69%	1.19%
	(−1.80)	(0.13)	(0.93)	(1.15)	(3.20)	(4.02)
Uncertainty Proxied by SIGMA						
U1 (low)	1.11%	1.37%	1.36%	1.51%	1.75%	0.63%
						(2.04)
U2	0.98%	1.32%	1.34%	1.50%	1.97%	1.00%
						(2.85)
U3	0.61%	1.09%	1.39%	1.47%	2.06%	1.45%
						(3.65)
U4	0.12%	1.03%	1.25%	1.46%	2.23%	2.10%
						(4.84)
U5 (high)	−0.35%	0.65%	0.95%	1.30%	2.28%	2.63%
						(5.91)
U5 − U1	−1.47%	−0.72%	−0.41%	−0.21%	0.53%	2.00%
	(−3.04)	(−1.84)	(−0.98)	(−0.47)	(1.01)	(5.62)
Uncertainty Proxied by CVOL						
U1 (low)	1.04%	1.28%	1.33%	1.27%	1.72%	0.68%
						(1.85)
U2	0.98%	1.16%	1.27%	1.39%	1.72%	0.74%
						(2.00)
U3	0.81%	0.92%	1.17%	1.47%	2.05%	1.24%
						(3.44)
U4	0.56%	1.06%	1.16%	1.31%	2.22%	1.67%
						(3.97)
U5 (high)	0.06%	0.56%	1.19%	1.38%	2.11%	2.05%
						(5.18)
U5 − U1	−0.97%	−0.73%	−0.14%	0.11%	0.40%	1.37%
	(−2.92)	(−2.45)	(−0.41)	(0.34)	(1.13)	(4.74)

quintile, compared to only 0.40% (t = 1.08) for the oldest firm quintile. The return differential between these two momentum strategies is 2.50% (t = 7.98). The return differential between the momentum strategies for high-uncertainty stocks (U5) and low-uncertainty stocks (U1) ranges from 1.19% to 2.00% per month for other information uncertainty proxies and is highly significant in each case.

The above results are based on five price momentum portfolios and five uncertainty portfolios (5×5). My results are not specific to this partitioning. In analyses untabulated, I use 10 price momentum and 3 uncertainty portfolios (10×3) and use 3 price momentum and 10 uncertainty portfolios (3×10). Generally, the uncertainty effect is as strong as that reported in Table IV. For each proxy, the return differential between the momentum strategy for high-uncertainty stocks and that for low-uncertainty stocks is positive and significantly different from zero. These results are consistent with the underreaction explanation for the momentum phenomenon, in the sense that investors underreact to a higher degree when there is greater information uncertainty.

D. *Portfolio Returns by Forecast Revision, Momentum, and Information Uncertainty Proxy*

The final portfolio strategy uses a four-way sort by forecast revision, momentum, and two information uncertainty proxies. Double sorts by analyst forecast revision and momentum should better identify firms with really bad and really good news, and therefore provide a more precise test of the effect of information uncertainty on investor underreaction behavior. I focus on the really bad-news groups (losers with downward revisions) and really good-news groups (winners with upward revisions) in the test. On the information uncertainty side, I sort by size and each of the other information uncertainty proxies because firm size is extensively studied in the prior literature.

To form portfolios, I first sort stocks into three categories based on forecast revisions in the current month. Within each revision category, I sort the stocks into three groups based on past returns from $t - 11$ to $t - 1$. Then for each revision and momentum group, I further sort the stocks into three divisions by size, and finally into three uncertainty subsets. This four-way sort classifies stocks into 81 portfolios. For each month there is an average of 24, 38, and 19 stocks in each portfolio for the negative, zero, and positive revision categories, respectively.

Table V presents the 1-month-ahead returns for the really bad- and really good-news groups. Following bad news, stock returns monotonically decrease in each size group as information uncertainty increases for most categories. The return differential between high- and low-uncertainty firms (U3-U1) is significantly negative for 8 out of 15 size groups. After good news, high-uncertainty firms have higher future returns than do low-uncertainty ones. The U3-U1 strategy yields positive returns in all but one size group. These results provide further support for my hypothesis. Consistent with the evidence in Table III, the size premiums are uniformly negative following bad news and highly posi-

Table V

Portfolio Returns by Forecast Revision, Momentum, and Information Uncertainty Proxy

This table reports average monthly returns for really bad (losers with REV < 0) and really good (winners with REV > 0) portfolios, using double sorts by the nature of news and double sorts by information uncertainty proxies. Each month I sort stocks into three categories depending on whether the forecast revision is negative, zero, or positive. The forecast revision is the average of individual forecast revisions by analysts who covered the firm in both month $t-1$ and t. For each category, I sort stocks into three groups based on returns from months $t-11$ to $t-1$. For each news group, I further sort stocks into three divisions by firm size, and finally into three subsets based on another uncertainty proxy. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. 1/MV, 1/AGE, and 1/COV are the reciprocals of MV, AGE, and COV, respectively. Stocks with a price less than \$5 at the portfolio formation date are excluded from the sample. Stocks are held for 1 month, and portfolio returns are equally weighted. The sample period is from January 1983 to December 2001; t-statistics in parentheses are adjusted for autocorrelation.

	Bad News (Losers with REV < 0)				Good News (Winners with REV > 0)				Good News – Bad News		
	Small Cap	Mid Cap	Large Cap	Small-Large	Small Cap	Mid Cap	Large Cap	Small-Large	Small Cap	Mid Cap	Large Cap
					Uncertainty Proxied by 1/AGE						
U1	0.37%	1.21%	1.10%	−0.73%	2.69%	1.92%	1.72%	0.97%	2.32%	0.71%	0.62%
				(−2.14)				(3.27)	(5.34)	(1.58)	(1.66)
U2	0.16%	0.64%	1.18%	−1.02%	3.39%	2.25%	1.81%	1.58%	3.23%	1.61%	0.63%
				(−2.64)				(4.07)	(7.52)	(3.19)	(1.38)
U3	−0.93%	−0.24%	0.50%	−1.43%	3.57%	2.86%	2.42%	1.15%	4.50%	3.10%	1.92%
				(−3.77)				(3.03)	(10.32)	(6.30)	(4.09)
U3 − U1	−1.30%	−1.45%	−0.60%		0.88%	0.94%	0.70%				
	(−3.15)	(−3.59)	(−1.64)		(3.26)	(2.09)	(2.01)				
					Uncertainty Proxied by 1/COV						
U1	0.09%	0.72%	0.71%	−0.62%	3.24%	2.08%	2.00%	1.24%	3.15%	1.36%	1.29%
				(−1.58)				(3.25)	(7.06)	(2.85)	(2.77)
U2	0.16%	0.54%	1.04%	−0.88%	3.03%	2.65%	2.13%	0.90%	2.87%	2.11%	1.09%
				(−2.42)				(2.52)	(6.81)	(4.51)	(2.46)
U3	−0.79%	0.15%	0.78%	−1.57%	3.71%	2.09%	1.93%	1.78%	4.50%	1.94%	1.15%
				(−4.86)				(4.93)	(10.37)	(4.17)	(2.84)
U3 − U1	−0.88%	−0.57%	0.07%		0.47%	0.00%	−0.06%				
	(−2.68)	(−1.51)	(0.23)		(1.42)	(0.13)	(−0.06)				

					Uncertainty Proxied by DISP						
U1	0.55%	0.79%	0.84%	−0.29%	2.89%	2.19%	1.71%	1.18%	2.34%	1.40%	0.87%
				(−0.73)				(3.46)	(5.23)	(2.79)	(1.83)
U2	−0.18%	0.69%	0.84%	−1.02%	3.59%	2.06%	2.21%	1.38%	3.77%	1.37%	1.37%
				(−2.88)				(3.80)	(8.86)	(3.33)	(3.15)
U3	−0.47%	0.41%	0.98%	−1.45%	3.13%	2.43%	1.98%	1.15%	3.60%	2.02%	1.00%
				(−4.00)				(3.13)	(8.44)	(4.43)	(2.64)
U3 − U1	−1.02%	−0.38%	0.15%		0.24%	0.24%	0.27%				
	(−2.89)	(−1.14)	(0.54)		(1.05)	(0.83)	(1.05)				
					Uncertainty Proxied by SIGMA						
U1	0.51%	0.99%	1.32%	−0.81%	2.75%	2.07%	1.72%	1.03%	2.24%	1.08%	0.40%
				(−2.76)				(3.64)	(6.45)	(3.07)	(1.32)
U2	0.01%	0.66%	0.98%	−0.97%	3.20%	2.16%	1.86%	1.34%	3.19%	1.50%	0.88%
				(−2.68)				(3.92)	(7.26)	(3.10)	(1.93)
U3	−0.90%	−0.01%	0.47%	−1.37%	3.81%	2.66%	2.35%	1.46%	4.71%	2.67%	1.88%
				(−3.29)				(3.77)	(9.70)	(4.56)	(3.80)
U3 − U1	−1.41%	−1.00%	−0.85%		1.06%	0.59%	0.63%				
	(−3.00)	(−2.04)	(−2.22)		(2.03)	(1.13)	(1.57)				
					Uncertainty Proxied by CVOL						
U1	0.50%	0.92%	1.13%	−0.62%	3.00%	1.81%	1.73%	1.27%	2.53%	0.87%	0.58%
				(−1.76)				(3.23)	(5.97)	(2.16)	(1.41)
U2	0.37%	1.16%	0.90%	−0.53%	3.01%	1.93%	1.91%	1.10%	2.64%	0.77%	1.01%
				(−1.48)				(2.81)	(5.39)	(1.73)	(2.26)
U3	−0.25%	0.46%	0.56%	−0.81%	3.82%	2.42%	2.50%	1.32%	4.07%	1.96%	1.95%
				(−2.06)				(3.39)	(8.25)	(3.50)	(3.94)
U3 − U1	−0.74%	−0.46%	−0.56%		0.82%	0.61%	0.77%				
	(−2.01)	(−1.36)	(−1.87)		(1.86)	(1.49)	(2.31)				

tive following good news, and they are significantly different from zero in most uncertainty groups.

Furthermore, firm size and other information uncertainty proxies interact in a plausible way. The uncertainty effect is greatest for the smallest size group in both good- and bad-news categories, indicating that other information uncertainty proxies play a more significant role for smaller firms. Similarly, the size effect is typically the strongest for the highest uncertainty group following good or bad news. In untabulated results, I find that uncertainty proxies for the bad-news category closely match those for the good-news category in each case, which implies that information uncertainty alone cannot explain the observed return pattern.

The double sorts in each dimension do not subsume each other, which suggests that each sort has incremental information and no proxy is perfect. A trading strategy that uses this categorization achieves remarkable returns. For example, for high-uncertainty stocks (small size and young age), the trading strategy of buying past winners with upward revisions and shorting past losers with downward revisions generates an average 4.50% ($t = 10.32$) monthly return. The same strategy yields 2.32% ($t = 5.34$), 1.92% ($t = 4.09$), and 0.62% ($t = 1.66$) for small firms with a long history, large firms with a short history, and large firms with a long history, respectively. These results indicate that market reaction to new information is quite complete for low-uncertainty firms but not for high-uncertainty firms, and that size and other proxies for information uncertainty have similar effects on investor underreaction but do not subsume each other.

IV. Four-Factor Model Results

In this section, I examine whether my information uncertainty results can be explained using a rational approach. Fama and French (1996) show that their three-factor model (*Rm-Rf*, SMB, and HML) can explain most commonly documented Capital Asset Pricing Model (CAPM) anomalies except for the continuation of short-term returns. They argue that the three-factor model works like an equilibrium pricing model in the spirit of Merton's (1973) intertemporal CAPM or Ross's (1976) arbitrage pricing theory and that SMB and HML mimic combinations of two underlying risk factors or state variables of special hedging concern to investors. Empirically, SMB represents the size premium and equals the return differential between portfolios of small and large stocks. Similarly, HML represents the value premium and equals the return differential between portfolios of stocks with high book-to-market ratios and low book-to-market ratios (see Fama and French (1996) for details on these three factors).

Since the Fama–French three-factor model does not capture the momentum effect, I use a four-factor model (e.g., Carhart (1997)) to test portfolio returns. If the four-factor model can capture the cross-sectional variation in stock returns, then the intercept from the following regression should be statistically indistinguishable from zero,

$$R_{it} - R_{ft} = \alpha + b_{iM}(R_{Mt} - R_{ft}) + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + m_i \mathrm{UMD}_t + \varepsilon_{it}, \quad (1)$$

where $R_{it} - R_{ft}$ is the return of portfolio i in excess of the risk-free rate in month t, $R_{Mt} - R_{ft}$ is the excess return of the market value-weighted portfolio, and UMD is the return difference between portfolios of past winners and past losers.[19]

Table VI reports the intercepts of the four-factor model for 15 portfolios for each uncertainty proxy. Each month I sort stocks into three categories depending on whether the forecast revision in the past month is negative, zero, or positive. For each category, I further sort stocks into five portfolios based on an information uncertainty proxy. The intercepts from the four-factor model are uniformly negative for bad-news portfolios and positive for good-news portfolios. More importantly, the magnitude of the intercept is positively related to the level of uncertainty, which implies that high-uncertainty portfolios earn more negative abnormal returns following bad news and more positive abnormal returns following good news in a four-factor world. For example, young firm portfolios have intercepts of -0.709 ($t = -4.18$) following bad news and 1.176 ($t = 7.29$) following good news, which correspond to -8.51% and 14.11% annual abnormal returns, respectively. A trading strategy with a short position in young firms with downward revisions and a long position in young firms with upward revisions generates a 22.62% annual abnormal return after controlling for the market, size, value, and momentum effects. For no-news portfolios, the intercepts are indistinguishable from zero in most cases. This pattern of intercepts from the four-factor model further confirms my hypothesis.

Untabulated results show that the risk loadings on $R_{Mt} - R_{ft}$, SMB, HML, and UMD are as expected. The risk loadings on the market premium are each close to one for all 90 portfolios with t-statistics over 30. High-uncertainty portfolios have higher loadings on SMB, suggesting that high-uncertainty firms tend to be small. The loadings on HML are typically lower for high-uncertainty stocks except when information uncertainty is proxied by firm size or analyst forecast dispersion, which suggests that high-uncertainty firms are more likely to be growth firms. The risk loadings on UMD are uniformly negative for bad-news portfolios but usually positive for good-news portfolios, confirming momentum as a proxy for the nature of news. The adjusted R^2 is around 0.9 across portfolios, suggesting that the four-factor model has reasonable explanatory power.

In summary, the level of uncertainty is positively (negatively) related to abnormal stock returns following good (bad) news. Although each proxy might also capture other risk factors or contain substantial measurement error, consistent results across different proxies lend strong support to the view that information uncertainty magnifies behavioral biases and is not a priced risk factor. Because the information uncertainty proxies consistently increase returns following good news but decrease returns following bad news, it is difficult to construct a risk-based story for this effect. Finally, the inclusion of a

[19] I construct UMD in the same way as in Carhart (1997), and download the Fama–French three factors from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table VI

Four-Factor Model Results

This table reports the intercepts of the four-factor regression model for monthly excess returns of the information uncertainty quintiles for three news categories based on analyst forecast revisions. The model estimated is

$$R_{it} - R_{ft} = a + b_{iM}(R_{Mt} - R_{ft}) + s_i \mathrm{SMB}_t + h_i \mathrm{HML}_t + m_i \mathrm{UMD}_t + \varepsilon_{it},$$

where $R_{Mt} - R_{ft}$, SMB, and HML are as defined in Fama and French (1996), and UMD is momentum as defined in Carhart (1997). Each month I sort stocks into three categories depending on whether the forecast revision is negative (bad news), zero (no news), or positive (good news) in month $t-1$. For each news category, I further sort stocks into five portfolios based on an information uncertainty proxy. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month $t-1$. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month $t-1$. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. 1/MV, 1/AGE, and 1/COV are the reciprocals of MV, AGE, and COV, respectively. The sample period is from January 1983 to December 2001. Stocks with a price less than $5 at the portfolio formation date are excluded from the sample, and White heteroskedasticity-adjusted t-statistics are in parentheses.

News	Uncertainty	1/MV	1/AGE	1/COV	DISP	SIGMA	CVOL
Bad News	Q1 (Low)	−0.173	−0.152	−0.012	−0.185	−0.066	−0.153
(REV < 0)		(−1.80)	(−1.10)	(−0.69)	(−0.89)	(−0.47)	(−1.00)
	Q2	−0.092	−0.102	−0.123	−0.074	−0.319	−0.088
		(−0.48)	(−0.64)	(−0.77)	(−0.36)	(−2.29)	(−0.55)
	Q3	−2.85	−2.212	−0.285	−0.362	−0.457	−0.244
		(−1.60)	(−1.33)	(−1.82)	(−2.28)	(−2.95)	(−3.33)
	Q4	−0.370	−0.318	−0.319	−0.244	−0.240	−0.214
		(−2.26)	(−1.82)	(−1.99)	(−1.75)	(−1.42)	(−1.16)
	Q5 (high)	−0.519	−0.709	−0.724	−0.415	−0.361	−4.410
		(−3.17)	(−4.18)	(−5.62)	(−2.50)	(−1.57)	(−2.10)
No News	Q1 (Low)	−0.210	−0.139	0.161	−0.003	0.157	0.082
(REV = 0)		(−1.86)	(−0.96)	(1.40)	(−0.51)	(1.17)	(0.64)
	Q2	0.008	0.317	0.226	0.206	0.032	0.082
		(0.10)	(2.33)	(1.76)	(1.76)	(0.20)	(0.60)
	Q3	0.186	0.292	0.077	0.241	0.138	0.357
		(1.84)	(2.89)	(0.72)	(1.69)	(1.10)	(2.67)
	Q4	0.451	0.148	0.183	0.321	0.456	0.263
		(2.94)	(1.09)	(1.58)	(2.89)	(3.44)	(1.84)
	Q5 (high)	0.483	0.270	0.156	0.137	0.116	0.219
		(2.81)	(1.62)	(1.10)	(1.62)	(0.59)	(1.10)
Good News	Q1 (Low)	0.169	0.074	0.419	0.369	0.210	0.250
(REV > 0)		(1.91)	(0.57)	(3.76)	(3.05)	(1.82)	(1.53)
	Q2	0.236	0.251	0.170	0.767	0.198	0.329
		(1.65)	(1.86)	(1.15)	(4.78)	(1.74)	(2.60)
	Q3	0.284	0.675	0.685	0.664	0.363	0.624
		(1.66)	(4.47)	(4.60)	(4.76)	(2.28)	(3.75)
	Q4	0.888	0.892	0.751	0.587	0.791	0.766
		(5.57)	(5.72)	(4.85)	(4.02)	(4.71)	(3.87)
	Q5 (high)	1.591	1.176	1.087	0.588	1.596	1.318
		(9.20)	(7.29)	(7.52)	(3.40)	(7.24)	(6.81)

size factor in the four-factor model cannot subsume the abnormal stock returns based on size and the nature of news, confirming early evidence that firm size is more likely to be associated with information uncertainty rather than being a common risk factor in the cross-section of stock returns.

V. Market Reaction to Subsequent Earnings Announcements

The evidence in the previous sections indicates that post-news price drift increases with information uncertainty. A limitation of my previous analyses is that this relationship could be attributable to unidentified risk factors or unknown research design flaws. This section mitigates these concerns by examining stock price reactions to earnings announcements after the portfolio formation date. Because daily expected returns are close to zero, the model used for expected returns does not have a large effect on inferences about abnormal returns (Fama (1998)). Therefore, risk-based models would predict zero returns over this short window. If investor behavior exhibits underreaction to news related to future earnings, investors should correct their misvaluations around subsequent earnings announcement dates. Therefore, we should observe a positive relation between the nature of news and the stock price reactions to the subsequent earnings announcement (Chan, Jegadeesh, and Lakonishok (1999)). In particular, we expect to see a negative market reaction on the earnings announcement date following bad news and a positive one following good news. If information uncertainty exacerbates an investor's behavioral bias, we expect to see more positive (negative) reactions following good (bad) news for high-uncertainty stocks than for low-uncertainty stocks.

Since earnings are announced on a quarterly basis, I form five uncertainty portfolios for each calendar quarter following bad and good news, respectively. Good news refers to upward analyst forecast revisions in the previous month or past winners (top quintile) and vice versa for bad news. Following Bernard and Thomas (1990) and Jegadeesh and Titman (1993), the announcement period for each quarterly announcement is defined as the 3-day period beginning two days prior to the Compustat earnings announcement date.

Table VII presents the average daily market excess returns (measured as raw return minus the contemporaneous value-weighted market return) from the announcement period tests. Panel A reports the results when the nature of news is based on analyst forecast revisions, and in Panel B it is based on the past 11-month stock returns. Both panels show that the 3-day excess returns around earnings announcements are predictable. The signs and magnitudes of the excess returns are consistent with my hypothesis. The market reaction to earnings announcements is negative for bad-news portfolios and positive for good-news portfolios for all uncertainty proxies. More importantly, the magnitude of excess returns around the quarterly earnings announcement date increases with the level of information uncertainty. In both panels, a zero-investment portfolio with a long position in good-news stocks and a short position in bad-news stocks generates the highest returns for high-uncertainty stocks for both types of news measures and for all proxies except for the AGE/REV combination.

Table VII

Excess Returns Around a 3-Day Earnings Announcement Window

This table reports average daily excess returns around a 3-day earnings announcement window. Excess returns are measured as raw returns minus the value-weighted market return. The 3-day window starts two days prior to the Compustat earnings announcement date. Each quarter I sort stocks into bad and good news categories. For each category, I further sort stocks into five portfolios based on information uncertainty. In Panel A, bad news refers to downward analyst forecast revisions (REV), and good news refers to upward analyst forecast revisions in month t. In Panel B, bad news refers to the bottom momentum quintile (past losers), and good news refers to the top momentum quintile (past winners), where momentum is the accumulated return from month $t-11$ to $t-1$. GMB is a zero-investment portfolio with a long position in good-news stocks and a short position in bad-news stocks. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. 1/MV, 1/AGE, and 1/COV are the reciprocals of MV, AGE, and COV, respectively. Stocks with a price less than 5 dollars at the portfolio formation date are excluded from the sample. Portfolio returns are equally weighted. The sample period is from January 1983 to December 2001.

Panel A. Bad News—Downward Revisions (REV < 0), Good News—Upward Revisions (REV > 0)

	Sorted by 1/MV			Sorted by 1/AGE			Sorted by 1/COV		
	REV < 0	REV > 0	GMB	REV < 0	REV > 0	GMB	REV < 0	REV > 0	GMB
Q1 (low)	0.02%	0.13%	0.11%	−0.01%	0.09%	0.10%	0.05%	0.14%	0.09%
			(3.27)			(3.95)			(1.97)
Q2	−0.03%	0.16%	0.18%	−0.01%	0.17%	0.18%	−0.03%	0.11%	0.14%
			(4.39)			(4.91)			(3.01)
Q3	−0.02%	0.21%	0.23%	−0.03%	0.25%	0.27%	−0.13%	0.23%	0.35%
			(4.42)			(5.14)			(6.81)
Q4	−0.08%	0.24%	0.31%	−0.12%	0.31%	0.43%	−0.07%	0.26%	0.33%
			(6.37)			(8.08)			(5.18)
Q5 (high)	−0.11%	0.35%	0.46%	−0.07%	0.28%	0.35%	−0.11%	0.28%	0.38%
			(8.34)			(7.50)			(7.72)
Q5 − Q1	−0.13%	0.22%		−0.06%	0.19%		−0.16%	0.14%	
	(−3.23)	(4.33)		(−1.15)	(3.10)		(−3.80)	(2.63)	

	Sorted by DISP			Sorted by SIGMA			Sorted by CVOL		
	REV < 0	REV > 0	GMB	REV < 0	REV > 0	GMB	REV < 0	REV > 0	GMB
Q1 (low)	−0.07%	0.20%	0.27%	0.01%	0.12%	0.11%	−0.06%	0.14%	0.19%
			(4.56)			(3.62)			(5.48)
Q2	−0.01%	0.19%	0.19%	−0.01%	0.14%	0.15%	−0.04%	0.15%	0.18%
			(4.60)			(4.07)			(4.34)
Q3	0.00%	0.22%	0.22%	−0.08%	0.26%	0.34%	−0.03%	0.24%	0.27%
			(5.38)			(5.10)			(4.72)
Q4	−0.03%	0.24%	0.28%	−0.06%	0.23%	0.29%	−0.05%	0.22%	0.27%
			(5.48)			(4.92)			(5.02)
Q5 (high)	−0.10%	0.24%	0.33%	−0.08%	0.32%	0.40%	−0.11%	0.36%	0.47%
			(5.80)			(5.62)			(6.24)
Q5 − Q1	−0.02%	0.04%		−0.09%	0.20%		−0.05%	0.22%	
	(−0.42)	(0.76)		(−1.40)	(2.75)		(−0.93)	(2.95)	

(*continued*)

A comparison between Table IV and Table VII, Panel B reveals additional evidence. Table IV reports average monthly returns and Table VII, Panel B reports average daily returns. Given that a month typically has at least 20 trading days, the announcement period reactions represent a disproportionate share of

Table VII—*Continued*

Panel B. Bad News—Past Losers, Good News—Past Winners

	Sorted by 1/MV			Sorted by 1/AGE			Sorted by 1/COV		
	Losers	Winners	GMB	Losers	Winners	GMB	Losers	Winners	GMB
Q1 (low)	0.00%	0.19%	0.19%	−0.04%	0.16%	0.21%	0.00%	0.17%	0.18%
			(2.97)			(3.94)			(2.35)
Q2	−0.02%	0.19%	0.21%	−0.06%	0.21%	0.26%	−0.09%	0.22%	0.31%
			(3.02)			(4.01)			(5.17)
Q3	−0.14%	0.18%	0.31%	−0.14%	0.20%	0.34%	−0.03%	0.19%	0.22%
			(6.27)			(5.22)			(3.31)
Q4	−0.07%	0.26%	0.33%	−0.03%	0.24%	0.27%	−0.12%	0.20%	0.33%
			(4.98)			(4.07)			(3.89)
Q5 (high)	−0.11%	0.34%	0.44%	−0.07%	0.31%	0.38%	−0.10%	0.30%	0.40%
			(6.82)			(5.03)			(6.41)
Q5 − Q1	−0.11%	0.15%		−0.03%	0.14%		−0.10%	0.12%	
	(−1.90)	(2.19)		(−0.52)	(2.03)		(−1.67)	(1.87)	

	Sorted by DISP			Sorted by SIGMA			Sorted by CVOL		
	Losers	Winners	GMB	Losers	Winners	GMB	Losers	Winners	GMB
Q1 (low)	0.00%	0.17%	0.17%	−0.04%	0.17%	0.21%	−0.01%	0.17%	0.18%
			(2.46)			(4.23)			(2.72)
Q2	0.04%	0.21%	0.17%	−0.04%	0.23%	0.27%	−0.09%	0.22%	0.31%
			(2.43)			(4.24)			(4.39)
Q3	−0.11%	0.23%	0.34%	−0.05%	0.25%	0.30%	−0.05%	0.27%	0.32%
			(3.76)			(4.36)			(4.60)
Q4	−0.08%	0.21%	0.29%	−0.07%	0.26%	0.33%	−0.04%	0.27%	0.32%
			(4.73)			(4.83)			(3.93)
Q5 (high)	−0.14%	0.26%	0.40%	−0.13%	0.26%	0.39%	−0.14%	0.24%	0.38%
			(6.81)			(5.40)			(5.42)
Q5 − Q1	−0.14%	0.09%		−0.09%	0.09%		−0.13%	0.06%	
	(−1.94)	(1.76)		(−1.16)	(1.48)		(−2.03)	(1.09)	

the drift. For example, a zero-investment portfolio on the top SIGMA quintile has a 2.63% monthly return in Table IV. The average of 0.39% daily returns in Table VII, Panel B means that on average at least 15% [=(0.39 × 3)/(2.63 × 3)] of the predictable stock returns are concentrated around subsequent earnings announcement dates, which accounts for only 5% [=3/(20 × 3)] of trading days.

Overall, the signs and relative magnitudes of the excess returns around subsequent earnings announcement dates are in general accordance with my hypothesis. Given that expected returns should be trivial on a daily basis, this analysis presents more direct evidence that short-term price continuation anomalies are rooted in a failure of information to flow completely into stock prices rather than being driven by missing risk factors.

VI. Robustness Checks

A. Characteristics of Various Trading Strategies

The previous sections show that trading strategies based on the nature of news and/or the level of uncertainty yield significant returns. Table VIII provides a summary of returns from various trading strategies. The Fama–French factors ($R_m - R_f$, SMB, and HML) are defined in Section IV and in Fama and

Table VIII

Characteristics of a Variety of Trading Portfolios

This table presents characteristics of various trading strategies discussed in Section III. The Fama–French factors are as defined in Fama and French (1996). The momentum strategy (MOM) has a short position in past losers and a long position in past winners and is defined in Table IV. The trading strategy (REV_MOM) has a short position in past losers with downward revisions and a long position in past winners with upward revisions and is defined in Table V. Portfolios with less than five stocks in either the short or long position are deleted. M is the number of months with available portfolio returns from 1983 to 2001. M_neg is the number of months with negative returns. RET is average monthly portfolio return over the sample period. Sharpe is the Sharpe ratio, defined as the mean return divided by its standard deviation. VOL_long and VOL_short are the average monthly dollar trading volume (in millions of dollars) for each stock, and N_long and N_short are the average number of stocks in the long and short positions, respectively. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets.

Trading Strategy	M	M_neg	RET	Sharpe	VOLM_long	VOLM_short	N_long	N_short
Fama—French Three Factors								
Rm-Rf	228	87	0.71%	0.16				
SMB	228	121	−0.06%	−0.02				
HML	228	101	0.38%	0.11				
The Momentum Strategy (MOM) by Shorting Past Losers and Buying Past Winners (Table IV)								
All stocks	228	68	1.55%	0.28	352	135	422	422
The bottom MV quintile	228	60	2.23%	0.43	13	5	84	84
The bottom AGE quintile	228	64	2.90%	0.46	288	59	84	85
The bottom COV quintile	222	60	2.18%	0.38	40	12	82	80
The top DISP quintile	228	66	2.29%	0.42	221	80	72	72
The top SIGMA quintile	228	72	2.63%	0.38	241	89	84	84
The top CVOL quintile	228	69	2.05%	0.33	375	131	61	61
The Trading Strategy (REV_MOM) by Shorting Past Losers with Downward Revisions and Buying Past Winners with Upward Revisions (Table V)								
Small AGE and small cap	217	53	4.51%	0.68	42	19	19	25
Small COV and small cap	213	42	4.50%	0.68	28	10	18	24
Big DISP and small cap	221	51	3.68%	0.55	41	20	18	23
Big SIGMA and small cap	221	52	4.73%	0.62	52	25	19	24
Big CVOL and small cap	220	63	4.05%	0.53	48	22	14	19

French (1996). The momentum trading strategy (MOM) has a short position in past losers and a long position in past winners and is defined in Table IV. The trading strategy (REV_MOM) has a short position in past losers with downward revisions and a long position in past winners with upward revisions as defined in Table V. Table VIII shows the results from MOM and REV_MOM strategies using high-uncertainty stocks. The average market excess return is 0.71% per month with a Sharpe ratio of 0.16. Both the average return and the Sharpe ratio are smaller for HML and are slightly negative for SMB. The MOM strategy for the whole sample yields a 1.55% monthly return with a Sharpe ratio of 0.28. When trading is limited to high-uncertainty stocks, the strategy produces significantly higher returns and Sharpe ratios. The return ranges from 2.05% to 2.90% and the Sharpe ratio ranges from 0.33 to 0.46 for six information uncertainty proxies. Both returns and Sharpe ratios are even higher when the REV_MOM strategy is used.[20] Additionally, REV_MOM yields negative returns (N_neg) in fewer months than the MOM strategy.

In short, the trading strategies based on the nature of news and the level of uncertainty produce impressive average returns and Sharpe ratios, supporting my hypothesis. Certainly, I cannot definitely rule out the possibility that some risk-based model might explain the returns of these strategies, but given the high Sharpe ratios of the portfolios, such a model, based on the arguments of Hansen and Jagannathan (1991), would require investors to have very peculiar preferences.

B. Lag in Portfolio Formation

To examine the persistence of the information uncertainty effect, I duplicate the analysis but wait several months before assigning stocks to portfolios to see how long it takes the market to react completely to the news. Figure 1 shows the effect of uncertainty following good and bad news and the momentum effect among high- and low-uncertainty stocks when I use firm age as the information uncertainty proxy (other proxies produce similar patterns). As the lag increases and uncertainty is resolved, the magnitude of return differentials between high and low uncertainty stocks decreases. The return differential disappears after 6 months for bad news and 1 month for good news. As previously discussed, the persistence of negative returns in the bad-news case is probably due to short-sale restrictions. The fact that the uncertainty effect is

[20] Two caveats about the REV_MOM strategy are in order. First, as we push for a higher return, the size of the zero-investment portfolio becomes an issue. Certainly, a monthly return of 4.73% and a Sharpe ratio of 0.62 are not achievable for a multibillion-dollar fund, although the investment opportunity is still attractive. Assuming a position in any stock is 5% of average monthly trading volume, the portfolio size of the REV_MOM strategy on the SIGMA/SIZE combination would be \$60 million. The reason is as follows. The short position has an upper bound of \$30 million ($=24\times 25\times 5\%$), while the long position has an upper bound of \$49.4 million ($=19\times 52\times 5\%$). The short position is constrained in a zero-investment portfolio. Second, investors may not be able to diversify idiosyncratic risks. Because I sort stocks into 81 portfolios and the REV_MOM strategy focuses on two portfolios only, the short or long position has only about 20 stocks.

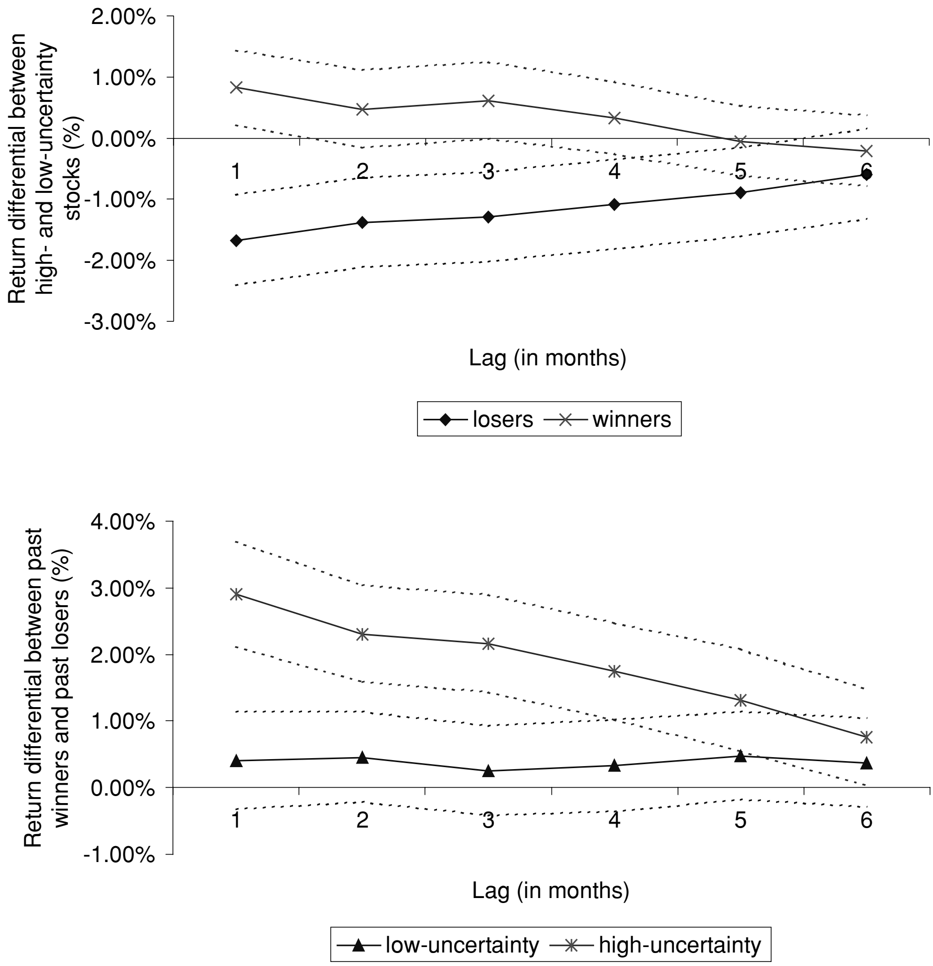

Figure 1. Lag in portfolio formation. At the end of each month, all stocks with prices of $5 or higher are ranked into five quintiles based on the 11-month stock returns (momentum) with a certain lag. Stocks in the top (winners) and bottom (losers) momentum quintiles are further sorted into five portfolios based on uncertainty proxied by the reciprocal of firm age. Stocks are equally weighted and held in the portfolio for 1 month. The first panel depicts the average monthly return differential between the highest- and lowest-uncertainty portfolios for winners and losers, respectively. The second panel depicts the average monthly return differential between winners and losers for the highest- and lowest-uncertainty quintiles, respectively. The broken lines indicate the 95% confidence interval (adjusted for autocorrelation).

much more short-lived following good news than following bad news might explain why high-uncertainty stocks tend to have relatively lower future returns than do low-uncertainty stocks in the overall market (Table II). As shown in the second panel of Figure 1, the return of the momentum strategy is never statistically significant for low-uncertainty stocks, but it is still significant for high-uncertainty stocks even at a lag of 6 months.

Table IX

Subperiod Analysis

This table summarizes the effect of information uncertainty following bad and good news and its interaction with momentum strategies in two subperiods. The return differential between high- and low-uncertainty stocks is D10 − D1 in Panel A (decile 10 minus decile 1, following the procedure in Table III) and U5−U1 in Panel B (quintile 5 minus quintile 1, following the procedure in Table IV). The interaction with momentum is measured by returns to a zero-investment portfolio with a long position in good-news stocks and a short position in bad-news stocks (GMB) for low- and high-uncertainty, respectively. Firm size (MV) is the market capitalization (in millions of dollars) at the end of month t. Firm age (AGE) is the number of years since the firm was first covered by CRSP. Analyst coverage (COV) is the number of analysts following the firm in the previous year. Forecast dispersion (DISP) is the standard deviation of analyst forecasts in month t scaled by the prior year-end stock price. Stock volatility (SIGMA) is the standard deviation of weekly market excess returns over the year ending at the end of month t. Cash flow volatility (CVOL) is the standard deviation of cash flow from operations in the past 5 years (with a minimum of 3 years), where cash flow from operations is earnings before extraordinary items minus total accruals, scaled by average total assets. Stocks with a price less than $5 at the portfolio formation date are excluded, and portfolio returns are equally weighted. The sample period is from January 1983 to December 2001; t-statistics in parentheses are adjusted for autocorrelation.

Panel A: Bad News—Downward Revisions (REV < 0), Good News—Upward Revisions (REV > 0)

	1/MV	1/AGE	1/COV	DISP	SIGMA	CVOL
			Time Period: 1983–1992			
D10 – D1	−0.86%	−0.68%	−0.76%	−0.41%	−1.54%	−1.07%
(bad news)	(−2.18)	(−1.84)	(−2.39)	(−1.09)	(−2.46)	(−2.14)
D10 – D1	0.67%	0.49%	0.62%	−0.20%	0.09%	0.14%
(good news)	(1.65)	(1.23)	(1.23)	(−0.55)	(0.14)	(0.24)
GMB	0.43%	0.54%	0.60%	1.06%	0.60%	0.69%
(low uncertainty)	(2.49)	(2.46)	(2.56)	(4.12)	(4.31)	(3.43)
GMB	1.95%	1.72%	1.98%	1.27%	2.23%	1.91%
(high uncertainty)	(7.25)	(6.44)	(8.64)	(5.04)	(7.00)	(5.93)
			Time Period: 1993—2001			
D10 – D1	−0.88%	−1.74%	−0.96%	−0.05%	−1.40%	−0.85%
(bad news)	(−2.07)	(−1.98)	(−1.96)	(−0.10)	(−1.17)	(−1.07)
D10 – D1	1.27%	0.46%	0.67%	1.37%	0.82%	0.96%
(good news)	(2.38)	(0.53)	(1.42)	(2.86)	(0.65)	(1.17)
GMB	0.41%	0.37%	0.69%	0.46%	0.32%	0.75%
(low uncertainty)	(1.63)	(1.45)	(2.19)	(1.22)	(1.78)	(2.93)
GMB	2.56%	2.57%	2.32%	1.87%	2.54%	2.56%
(high uncertainty)	(9.52)	(6.05)	(8.29)	(4.37)	(5.30)	(5.60)

Panel B: Bad News—Past Losers, Good News—Past Winners

	1/MV	1/AGE	1/COV	DISP	SIGMA	CVOL
			Time Period: 1983–1992			
U5 – U1	−0.34%	−1.20%	−0.81%	−0.75%	−1.37%	−0.76%
(bad news)	(−0.95)	(−3.31)	(−2.22)	(−2.37)	(−3.02)	(−1.97)
U5 – U1	0.75%	0.70%	0.51%	0.64%	0.17%	0.44%
(good news)	(2.41)	(1.93)	(1.69)	(2.51)	(0.37)	(1.15)
GMB	0.49%	0.23%	0.63%	0.81%	0.45%	0.28%
(low uncertainty)	(1.24)	(0.60)	(1.44)	(2.37)	(1.21)	(0.69)
GMB	1.58%	2.14%	1.91%	2.20%	1.98%	1.47%
(high uncertainty)	(5.04)	(6.10)	(5.76)	(6.79)	(5.00)	(4.13)

(*continued*)

Table IX—*Continued*

Panel B: Bad News—Past Losers, Good News—Past Winners						
	1/MV	1/AGE	1/COV	DISP	SIGMA	CVOL
			Time Period: 1993–2001			
U5 – U1	−0.47%	−2.19%	−0.98%	−0.22%	−1.58%	−1.22%
(bad news)	(−0.90)	(−3.20)	(−2.05)	(−0.47)	(−1.77)	(−2.19)
U5 – U1	1.38%	0.96%	0.25%	0.73%	0.95%	0.35%
(good news)	(3.15)	(1.84)	(0.56)	(2.10)	(0.94)	(0.58)
GMB	1.10%	0.59%	1.23%	1.46%	0.84%	1.13%
(low uncertainty)	(1.31)	(0.90)	(1.61)	(1.79)	(1.64)	(1.79)
GMB	2.95%	3.75%	2.45%	2.41%	3.37%	2.70%
(high uncertainty)	(4.64)	(5.06)	(3.62)	(3.85)	(4.09)	(3.69)

C. Subperiod Analysis

In Table IX, I check the robustness of the results across time periods to see if they are time-specific. This analysis will also show if investor behavior changes over time. Arguably, the information environment has become richer and investors might learn from past mistakes. In Table IX, I report results for the 1983 to 1992 and 1993 to 2001 subperiods. The return differentials between high- and low-uncertainty stocks following good or bad news are similar in these two subperiods. Although the uncertainty effect is insignificant in some bad- or good-news cases, the effect of information uncertainty on momentum trading strategies is still evident. In both subperiods, a zero-investment portfolio with a long position in good-news stocks and a short position in bad-news stocks generates much higher returns for high-uncertainty portfolios than it does for low-uncertainty portfolios. Overall, the return patterns are similar in these two subperiods, although the later subperiod has more firms with good news due to the booming economy from 1992 to 1999.

D. Analysis on NYSE Stocks Only

To ensure that the results are not driven by a few small stocks, I also check the robustness of the results using only NYSE stocks. The returns (untabulated) are consistent with previous results. In fact, the uncertainty effect as measured by the return differential between high- and low-uncertainty stocks is more pronounced following good news than following bad news, which complements the evidence from the whole sample in supporting my hypothesis. Although this result may be partly due to the fact that non-NYSE stocks have more short-sale restrictions, I am otherwise unable to explain this feature of the data.

I also conduct other robustness checks for the whole sample, such as holding a stock in the portfolio for longer than 1 month, with a portion of each portfolio rebalanced monthly. The return follows a similar pattern to that previously observed. Finally, I try independent sorts or different sorting orders in portfolio formation, such as sorting stocks first by information uncertainty proxy and then by momentum. The results are robust to these tests.

VII. Conclusion

In this paper, I examine the role of information uncertainty in short-term price continuation anomalies and cross-sectional variations in stock returns. I use analyst forecast revisions and price momentum to distinguish good news from bad news and use firm size, firm age, analyst coverage, dispersion in analyst earnings forecasts, stock volatility, and cash flow volatility to proxy for information uncertainty.

There is clear evidence that the initial market reaction to new public information is incomplete, which implies that bad news predicts relatively lower future returns and good news predicts relatively higher future returns. More importantly, the degree of incompleteness of the market reaction increases monotonically with the level of information uncertainty, suggesting that investors tend to underreact more to new information when there is more ambiguity with respect to its implications for firm value. As a result, greater information uncertainty produces relatively lower future returns following bad news and relatively higher future returns following good news. The opposite effects of information uncertainty on stock returns following good versus bad news amplify the profitability of certain trading strategies. For example, the momentum strategy works particularly well when limited to high-uncertainty stocks.

Although I cannot definitively rule out the possibility that each information uncertainty proxy may capture other effects, the six proxies draw a consistent picture that investors underreact to a higher degree when there is greater information uncertainty. The predictability of stock returns based on the nature of news and the level of uncertainty is of its own value to individual investors and fund managers. For researchers and standard setters, there are more fundamental questions to be addressed. The evidence that greater information uncertainty predicts higher expected returns following good news and lower expected returns following bad news is inconsistent with the notion that information uncertainty is a cross-sectional risk factor and is compensated by higher stock returns. It also suggests that price and earnings momentum are more likely to be rooted in a failure of information to flow completely into stock prices.

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