Information uncertainty and investors' expectations: evidence from earnings announcements

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Abstract

This paper investigates the relationships among information uncertainty, investors' expectation errors, and earnings announcement returns. I use earnings announcement periods to observe the change in investors' expectations about the firms' future earnings prospects. Investors are too optimistic (pessimistic) about the prospects of stocks with low (high) expected earnings. Thus, stocks with low and high expected earnings tend to be overpriced and underpriced before the earnings announcements, respectively. The errors in expectations are larger for stocks with high information uncertainty. Hence, the effect of information uncertainty on earnings announcement returns is conditional on the stocks' mispricing levels. Information uncertainty is positively (negatively) related to earnings announcement returns for underpriced (overpriced) stocks.

Keywords: analysts' consensus forecasts, earning announcements, expectation errors, information uncertainty

JEL: D84, G10, G12, G14

1 Introduction

Investors may exhibit expectational errors. Lakonishok *et al.* (1994), La Porta *et al.* (1997), and Skinner and Sloan (2002) suggest that investors can be too optimistic or pessimistic about the prospects of growth and value stocks, respectively. I hypothesize that information uncertainty amplifies the biases in investors' expectations. Following Zhang (2006) and Jiang *et al.* (2005), information uncertainty in this paper is defined as the ambiguity effect of new information on stock prices. This ambiguity may come from poor information quality or uncertainty in the firm's fundamentals. Shleifer and Vishny (1997) suggest that arbitrageurs may ignore the mispricing in high volatility stocks because shorting them is risky since noise traders can push the stock prices further from the true fundamental values. Thus, stocks with

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high information uncertainty tend to have high arbitrage risk and are likely to be mispriced. Furthermore, Baker and Wurgler (2006) argue that stocks that have high arbitrage risk are usually hard to value.

This paper's main contribution is to show the relationships among investors' expectation errors, information uncertainty, and earnings announcement returns. I find that investors, on average, have biased expectations that are amplified by information uncertainty before the earnings announcement days. Previous studies suggest that information uncertainty's average effect on stock returns is negative (see, e.g., Ang *et al.* (2006), Berkman *et al.* (2009), Diether *et al.* (2002), Jiang *et al.* (2005)). In this paper, I examine the effect of information uncertainty on earnings announcement returns conditional on stocks' mispricing levels. I find that information uncertainty is positively (negatively) related to earnings announcement returns for underpriced (overpriced) stocks. This finding is consistent with Stambaugh *et al.* (2015). They document that the return volatility effect on stock returns is conditional on stocks' mispricing levels.

I use earnings announcement periods to observe the change in investors' expectations about the firm's future earnings prospects and examine if investors exhibit expectation errors. If investors have unbiased expectations about firm's earnings, sorting stocks on actual earnings scaled with stock prices will not predict the earnings announcement returns. I show that investors are generally too optimistic (pessimistic) about the prospects of stocks with low (high) actual earnings scaled with stock prices.[1] I use analyst estimates to proxy for investors' expected earnings since investors' expectations are unobservable. I show that stocks with low (high) analysts' forecasts scaled with stock prices earn low (high) earnings announcement returns.[2]

The positive predictive relationship between analysts' forecasts and earnings announcement returns is stronger for stocks with high information uncertainty, for which analysts' forecasts tend to be too optimistic. I use eight different information uncertainty proxies that include analyst coverage, dispersion in analysts' earnings forecasts, analysts' forecast accuracy in previous quarters, dispersion in changes of mutual funds' holdings, firm age, firm size, number of mutual funds investing in the stock, and return volatility. For the main analysis, I aggregate eight individual information uncertainty proxies using two different dimension reduction methods, Principal Component Analysis (PCA) and Partial Least Squares (PLS). I use the first direction of PCA or PLS as the composite information uncertainty proxy. For stocks with high information uncertainty proxied by the first direction of PCA, the strategy of long and short stocks with high and low analysts' earnings estimates has three-day earnings announcement returns of 1.1%. On the other hand, for stocks with low information uncertainty, the same strategy yields average announcement returns of -0.2%.

[1] The effect of earnings to price ratio (EP) on stock returns is documented in Basu (1977). My paper focuses on the effect of information uncertainty on investors' expected earnings reflected in earnings announcement returns. This paper uses analysts' forecasts to proxy for investors' expectations. In Basu (1977), the portfolio constructions are based on realized earnings while examining monthly returns with annual portfolio rebalancing.

[2] Elgers *et al.* (2001) document that portfolios sorted based on analysts' annual earnings forecasts have positive long-short returns over the earnings year. My paper complements this study by showing how information uncertainty affects investors' and analysts' expectations before earnings announcements.

The relationship between earnings announcement returns and analysts' estimates is significant on the earnings announcement days and close to zero in the four weeks before and after the earnings announcements. This result shows that investors have incorrect expectations about firms' prospects before the earnings announcements and update their beliefs accordingly during the earnings announcement days. Thus, prices before earnings announcements contain investors' biased expectations, particularly for high information uncertainty stocks. Furthermore, this result indicates that the effect of analysts' estimates on returns is not due to risk.

To understand if biases in analysts' forecasts drive investors' expectational errors, I examine the level of investors' price implied expectation relative to analysts' estimates. I use firms' quarterly earnings announcements returns to measure the investors' price implied expectations. The stock price changes on earnings announcement days reflect the differences between actual earnings and investors' expected earnings prior to the earnings announcement. I model investors' expectations about firms' earnings as a function of analysts' expectations and the noisy signal of the actual earnings. If investors fully agree with analysts, analysts' estimates cannot predict stock returns at earnings announcement after controlling for analyst forecast errors. On the other hand, if investors' beliefs deviate from analysts' forecasts, and investors are more optimistic (pessimistic) than analysts' estimates for stocks with low (high) analysts' forecasts, analysts' estimates will predict earnings announcement returns even after controlling for analyst forecast errors.

I find that analysts' forecasts are accurate for stocks with low information uncertainty, and investors' disagreement with analysts is small. On the other hand, analysts tend to be too optimistic on average for stocks with high information uncertainty, and investors' beliefs deviate from analysts' estimates. On average, investors are more optimistic than optimistic analysts in stocks with low analysts' earnings forecasts and high information uncertainty. Hence this kind of stock tends to be overvalued before earnings announcement since the stock prices reflect optimistic views. In contrast, investors are pessimistic about the firm payoffs despite optimistic analysts' estimates for stocks with high analysts' forecasts and high information uncertainty. Thus, these kinds of stocks tend to be underpriced. These findings illustrate that for high information uncertainty stocks, the average bias direction of investors and analysts are the same (different) for stocks with low (high) analysts' forecasts.

Previous studies show that information uncertainty's average effect on returns is negative. Miller (1977) suggests that, if investors face short-sales constraints, stocks with high differences of opinion will be overpriced since the prices reflect optimistic investors' opinions. Thus, stocks with high differences of opinion have low future returns. This study's contribution is to show that information uncertainty's effects on earning announcement returns are conditional on stocks' mispricing levels. I use analysts' expected earnings to proxy for stocks' mispricing and demonstrate that the relationship between information uncertainty and returns is negative (positive) for overpriced (underpriced) stocks. Consistent with previous studies, I find that the unconditional effect of information uncertainty on stock returns is negative.

This study contributes to the expectational errors hypothesis literature. Several studies document that the value premium is attributable to expectational errors of investors (see, e.g., Lakonishok *et al.* (1994), La Porta *et al.* (1997), Skinner and Sloan (2002)). Specifically, investors are overly optimistic (pessimistic) about growth (value) stocks. The return differences between value and growth stocks are persistent until five years after portfolio formation. Investors slowly realize that the earnings growth rate of growth (value) stocks are lower (higher) than they previously expected. La Porta *et al.* (1997) show that earnings announcement return differences between value and growth stocks account for a significant portion of the annual value premium. This finding is inconsistent with the notion that value premium is due to risk. This study shows that, on average, investors systematically make incorrect earnings expectations about stocks, regardless of the stocks are categorized as value or growth. The investors' and analysts' expectation errors are particularly strong for stocks with high information uncertainty.

This paper is related to the importance of analysts in reducing information asymmetries between firms and investors. While previous studies suggest that analyst coverage reduces information asymmetries, this study suggests that for high information uncertainty stocks, the influence of analysts on investors' beliefs is smaller. If stocks have high information uncertainty, analysts' estimates tend to be inaccurate and imprecise, so investors underweight analysts' consensus forecasts. Furthermore, many studies use analysts' consensus forecasts as a proxy for market expectations. My paper suggests that investors' beliefs deviate from analysts' estimates for high information uncertainty stocks.

My study also relates to Elgers *et al.* (2001), who find that portfolios sorted based on analysts' annual earnings forecasts have positive long-short returns over the earnings year. Elgers *et al.* (2001) suggest that the predictive relationship between analysts' annual earnings forecasts and returns is because investors fail to incorporate analysts' estimates. My study shows that analysts' estimates are less informative, both biased and imprecise, when information uncertainty is high. Thus, for this kind of stocks, the investors' expectation errors are particularly strong. Furthermore, I examine the expectation errors around earnings announcement periods. I find that most of the price adjustments to unexpected earnings occur on the three-day around earnings announcements.

This paper also contributes to the earnings announcement literature. Previous studies document that the arrival of good (bad) news is accompanied by positive (negative) announcement returns[3]. Berkman *et al.* (2009) use the new information at earnings announcement as news for investors to update their beliefs and reduce differences of opinion among investors. They examine the effect of differences of opinion on stock returns at earnings announcements. So and Wang (2014) document that market makers anticipate the uncertainty associated with earnings announcements. Akbas (2016) shows that during the earnings announcement period, informed investors who have bad news about a firm may choose to hold their trade instead of short sell the stock due to increased uncertainty. Veenman and Verwijmeren (2018) document that investors do not fully reflect analysts' pessimism prior to the earnings announcements. Thus, analysts' consensus forecast pessimism contains information about announcement returns. Johnson *et al.* (2020) suggest that firms manage investors' expectations that affect firms' earnings announcement returns. This paper complements these studies by showing that earnings announcement returns contain information about investors' expectational errors.

[3]See, for example, Rendleman *et al.* (1982), Foster *et al.* (1984), and Bernard and Thomas (1989). These studies also examine the post-earnings announcement anomaly.

The paper is organized as follows. Section 2 describes the empirical methodology of the paper. Section 3 describes the data and variables used for the main analysis. Section 4 presents the effect of investors' expectational errors on stock returns. Section 5 presents how information uncertainty amplifies the effect of investors' expectational errors on stock returns and how the effect of information uncertainty on announcement returns is conditional on stocks' mispricing levels. Section 6 presents the robustness tests. Finally, section 7 concludes the paper.

2 Empirical methodology

2.1 Expectation errors and information uncertainty

Lakonishok *et al.* (1994) and La Porta *et al.* (1997) suggest that investors make expectation errors because they incorrectly extrapolate firms' past performances to the future. Hence, some stocks' values are biased upward or downward. These expectation errors drive the value premium puzzle. Specifically, investors are overly optimistic (pessimistic) about growth (value) stocks. The return differences between value and growth stocks are persistent until five years after portfolio formation because investors slowly realize that earnings growth rate of growth (value) stocks are lower (higher) than they previously expected. La Porta *et al.* (1997) show that earnings announcement returns differences, between value and growth stocks, account for significant portion of the annual value premium. This finding is inconsistent with the notion that value premium is due to risk.

In this paper, I investigate if investors make expectation errors about firms' prospect in general, regardless of whether the firms are categorized as value or growth stocks. I analyze the period around earnings announcements because investors update their beliefs about the prospects of firms at this period. I assume prices follow one period Gordon growth model (Gordon and Shapiro (1956)) with one year ahead EPS equals EPS_{y1}. On earnings announcement day, t, we can observe the actual quarterly earnings per share, EPS_t. The unobservable unexpected earnings for the current quarter, $EPS_t - E_{inv,t-1}[EPS_t]$, and the change in the firms' prospect, $E_{inv,t}[EPS_{y1}] - E_{inv,t-1}[EPS_{y1}]$, will be reflected through earnings announcement returns, EAR_t. Thus, assuming the discount rate between t and $t-1$ are close to zero, return at quarterly earnings announcement day can be written as:

$$EAR_t = \frac{P_t - P_{t-1}}{P_{t-1}} = \frac{EPS_t - \mathrm{E}_{inv,t-1}[EPS_t]}{P_{t-1}} + \frac{\mathrm{E}_{inv,t}[EPS_{y1}] - \mathrm{E}_{inv,t-1}[EPS_{y1}]}{P_{t-1}} \frac{\delta}{r-g} \tag{1}$$

Where t and $t-1$ are the earnings announcement day and the day before earnings announcement. $\mathrm{E}_{inv,t}[EPS_{y1}]$ is investors' expectation, at time t, on one year ahead EPS. δ, r, and g are dividend payout ratio, discount rate, and growth rate, respectively. Assuming the value of δ, r, and g are constant and the value of $(\mathrm{E}_{inv,t}[EPS_{y1}] - \mathrm{E}_{inv,t-1}[EPS_{y1}])$ are proportional with $EPS_t - \mathrm{E}_{inv,t-1}[EPS_t]$, we can rewrite the EAR as in equation (2).

$$EAR_t = \beta \frac{(EPS_t - \mathrm{E}_{inv,t-1}[EPS_t])}{P_{t-1}} + \epsilon_{ear,t} \tag{2}$$

Equation (2) suggests that if investors have unbiased expectation on firms' earnings, the realized quarterly earning scaled with the price before the earnings announcement will not predict EAR. If investors are biased, for example, if they are too optimistic (pessimistic) about the earnings of stocks with low (high) earnings, actual earnings scaled with price, EPS_t/P_{t-1}, will predict EAR_t.

The investors' expectation errors in this study are different from expectational errors commonly studied in the literature. The literature has focused mainly on expectational errors about prospects of value and growth stocks. In this article, I examine if investors make incorrect expectations for firms' earnings, regardless of whether the firms are categorized as value or growth stocks.

I use analysts' forecasts of earnings over price (FEP), $\frac{\mathrm{E}_{an,t-1}[EPS_t]}{P_{t-1}}$, to proxy for investors' expectations. FEP is the median of analyst earnings per share (EPS) forecast divided by stock price. Previous studies suggest that analyst forecasts are a proxy for market expectations (see, e.g., Fried and Givoly (1982), Hughes *et al.* (1987), O'brien (1988)). In section 2.2, I will explain why although FEP is a proxy for investors' expectations, investors' expectations may deviate from analysts' estimates.

Following Zhang (2006) and Jiang *et al.* (2005), information uncertainty in this paper refers to the ambiguous effect of new information on stock prices. The ambiguity can come from poor information quality or uncertainty in the firm's fundamentals. For example, a firm can have high information uncertainty if it has a high dispersion in analysts' earnings forecasts. This dispersion reflects the low precision of analysts' forecasts, which can be due to the firm's fundamentals being difficult to estimate. One proxy for information uncertainty is return volatility. Shleifer and Vishny (1997) suggest that stocks with high return volatility may be prone to mispricing since arbitrageurs cannot correct the mispricing due to short selling risk. Particularly, taking short positions is risky since noise traders can push the stock prices further from the fundamental values. Thus, stocks with high information uncertainty tend to have high arbitrage risk and are prone to mispricing. Furthermore, Baker and Wurgler (2006) suggest that stocks that have high arbitrage risk are likely to be hard to value. I hypothesize that information uncertainty may amplify investors' expectation errors.

I use several proxies for information uncertainty. To construct some of the proxies, I follow Zhang (2006) and Berkman *et al.* (2009). AGE is the number of months since a firm was included in CRSP database. NUMEST is the number of analysts following a firm. SIZE is the log of market capitalization of firms, where market equity is in USD million. FDISP is dispersion in analysts' earnings forecast for the upcoming quarter scaled with the stock price. I set FDISP to missing if the number of analysts is less than two. RETVOL is the volatility of daily excess stock returns. The excess returns are stock returns minus value-weighted returns of stocks in CRSP.

In addition, I also use some other proxies for information uncertainty. MFN is the number of mutual funds that hold the stocks scaled with the number of existing funds at the time. MFN is calculated using Thomson Reuters S12 mutual fund holdings data. MFDISP is the standard deviation of the net change in mutual fund holding scaled with the number of shares outstanding of the firm. LAAFE is the average of absolute analysts' forecast errors, AFE, in the previous four quarters. AFE is calculated as actual EPS minus FEP, scaled with the stock price. LAAFE shows the accuracy of median analysts' forecasts. The Appendix provides the variable definitions in more detail.

I use two different dimension reduction methods, Principal Component Analysis (PCA) and Partial Least Squares (PLS), to aggregate the information uncertainty proxies. I extract the first component (i.e., the first direction) in both methods and use it as an information uncertainty proxy. PCA is an unsupervised learning method. Thus, I do not provide an assumption about the target variable. On the other hand, PLS is a supervised learning method that requires a target variable. I assume that the absolute value of EAR has information about information uncertainty. Thus, I set the absolute value of EAR as the target variable in PLS method. It is likely that the higher the information uncertainty, the larger the price movement at the earnings announcement days. If a stock has low information uncertainty, most likely the stocks are correctly priced, and the unexpected earnings at the earnings announcement days are small. Using PLS is potentially beneficial because the directions extracted from the information uncertainty proxies are related to the response variable. To extract the first PLS direction, I use the algorithm as explained in Hastie *et al.* (2009). Both PCA and PLS have been used in previous studies for dimension reduction (see, e.g. Baker and Wurgler (2006), Kelly and Pruitt (2013), Huang *et al.* (2014), and Johnson *et al.* (2020)).

To calculate the first direction of PLS and PCA, I extract the weight matrix that transforms the matrix of information uncertainty proxies to the PLS or PCA directions. I use 90 days period ending on the last day of month $t-1$ to calculate the weight matrix and calculate the PCA and PLS first directions for firms with earnings announcements date within month t. For example, I use training data for the period over 90 days ending on 31st of May 2010, and use the weight matrix from the training data to calculate the directions of PCA and PLS for firms that have earnings announcement days on June 2010.

2.2 Deviation of investors' expectations from analysts' estimates

Analysts are important market participants who act as information intermediaries between firms and the market. Previous studies document that analyst coverage improves information dissemination in the market and helps to reduce asymmetric information between firms and investors (see, e.g., Brennan and Subrahmanyam (1995), Hong *et al.* (2000), Mansi *et al.* (2011), Piotroski and Roulstone (2005)). Furthermore, many studies suggest that information from analysts affects investors' beliefs about a stock's future payoffs and is reflected in prices. Thus, analyst forecasts are a proxy for market expectations (see, e.g., Fried and Givoly (1982), Hughes *et al.* (1987), O'brien (1988)).

However, analysts' forecasts can be biased. Hence investors may choose to disagree with analysts. Many studies show that analysts' forecasts are systematically optimistic. These optimistic forecasts are because of analysts' incentives structures, which include investment banking deals (Lin and McNichols (1998)), trading commissions (Jackson (2005), Cowen *et al.* (2006)), and relationship with management (Lim (2001)). Furthermore, McNichols and O'Brien (1997) suggest that analysts are disinclined to make unfavorable forecasts due to the risk of reducing their incentives. Thus, analysts may choose to cover firms with good prospects according to analysts' actual expectations, which leads to self-selection in coverage. On the other hand, some firms want to have positive earnings surprises. Hence they manage investors' expectations through analysts' forecasts (Matsumoto (2002), Richardson *et al.* (2004), Johnson *et al.* (2020)). Richardson *et al.* (2004) document that analysts' forecasts are optimistic for long horizons and become pessimistic before earnings announcements.

From investors' side, several studies document that the value premium is attributable to expectational errors of investors. Since both analysts and investors can have biased estimates about firms' earnings, it is likely for analysts and investors to have differences in expected earnings of firms.

To quantify differences between average expectations of analysts and unobservable expectations of investors, I use stock returns around firms' quarterly earnings announcements. In this study, I model the investors expectation about firms' earnings as a function of average analysts' expectations and noisy actual earnings.

$$\mathrm{E}_{inv,t-1}[EPS_t] = \gamma_1 \mathrm{E}_{an,t-1}[EPS_t] + \gamma_2(EPS_t + \epsilon_{inv,t-1}) \tag{3}$$

where EPS_t, $\mathrm{E}_{an,t-1}[EPS_t]$, and $\mathrm{E}_{inv,t-1}[EPS_t]$ are actual, median analyst forecast, and investors' expectations of firms' quarterly earnings per share, respectively. Both $\mathrm{E}_{an,t-1}[EPS_t]$ and $\mathrm{E}_{inv,t-1}[EPS_t]$ are expectations of analysts and investors prior to earnings announcement date. While EPS_t can be observed at earnings announcement date. I discuss variable definitions in more detail in section 3.

Equation (3) shows that investors' expectations is affected by analysts' expectations. Previous studies show that analysts' consensus forecasts are a good proxy for investors' expectations. Thus, analysts forecast errors have a strong relationship with earnings announcement returns (Hughes *et al.* (1987)). This shows that expectations of investors and analysts are positively related. Furthermore, equation (3) also shows that investors' expectations is a function of actual EPS, which is observed with some noises by investors. I hypothesize that if investors deviate their beliefs relative to analysts' estimates, the value of $\gamma_1 + \gamma_2$ will be less than one.

Previous studies suggest that earnings announcement returns contain information not only about firms' earnings, but also other information. For example, So and Wang (2014) suggest that market makers anticipate the uncertainty associated with earnings announcements, hence they require more compensation for liquidity provision. In equation (2), I exclude the effects of variables, other than unexpected earnings, on announcement returns. In the empirical tests, however, I will include other variables that predict announcement returns.

The empirical tests aim to measure the deviation of investors' expectations from analysts' expectations. Substituting equation (3) into equation (2), we can see that earnings announcement returns are a function of analysts' forecast errors and analysts' expectations as shown below.

$$EAR_t = \theta_1 \frac{(EPS_t - \mathrm{E}_{an,t-1}[EPS_t])}{P_{t-1}} + \theta_2 \frac{\mathrm{E}_{an,t-1}[EPS_t]}{P_{t-1}} + \epsilon_{ear2,t} \tag{4}$$

Where $\theta_1 = \beta(1-\gamma_2)$, $\theta_2 = \beta(1-\gamma_1-\gamma_2)$, and $\epsilon_{ear2,t} = -\beta\gamma_2\epsilon_{inv,t-1}/P_{t-1} + \epsilon_{ear,t}$. Thus, we can measure the differences in expectations, between analysts and investors, from θ_2. If investors are more optimistic (pessimistic) than analysts in stocks with low (high) expected earnings, $\gamma_1 + \gamma_2 < 1$. In addition, positive unexpected earnings will affect EAR positively, hence β is greater than zero. Thus, if investors have different expectations relative to analysts' estimates, θ_2 will be positive. On the other hand, if expectations of investors are the same with that of analysts, θ_2 will be zero.

I hypothesize that investors and analysts have similar expectations for stocks which have small information uncertainty because these kinds of stocks have abundant high-quality information. Furthermore, the abundant high-quality information makes investors' expectational errors less likely.

2.3 Methodology

I employ two commonly used methodologies in the empirical test: (1) portfolio sorts and (2) regression analysis. Portfolio sorts are useful to examine the variation of average returns across different level of explanatory variables. The advantage of this method is it does not make assumptions about the relationships between dependent and independent variables. However, it is hard to control for various variables using portfolio sorts when there are many explanatory variables. On the other hand, regression analysis allows us to examine the marginal effect of an independent variable on returns when there are many control variables. The disadvantage of regression, however, we make assumptions that the relationships between response and explanatory variables are linear. For regression analysis, I use Fama and MacBeth (1973) (FM) regression. To implement the method, I run a cross-sectional regression for each calendar quarter of earnings announcement date, then I take time series average of the quarterly regression coefficients. The standard errors from FM regression are corrected for cross-sectional correlation in the residuals. I calculate Newey and West (1987) standard errors to adjust for heteroskedasticity and autocorrelation. Previous studies have used similar quarterly FM regression in examining the effect of explanatory variables on announcement returns (see, e.g., Berkman *et al.* (2009), Rees and Thomas (2010), and Akbas (2016)).

3 Data and descriptive statistics

I sourced data from CRSP, Compustat, IBES, and Thomson Reuters S12 to construct my main dataset, which spans the period from the first quarter of 1986 to the third quarter of 2020. The dataset is in quarterly frequency since I analyze the effect of the news on returns at quarterly earnings announcements. I use the daily CRSP dataset for stock returns, Compustat for firms' data, IBES unadjusted detail for analyst estimates, and Thomson Reuters S12 for mutual funds holdings. I include firms that have analysts' quarterly EPS forecasts. The main dataset includes common stocks (SHRCD = 10 or 11 in CRSP) that are listed in NYSE, NYSE American, and Nasdaq. To limit the effect of small firms and penny stocks, I exclude firms with a market value less than $10 million and stock price less than $1 at the beginning of the quarter.

Following Berkman *et al.* (2009), I define earnings announcement returns, EAR, as the stock's holding period returns for the three days around earnings announcement, starting from one day before the announcement, minus the corresponding holding period value-weighted CRSP index returns. Since I examine the investors' expectation errors from the four weeks before and after the earnings announcement, I measure eight weekly returns around the announcement days. Specifically, I calculate the stock returns at $(t-21, t-17)$, $(t-16, t-12)$, $(t-11, t-7)$, $(t-6, t-2)$, $(t+2, t+6)$, $(t+7, t+11)$, $(t+12, t+16)$, and $(t+17, t+21)$ for the periods around earnings announcement days. Where t is the earnings announcement day. Similar to EAR, I calculate the weekly stock returns as holding period for the week minus the corresponding value-weighted CRSP index returns.

Forecasts of earnings scaled by price (FEP) is defined as the median of analyst earnings per share (EPS) forecast divided by stock price. The forecasts are for the current fiscal quarter, FPI = 6 in IBES. I use IBES unadjusted detail history to construct the median of analysts' EPS forecast. Since I examine the effect of FEP on stock returns starting from 21 days before the earnings announcement days, I include analysts' estimates announced over 90 days period ending on 22 trading days before the earnings announcement. If an analyst makes more than one estimate during this period, I select the most recent estimate. To make the analyst estimates and stock price comparable, I adjust the EPS forecast and stock price for any stock split. Then, the median analyst forecast is divided by stock price on 22 trading days before the earnings announcement. Similarly, actual earnings (EP) are defined as actual EPS reported in IBES divided by stock price on 22 trading days before the earnings announcement. Analyst forecast errors, AFE, equals are EP minus FEP. The earnings announcement date is as reported in IBES.

In the main analysis, I incorporate several control variables that are related to risk. BETA is CAPM beta, calculated over one year, ending 22 trading days prior to earnings announcement. SIZE is the log firms' market equity, where market equity is in USD million. SIZE is measured at 22 days before the earnings announcement. BM is log one plus previous quarter book to market ratio. Where the book equity calculation follows Hou *et al.* (2020). Fama and French (1992) identify BM as a proxy for risk, while La Porta *et al.* (1997) argue that the value premium is due to investors' expectational error. I exclude observations with a negative value of the previous quarter book to market ratio. AGR, asset growth rate, is calculated as annual change in book asset in previous quarter. GMA, gross profitability margin to asset, is defined as revenue minus cost of goods sold, scaled with book asset.

I also add variables that are previously identified as predictors of earnings announcement returns in the main analysis. MOM (momentum) is calculated over six months period ending on 22 days before the earnings announcement. Momentum is the holding period returns of stock minus the cumulative market returns over the same period. RETVOL is daily excess return volatility over 45 days period ending on 22 days before the earnings announcement. The daily excess return is a stock return minus market return. I also include previous stock returns as a control variable. As shown in So and Wang (2014), pre-announcement return is a significant predictor of announcement return. TURN is the average daily turnover. TURN is defined as volume divided by the number of shares outstanding over 45 days, ending on 22 days before the earnings announcements. Other variables that are not defined in this section will be explained when they are used in the analysis. The Appendix provides the variable definitions in more detail.

Table 1 presents descriptive statistics of the main variables used in the analysis. For the main dataset, I require all the variables to be non-empty. There are 228,744 stock-quarter observations in the main dataset. To avoid the effect of extreme outliers, I winsorized the data at 1% and 99%. Returns, AFE, FDISP, FEP, MFDISP, RETVOL, and TURN are in percentage.

Table 2 presents the correlations across variables. I calculate the time-series average of quarterly cross-sectional correlation. The numbers above and below the diagonal are the Pearson and Spearman correlations, respectively. The table shows that the information uncertainty proxies tend to have positive correlations with other uncertainty proxies. Furthermore, the relationship between EAR and information uncertainty proxies tend to be negative.

The first principal component from PCA analysis, on average, explains 39% of the variation in the information uncertainty proxies. Furthermore, I find that the information uncertainty proxies have the same sign for the first principal component. Thus, all of the information uncertainty proxies that are used in this paper correctly capture, at least partially, the common latent component of information uncertainty. For the PLS method, on average, all proxies have a positive relationship with the absolute EAR.

4 The expectation of investors and analysts

4.1 Portfolio analysis

This section examines if investors and analyst make biased expectations about firms' earnings and how analysts' estimates influence investors' expectations. I run univariate sorts of EAR on AFE, EP, and FEP. At each quarter, I assign stocks into deciles based on AFE, EP, or FEP value and calculate the equal-weighted cross-sectional average of EAR for each portfolio deciles. The cutoff values for the portfolio constructions are based on all stocks in the calendar quarter. Next, I calculate the time-series average of the cross-sectional average of EAR for each portfolio deciles. I adjust the standard errors of the portfolios' time-series average returns using Newey and West (1987) with 4 lags.

Figure 1 presents the results of the univariate sorts. At each panel, I show the univariate relationship between EAR and AFE, EP, or FEP. Each point within a panel represents the portfolio decile. For each point, I plot the 99% confidence interval for the mean of EAR estimate. I plot each point based on the portfolio's time-series average of the cross-sectional mean of EAR for the y axis and the time-series average of the cross-sectional mean of the sorting variable for the x axis.

The first panel in figure 1 shows a positive relationship between EAR and AFE. The positive relationship is S-shape, which means the marginal effect of AFE on EAR decreases as the absolute value of AFE increases. Freeman and Tse (1992) suggest that the S-shape relationship is because AFE contains unexpected permanent and transitory earnings. When the value of AFE is large, AFE has a higher proportion of transitory components, which reduces the marginal effect of AFE on returns. The positive association between AFE and EAR indicates that analysts' estimates are a good proxy for investors' expectations.

Figure 1 presents a positive relationship between EP and EAR in the second panel. EP is not a strong predictor of EAR if investors estimate the value of EP with high accuracy. On the other hand, if investors systematically have incorrect expectations about firms' earnings as discussed in section 2, then the relationship of EAR and EP is positive. Thus, the positive relationship suggests that investors are too optimistic (pessimistic) about the prospects of stocks with low (high) actual earnings. This result is consistent with investors' expectation errors hypothesis.

The third panel of figure 1 shows a predictive univariate relationship between EAR and FEP. If investors make expectation errors and analysts' forecasts are informative about the actual earnings of firms, we will see a positive relationship between EAR and FEP. I further examine if investors' expectation errors are due to analysts' biases. For example, it is possible that investors fully agree with analysts and analysts are too optimistic and pessimistic in low and high expected earnings stocks, respectively. Thus, the incorrect expectations of investors are due to analysts' forecasts biases. Alternatively, investors may be overly optimistic or pessimistic and disagree with analysts, when analysts' estimates are imprecise and inaccurate.

To further examine the expectational errors across FEP decile portfolios, I calculate the mean of AFE and information uncertainty proxies for each FEP decile. Figure 2 presents the summary statistics for each FEP decile. Each point represents the portfolio's time-series mean of cross-sectional average characteristics and its 99% confidence interval. If the investors' expectational errors are driven by analysts, AFE and FEP will have positive relationship. Thus, I analyze if the value of AFE is negative and positive in low and high FEP decile, respectively. The result shows that analysts are optimistic in decile one, two, and ten, which lead to large negative AFE. This result shows that, for low expected earnings stocks, the low earnings announcement returns can be driven by overly optimistic analysts' estimates, which are reflected in investors' expectations. On the other hand, EAR is large and positive despite analysts being overly optimistic in decile ten of FEP. These findings indicate that investors deviate their beliefs from analysts. On average, for stocks with high FEP, investors have lower expectations about firms' earnings than analysts' estimates or the actual earnings. Thus, investors have the same (different) bias direction with analysts for low (high) FEP stocks. Section 4.2 investigates how investors' expectations deviate from analysts' expectations using regression analysis.

To examine if information uncertainty makes investors deviate their beliefs from analysts' estimates, I analyze the information uncertainty for each FEP decile portfolio. Figure 1 indicates that the positive relationship between EAR and FEP is driven by decile one, two, and ten portfolios. Figure 2 shows that decile one, two, and ten portfolios tend to have high information uncertainty. Thus, information uncertainty may amplify investors' expectational errors.

4.2 Regression analysis

In this section, I investigate the price implied expectations of investors relative to analysts' estimates using Fama-Macbeth regression. As discussed in section 2, if investors' expectations are similar with analysts' estimates, the coefficient of FEP after controlling for AFE should be statistically not different from zero. If FEP is statistically different from zero and positive, investors tend to be more optimistic (pessimistic) than analysts' estimates at low (high) FEP stocks.

I implement several specifications to account for potentially different effects of AFE on EAR. In the first specification, I run predictive univariate regression of EAR on FEP. In the second and third specifications, I assume that the effect of AFE on EAR is linear. In addition, the third specification allows different slopes for positive and negative AFE. Soffer *et al.* (2000) document that firms with bad news tend to pre-announce their quarterly earnings before earnings announcements days. Equation (5) shows the regression model for the third specification.

$$EAR_{i,t} = \alpha + \beta_1 \cdot FEP_{i,t} + \beta_2 \cdot AFE_{i,t} \cdot 1_{AFE>0} + \beta_3 \cdot AFE_{i,t} \cdot 1_{AFE<0} + \epsilon_{i,t} \tag{5}$$

The fourth and fifth specifications allow for a non-linear relationship between AFE and EAR. As shown in figure 1 and suggested in Freeman and Tse (1992), the effect of AFE on EAR is non-linear. I transform AFE into AFENL by assigning the absolute value of AFE into 100 group rank based on its quarterly value, then multiplying the rank with minus one if the original AFE is negative. The transformation will make AFENL and AFE have an S-shape relationship. Hence, the regression of EAR on AFENL will make the marginal effect of AFE on EAR smaller as the absolute value of AFE increases. In addition, the fifth specification allows different slopes between positive and negative AFE. Finally, in the sixth specification, I use the fifth specification and add various control variables that include risk proxies and other variables that predict EAR as documented in the literature. The risk proxies are BETA, SIZE, BM, AGR, and GMA. Other control variables include pre-announcement returns, MOM, RETVOL, and TURN. Pre-announcement returns (PAR1) are holding period stock returns from $t-6$ to $t-2$ minus the holding period returns of value-weighted CRSP index returns for the same period. Where t is the earnings announcement day.

Table 3 presents the results of the regression analysis. The t-statistics (in parentheses) is adjusted using Newey and West (1987) standard errors. The first column shows a positive predictive relationship between FEP and EAR, which is consistent with the univariate sort analysis. In the second until sixth specifications, the coefficient of FEP is positive and significant at the 1% level. The positive coefficient of FEP after controlling for AFE indicates that the sum of γ_1 and γ_2 is less than one. Thus, investors are more optimistic (pessimistic) than analysts at low (high) FEP stocks.

In column 2, I include AFE as control variables. As expected, including AFE in the regression improves adjusted R^2 compared to the univariate regression in column 1. The third and fifth specifications show that the effect of positive AFE on EAR is larger than that of negative AFE. The fourth and fifth specifications suggest that accounting for non-linearity is crucial since it improves the adjusted R-squared. In the sixth specification, I control for risk proxies and other variables that predict EAR and find that the positive coefficient of FEP remains statistically significant.

The direction of investors' deviation from analysts' estimates is conditional on the level of FEP. As shown in figure 2, analysts tend to be optimistic in low and high FEP stocks. Combining this result with the regression analysis, investors are more optimistic than optimistic analysts for stocks with low FEP. On the other hand, for stocks with high FEP, investors have more pessimistic views relative to analysts.

5 Information uncertainty, expectation errors, and earnings announcement returns

This section investigates the relationship among information uncertainty, investors' expectation errors, and earnings announcement returns. In the portfolio analysis subsection, I use conditional double sorts to understand how the expectational errors increase as information uncertainty increases. I further examine the effect of information uncertainty on earnings announcement returns, conditional on mispricing levels based on expectational errors. In the regression analysis subsection, I identify if investors deviate their beliefs relative to analysts' estimates, and analyze if the deviation is larger for stocks with high information uncertainty. I also examine the effect of information uncertainty on announcement returns using regression analysis. Finally, I examine when investors update their beliefs around the earnings announcement periods.

5.1 Portfolio analysis

I perform conditional double sorts to investigate the conditional effect of expectation errors, proxied by FEP, on EAR, for different levels of information uncertainty. At each calendar quarter, first, I assign stocks to the quantile rank of their information uncertainty. Then, I assign the stocks within each quantile of information uncertainty to the quantile rank of FEP. The cutoff values for the portfolio constructions are based on all stocks in the calendar quarter. I calculate the time series mean of equal-weighted cross-sectional average of EAR and AFE for each portfolio.

Figure 3 presents the results of the conditional double sorts. I show the effect of FEP on EAR conditional on the stock information uncertainty. The information uncertainty proxy is indicated on the top of the panel. Inside each panel, there are 25 portfolios grouped into five different levels of information uncertainty. The first (last) five portfolios are the portfolios with low (high) information uncertainty. In the first five portfolios, the first (fifth) portfolio has a low (high) FEP value. The figure shows that as information uncertainty increases, the EAR difference between high and low FEP portfolios is higher. Thus, the portfolio analysis results indicate that stocks with high information uncertainty are prone to a higher degree of expectational errors and larger mispricing, which is corrected on earnings announcement days. For example, stocks with high PCA1 and low FEP tend to be overpriced due to the optimistic views of investors. Thus, these kinds of stocks have negative EAR.

Figure 4 presents the long-short portfolio returns and their t-statistics for each information uncertainty proxy. Each bar represents the time-series average of cross-sectional mean of long-short portfolio returns. The long-short portfolio strategy is taking long position in high FEP and short position in low FEP stock for each level of information uncertainty. I adjust the standard errors of the portfolios' time-series average returns using Newey and West (1987) with 4 lags. The figure shows that portfolios with high information uncertainty have economically and statistically significant long-short returns. PCA1 and PLS1 panels show monotonic increase in the long-short portfolio returns as the information uncertainty increases.

I further examine if and how investors deviate their expectations from analysts' estimates for stocks with high information uncertainty and arbitrage risk. In figure 5, I plot the AFE value for each portfolio. From the figure, we can see that analysts tend to be more accurate for stocks with low information uncertainty. But analysts are optimistic about stocks with high information uncertainty on average. Furthermore, the optimism of analysts also depends on the FEP level. Similar to the univariate sort results, investors' reactions towards information uncertainty are conditional on the level of FEP. In general, both investors and analysts are optimistic about stocks with high information uncertainty and low FEP. On the other hand, while analysts are too optimistic about stocks with high information uncertainty and high FEP, investors have more pessimistic views, which leads to a large positive EAR.

Conditional double sort is chosen over independent sort to ensure a similar number of observations across portfolios. In an untabulated test of independent portfolio sort, the number of stocks in a portfolio with low information uncertainty and low FEP value is smaller than the other portfolios. In contrast, the number of stocks in the portfolio with high information uncertainty and low FEP is high. The unbalanced number of stocks within the portfolios is due to the negative correlations between information uncertainty proxies and FEP, as shown in Table 2. Figure 6 shows the negative correlation mainly because as information uncertainty increases, the stocks with low FEP tend to have more negative FEP.

Figure 3 illustrates that high information uncertainty stocks with low (high) FEP tend to be overpriced (underpriced) before the earnings announcement days. I further analyze how information uncertainty affects EAR, conditional on stocks' mispricing level proxied by FEP. I perform conditional double sort first by expectation errors proxy, FEP, then by information uncertainty proxy. The result is shown in figure 7.

Figure 7 and 8 suggest that the effect of information uncertainty on EAR is conditional on the mispricing level. When stocks are overpriced (underpriced), information uncertainty has a negative (positive) effect on EAR. Berkman *et al.* (2009) suggest that FDISP has a negative direct impact on stock returns. In this analysis, I show that the effect of information uncertainty on stock returns is conditional on the mispricing level. As shown in panel PCA1 and PLS1 in figure 8, the effect of information uncertainty on EAR is increasing from negative in overpriced stocks to positive in underpriced stocks.

5.2 Regression analysis

This section examines the relationship of information uncertainty, expectation errors, and EAR using regressions. The regression method is similar to the regression analysis in the previous section. As shown in the previous section, the expectational errors are stronger in high information uncertainty stocks. Furthermore, investors may put less weight on analysts' estimates when information uncertainty is high, leading to a larger deviation of investors' expectations from analysts' estimates. In the regression analysis, I use interaction effects between FEP and information uncertainty dummy to allow for different effects between low and high information uncertainty. The regression specification is shown in equation (6).

$$EAR_{i,t} = \beta_0 + \beta_1 \cdot FEP_{i,t} \cdot IUlow_{i,t} + \beta_2 \cdot FEP_{i,t} \cdot IUhigh_{i,t} + \beta_3 \cdot IUlow_{i,t} + \sum_{k=1}^{K} \beta_k \cdot Control_{k,i,t} + \epsilon_{i,t} \tag{6}$$

Where i and t are the index for stock and time, respectively. $IUlow_{i,t}$ is a dummy variable that equals one if information uncertainty is less than its median value for the calendar quarter and zero otherwise. Similarly, $IUhigh_{i,t}$ is one if its value is higher than or equal to the median value of the information uncertainty proxy.

Table 4 presents the regression results. I present the result of information uncertainty proxied by first direction of PCA and PLS. The first two regressions are predictive, and similar with the portfolio analysis in figure 3. In the first regression, I do not include any control variables. In the second regression, I include MOM, TURN, PAR1, BETA, BM, AGR, and GMA as control variables. The third and fourth regressions are not predictive since they include AFE as a control variable. These regressions will show investors' expectations relative to analysts' estimates. In the third and fourth regression, I include the control variables as in the second regression. In the third regression, I add AFENL as a control variable. In the fourth regression, I add AFENLP, AFENLN, AFEPD, and AFEND as control variables.

The first two columns show that the expectational errors are stronger in stocks with high information uncertainty. Thus, the results are consistent with the portfolio sort in the previous section. To measure the economic significance of the FEP coefficient, we need to multiply the coefficient with the spread of FEP within the information uncertainty group. Figure 6 illustrates the spread of FEP for each quantile of information uncertainty. In general, we can observe that the FEP spread is lower for stocks with low information uncertainty. Thus, while EP_IUlow coefficients are statistically significant in table 4, the economic significance of the expectational errors is lower for stocks with low information uncertainty due to the spread of FEP is smaller.

The third and fourth columns show that investors have different expectations from analysts' forecasts for stocks with high information uncertainty, which can be seen from statistically significant FEP_IUhigh coefficients. For stocks with low information uncertainty, investors tend to agree with analysts. This result is consistent with the finding in figure 5, which shows that analysts' estimates are accurate for stocks with low information uncertainty. Hence, the AFE is close to zero.

Equation (4) shows that the expectation errors reflected in earnings announcement depends on the value of AFE and FEP. Thus, the deviation of investors' expectations from analysts' estimates alone does not fully explain the expectational errors that lead to the predictive relationship between EAR and FEP. The expectational errors are small for stocks with low information uncertainty because this kind of stocks have AFE values that are close to zero and small absolute value of FEP. Figure 5 suggest that AFE are close to zero for stocks with low information uncertainty. In addition, figure 6 suggests that stocks with low information uncertainty tend to have smaller absolute value of FEP relative to high information uncertainty stocks.

Table 5 shows the effect of information uncertainty on earnings announcement returns. In specifications one and two, I examine the unconditional effect of information uncertainty on announcement returns. Similar to Berkman *et al.* (2009), I find that information uncertainty negatively predicts announcement returns. In the third and fourth specifications, I run predictive regression to understand the effect of information uncertainty on announcement returns, conditional on stocks' mispricing levels based on expectation errors proxied by FEP. $FEPlow$ is a dummy variable that equals one if FEP is less than its 30th percentile for the calendar quarter and zero otherwise. Similarly, $FEPhigh$ is one if FEP is higher than or equal to its 70th percentile for the quarter and zero otherwise. I find that information uncertainty positively (negatively) predicts announcement returns for stocks with high (low) FEP values.

5.3 Timing of when investors update their beliefs

This section analyzes when investors update their beliefs around earnings announcement periods. I examine the performance of long-short portfolio returns of high and low FEP in the four weeks before and after earnings announcement days. I use both univariate sort and predictive regression for this analysis. I examine the FEP effect on returns for stocks with high information uncertainty. Thus, I only include stocks with information uncertainty value higher than the median of the respective information uncertainty proxy for each calendar quarter.

The univariate sort method is similar to portfolio sort in the section 4.1. I conducted nine different portfolio sorts for each information uncertainty proxy. The result is shown in figure 9. The figure shows that investors update their opinion about firms' earnings mostly on earnings announcement days.

I further examine using regression analysis that includes various control variables. In the regression, I control for RETVOL, MOM, TURN, BETA, SIZE, BM, AGR, and GMA. Furthermore, I control for the stock return in the previous period. For example, when regressing the stock returns in $(t-6, t-2)$, I include the stock returns in $(t-11, t-7)$ as a control variable. Where t is the earnings announcement day. I only include stocks with high information uncertainty and run nine different predictive regressions for each information uncertainty proxy. Figure 10 shows the coefficient of FEP on returns and its 99% confidence interval. The results are similar to the analysis in figure 9. I find that investors update their expectations about firms' earnings mostly at earnings announcement day. Furthermore, the relationship between analysts' forecasts and stock returns at the other weeks are not significantly different than zero at the 1% significance level. Thus, the relationship between analysts' forecasts and announcement returns reflects the investors' expectation errors and is not related to a risk factor.

6 Robustness tests

6.1 Sample split

This section examines if investors' expectational errors are particularly strong in the first or second half of the sample. Table 6 presents similar analysis with table 4, but split the sample into two. The first half of the sample spans from the first quarter of 1986 to the first quarter of 2003. The second half of the sample spans from the second quarter of 2003 to the third quarter of 2020. The results in table 6 column one and two show that investors have expectation errors in both the earlier and later parts of the sample. The positive and significant EP_IUhigh coefficients show the bias in investors' expectations. However, on average, the magnitude of EP_IUhigh is higher in the second half of the sample.

6.2 Excluding micro stocks

This section analyzes if micro stocks drive the effect of expectational errors. Thus, in this section, I remove firms with market values less than the 20th NYSE percentile. Table 7 presents similar analysis with table 4, but exclude the stocks categorized as microcaps. The results are robust after excluding the microcaps stocks. However, the t-statistics of FEP are smaller than the analysis in table 4. This finding is consistent with the previous analysis that expectational errors are stronger in small firms.

6.3 Additional control variables

This section examines if the effect of expectational errors is robust after including more control variables. Table 8 presents similar analysis with table 4, but include more control variables. The additional control variables are EPL1, EPL4, FS, PESSC, DLOWTURN, and EMI. EPL1 is actual earnings to price ratio in the previous fiscal quarter. EPL4 is actual earnings to price ratio in the previous four fiscal quarter. FS is failure probability score from Campbell *et al.* (2008). PESSC is analysts consensus pessimism from Veenman and Verwijmeren (2018). As in Akbas (2016), DLOWTURN equals to one if average of daily turnover at $t-6$ to $t-2$ is smaller than 20th percentile of daily turnover between $t-61$ to $t-12$. Where t is earnings announcement day. EMI is Expectation Management Incentives scores sourced from Johnson *et al.* (2020). The sample of the dataset is from the first quarter of 1986 to the fourth quarter of 2014 since I sourced the EMI variable, which only available until 2014.

Table 8 shows that the effect of investors expectation errors proxied by FEP are robust after including the control variables. Furthermore, adding EPL1 and EPL4 to the regression does not make FEP insignificant. Thus, the expectational errors proxied by FEP are not related to value and growth effect proxied by BM, EPL1, and EPL4.

6.4 Out of sample test and aggregating information uncertainty proxies

The focus in the previous analysis has been the in-sample relationship between information uncertainty, investors' expectation errors, and earnings announcement returns. This section examines the out-of-sample relationship by constructing portfolios with the cutoffs value obtained at the end of the month before the stocks' earnings announcement months. For each stock, I compute the cutoff based on the other stocks with announcement date within 90 days period ending at the end of the month before the stock's earnings announcement date. For example, if a firm's earnings announcement date is on 10th of June 2010. I calculate the cutoff based on the other firms' information uncertainty and expectation errors proxied by FEP for 90 days ending on 31st of May 2010. The cutoffs are conditional cutoffs, first based on an information uncertainty proxy, then based on FEP.

I make nine portfolios for each quarter. Cutting the data into three times three portfolios ensures that each portfolio has a sufficient number of stocks. In untabulated results, I sort the stocks into five times five portfolios, and some portfolios have five or fewer stocks for some periods. The change in the joint distribution of the sorting variables makes some portfolios have a small number of stocks. The main results are similar in both methods. Figure 11 presents the results of the conditional double sort, first based on information uncertainty proxy, then based on FEP. The results are similar to figure 4. Figure 11 presents the conditional double sort, first based on FEP, then based on information uncertainty proxy. The result is similar to the analysis in figure 8. Thus, the relationships between information uncertainty, investors' expectation errors, and announcement returns are robust to the cutoff selections. The sample spans from the second quarter of 1986 to the third quarter of 2020.

7 Conclusion

This paper shows that investors make biased expectations about firms' earnings. Stocks with low (high) expected earnings earn negative (positive) earnings announcement returns. I use analysts' estimates as a proxy for investors' expectations. Furthermore, investors' expectation errors are larger for stocks with high information uncertainty. For stocks with high information uncertainty proxied by the first PCA direction of eight information uncertainty proxies, the strategy of long and short stocks with high and low analysts' earnings estimates has three-day earnings announcement returns of 1.1%. On the other hand, for stocks with low information uncertainty, the same strategy yields average announcement returns of -0.2%. This result suggests that stocks with low (high) analysts' estimates tend to be overpriced (underpriced).

On the other hand, the effect of information uncertainty on earnings announcement returns is conditional on stocks' mispricing levels. Using investors' expectation errors proxied by analysts' forecasts as mispricing levels, I show that information uncertainty has a positive (negative) relationship with earnings announcement returns for underpriced (overpriced) stocks. This finding is consistent with Stambaugh *et al.* (2015). They show that the effect of return volatility on stock returns is conditional on stocks' mispricing levels. Furthermore, this finding complements Berkman *et al.* (2009). They suggest that the unconditional effect of disagreement on announcement returns is negative.

To understand if analysts' forecast biases drive the investors' expectational errors, I examine the level of investors' price implied expectation relative to analysts' estimates. I use earnings announcement periods to measure investors' price implied expectations. I find that investors are more optimistic (pessimistic) than analysts' estimates for stocks with low (high) analysts' earnings forecasts. For stocks with low information uncertainty, analysts' estimates are accurate and precise, and the differences in investors' and analysts' expectations tend to be small. Hence, the investors' expectation errors reflected in earnings announcement returns are small. On the other hand, analysts' estimates tend to be inaccurate and imprecise for stocks with high information uncertainty, and investors deviate their beliefs relative to analysts' forecasts. The high information uncertainty leads to large investors' expectation errors reflected in earnings announcement returns.

8 Tables and figures

8.1 Tables

Table 1: **Descriptive statistics**. This table presents the summary statistic of the main dataset. The maximum number of observations is 228,744 firm-quarter observations and spans from the first quarter of 1986 to the third quarter of 2020. The sample includes common stocks that are listed in NYSE, NYSE American, and Nasdaq. I use Compustat quarterly data for firms' characteristics, CRSP data for stock returns, IBES unadjusted details for earnings announcements information, and Thomson Reuters S12 for mutual funds' holdings. AGR, BM, and GMA are measured at the previous fiscal quarter. The Appendix provides the variable definitions.

Variable	Mean	Std	q25	Median	q75	N. obs
AFE	-0.086	1.238	-0.116	0.034	0.194	228744
AGE	21.143	18.942	6.833	15.417	28.833	228744
AGR	0.164	0.359	-0.003	0.077	0.208	228744
BETA	1.109	0.524	0.746	1.058	1.411	228744
BM	0.401	0.242	0.230	0.370	0.543	228744
EAR	0.194	8.886	-3.735	0.097	4.113	228744
FEP	0.712	2.606	0.507	1.185	1.780	228744
FDISP	0.277	0.554	0.042	0.101	0.251	228744
GMA	0.088	0.075	0.041	0.078	0.125	228744
LAAFE	0.540	1.058	0.096	0.218	0.507	228744
MFDISP	0.147	0.159	0.050	0.097	0.182	228744
MFN	0.022	0.029	0.007	0.012	0.027	228744
MOM	0.011	0.310	-0.168	-0.014	0.145	228744
NUMEST	6.920	5.260	3.000	5.000	9.000	228744
RETVOL	2.486	1.484	1.436	2.100	3.102	228744
SIZE	7.115	1.676	5.920	7.023	8.198	228744
TURN	0.903	0.809	0.359	0.662	1.156	228744

Table 2: **Variable correlations**. This table presents the time-series average of quarterly cross-sectional correlation between the information uncertainty proxies, EAR, and FEP. The numbers above (below) the diagonal are the Pearson (Spearman) correlations. I invert some variables to make the high value of an information uncertainty proxy translates to a high value of stocks' information uncertainty. The Appendix provides the variable definitions.

	1/AGE	EAR	FDISP	FEP	LAAFE	MFDISP	1/MFN	1/NUMEST	PCA1	PLS1	RETVOL	1/SIZE
1/AGE	1.00	0.00	0.07	-0.16	0.05	0.24	0.18	0.08	0.41	0.49	0.33	0.30
EAR	0.00	1.00	-0.02	0.03	-0.01	0.00	-0.01	0.00	-0.02	-0.02	-0.02	-0.01
FDISP	0.06	-0.03	1.00	-0.47	0.50	0.14	0.18	0.09	0.53	0.51	0.37	0.35
FEP	-0.22	0.03	-0.09	1.00	-0.37	-0.14	-0.19	-0.09	-0.44	-0.45	-0.40	-0.33
LAAFE	0.10	-0.02	0.59	-0.15	1.00	0.15	0.22	0.19	0.56	0.51	0.33	0.36
MFDISP	0.36	0.00	0.16	-0.15	0.23	1.00	0.19	0.20	0.54	0.57	0.35	0.45
1/MFN	0.42	-0.02	0.28	-0.22	0.43	0.48	1.00	0.32	0.61	0.50	0.29	0.54
1/NUMEST	0.14	-0.01	0.06	-0.06	0.29	0.26	0.62	1.00	0.53	0.40	0.18	0.54
PCA1	0.52	-0.02	0.40	-0.28	0.55	0.62	0.85	0.61	1.00	0.96	0.71	0.87
PLS1	0.58	-0.02	0.39	-0.32	0.51	0.64	0.77	0.45	0.96	1.00	0.81	0.82
RETVOL	0.44	-0.02	0.31	-0.34	0.38	0.44	0.49	0.19	0.73	0.82	1.00	0.56
1/SIZE	0.43	-0.02	0.32	-0.22	0.45	0.57	0.89	0.59	0.90	0.84	0.59	1.00

Table 3: **Expectation of investors and analysts**. This table analyzes the level of investors' expectations relative to analysts' estimates around the earnings announcements. The dependent variable is earnings announcement returns (EAR). Each column has different control variables. Specifically, columns two to five have different ways to control analysts' forecast errors (AFE). The third column allows different effects of positive and negative AFE. AFEPD and AFEPN are dummy variables equal to one if AFE is positive and negative, respectively. AFEP is AFE times AFEPD. AFEPN is AFE times AFEPND. The fourth and fifth specifications allow for a non-linear relationship between AFE and EAR. I transform AFE into AFENL by assigning the absolute value of AFE into 100 group rank based on its quarterly value, then multiplying the rank with minus one if the original AFE is negative. AFENLP is AFENL times AFEPD. AFENLN is AFENL times AFEND. The Appendix provides the variable definitions. The table reports Fama-Macbeth regression coefficients and t-statistics. At each quarter, I run cross-sectional regression of EAR on explanatory variables. The reported coefficients are the time-series average of quarterly cross-section regression coefficients. I report regression coefficients and their t-statistics (in parenthesis), calculated using Newey-West (1987) standard errors. The sample spans from the first quarter of 1986 to the third quarter of 2020. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Variable	1	2	3	4	5	6
FEP	0.114***	0.059***	0.144***	0.085***	0.125***	0.132***
	(6.225)	(3.240)	(8.095)	(5.082)	(7.132)	(8.141)
AFE		1.291***				
		(13.018)				
AFEP			1.667***			
			(13.437)			
AFEN			0.320***			
			(6.174)			
AFEPD			1.987***		-0.059	0.029
			(11.723)		(-0.619)	(0.295)
AFEND			-1.348***		-0.250**	-0.137
			(-12.341)		(-2.598)	(-1.410)
AFENL				0.039***		
				(14.697)		
AFENLP					0.053***	0.054***
					(14.897)	(16.053)
AFENLN					0.023***	0.026***
					(10.685)	(12.374)
RETVOL						0.015
						(0.518)
MOM						-0.793***
						(-5.871)
TURN						-0.176***
						(-3.364)
PAR1						-0.101***
						(-10.668)
BETA						0.149*
						(1.835)
SIZE						-0.033
						(-1.553)
BM						-0.200
						(-1.618)
AGR						-0.150*
						(-1.914)
GMA						1.049**
						(2.145)
(Intercept)	0.104**	0.233***	-0.828***	-0.190**	-0.812***	-0.621***
	(2.006)	(3.779)	(-5.861)	(-2.191)	(-5.756)	(-3.084)
Adj. R2	0.003	0.036	0.075	0.077	0.081	0.097

N	228744	228744	228744	228744	228744	228744

Table 4: **Expectations of investors and analysts for different information uncertainty levels**. This table analyzes the level of investors' expectations relative to analysts' estimates around the earnings announcements for different levels of information uncertainty (IU). The dependent variable is earnings announcement returns (EAR). The IU proxy is PCA1 or PLS1, as indicated on the top of the table. Each column has different control variables. Columns one and two are predictive regression without controlling for analysts' forecast errors. The first column does not include any control variables. The second column includes control variables, including MOM, TURN, PAR1, BETA, BM, AGR, and GMA. The third and fourth columns are not predictive since they include analysts' forecast errors as a control variable. These regressions will show investors' expectations relative to analysts' estimates. In the third and fourth regression, I include the control variables as in the second regression. In the third regression, I add AFENL as a control variable. In the fourth regression, I add AFENLP, AFENLN, AFEPD, and AFEND as control variables. AFEPD and AFEPN are dummy variables equal to one if AFE is positive and negative, respectively. AFEP is AFE times AFEPD. AFEPN is AFE times AFEPND. I transform analysts' forecast errors (AFE) into AFENL by assigning the absolute value of AFE into 100 group rank based on its quarterly value, then multiplying the rank with minus one if the original AFE is negative. AFENLP is AFENL times AFEPD. AFENLN is AFENL times AFEND. The Appendix provides the variable definitions. The table reports Fama-Macbeth regression coefficients and t-statistics. At each quarter, I run cross-sectional regression of EAR on explanatory variables. The reported coefficients are the time-series average of quarterly cross-section regression coefficients. I report regression coefficients and their t-statistics (in parenthesis), calculated using Newey-West (1987) standard errors. The sample spans from the first quarter of 1986 to the third quarter of 2020. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	PCA1				PLS1			
Variables	1	2	3	4	1	2	3	4
FEP_IUlow	0.061**	0.074***	-0.010	-0.024	0.051*	0.065**	-0.010	-0.025
FEP_IUlow	(2.111)	(2.743)	(-0.395)	(-0.851)	(1.753)	(2.338)	(-0.371)	(-0.891)
FEP_IUhigh	0.122***	0.108***	0.118***	0.145***	0.123***	0.110***	0.118***	0.146***
FEP_IUhigh	(6.921)	(6.358)	(7.141)	(8.387)	(6.838)	(6.282)	(6.973)	(8.263)
IUlow	0.060	-0.009	-0.132*	0.134*	0.088	0.009	-0.112	0.147**
IUlow	(0.874)	(-0.116)	(-1.735)	(1.797)	(1.257)	(0.115)	(-1.455)	(1.981)
AFEND				-0.167*				-0.167
AFEND				(-1.660)				(-1.635)
AFENL			0.041***				0.041***	
AFENL			(15.895)				(15.898)	
AFENLN				0.025***				0.025***
AFENLN				(12.534)				(12.559)
AFENLP				0.055***				0.055***
AFENLP				(15.752)				(15.650)
AFEPD				-0.016				-0.019
AFEPD				(-0.164)				(-0.190)
AGR		-0.289***	-0.228***	-0.164**		-0.290***	-0.230***	-0.163**
AGR		(-3.502)	(-2.908)	(-2.073)		(-3.513)	(-2.939)	(-2.075)
BETA		0.246***	0.166**	0.149*		0.241***	0.160**	0.147*
BETA		(3.089)	(2.170)	(1.952)		(3.084)	(2.133)	(1.973)
BM		0.052	0.229*	-0.155		0.057	0.245**	-0.152
BM		(0.443)	(1.920)	(-1.285)		(0.491)	(2.082)	(-1.270)
GMA		1.782***	0.667	1.027**		1.780***	0.662	1.018**
GMA		(4.430)	(1.405)	(2.159)		(4.398)	(1.398)	(2.150)
MOM		0.302**	-0.941***	-0.846***		0.297**	-0.941***	-0.847***
MOM		(2.349)	(-7.015)	(-6.442)		(2.302)	(-6.972)	(-6.414)
PAR1		-0.071***	-0.100***	-0.100***		-0.072***	-0.100***	-0.100***
PAR1		(-7.639)	(-10.583)	(-10.599)		(-7.642)	(-10.589)	(-10.608)
TURN		-0.158***	-0.133***	-0.175***		-0.159***	-0.146***	-0.179***
TURN		(-3.177)	(-2.706)	(-3.557)		(-3.193)	(-2.974)	(-3.634)
(Intercept)	0.108	-0.128	-0.230**	-0.808***	0.102	-0.125	-0.227**	-0.809***
(Intercept)	(1.517)	(-1.233)	(-2.313)	(-5.728)	(1.417)	(-1.253)	(-2.373)	(-5.758)

Table 4: **Expectations of investors and analysts for different information uncertainty levels**. This table analyzes the level of investors' expectations relative to analysts' estimates around the earnings announcements for different levels of information uncertainty (IU). The dependent variable is earnings announcement returns (EAR). The IU proxy is PCA1 or PLS1, as indicated on the top of the table. Each column has different control variables. Columns one and two are predictive regression without controlling for analysts' forecast errors. The first column does not include any control variables. The second column includes control variables, including MOM, TURN, PAR1, BETA, BM, AGR, and GMA. The third and fourth columns are not predictive since they include analysts' forecast errors as a control variable. These regressions will show investors' expectations relative to analysts' estimates. In the third and fourth regression, I include the control variables as in the second regression. In the third regression, I add AFENL as a control variable. In the fourth regression, I add AFENLP, AFENLN, AFEPD, and AFEND as control variables. AFEPD and AFEPN are dummy variables equal to one if AFE is positive and negative, respectively. AFEP is AFE times AFEPD. AFEPN is AFE times AFEPND. I transform analysts' forecast errors (AFE) into AFENL by assigning the absolute value of AFE into 100 group rank based on its quarterly value, then multiplying the rank with minus one if the original AFE is negative. AFENLP is AFENL times AFEPD. AFENLN is AFENL times AFEND. The Appendix provides the variable definitions. The table reports Fama-Macbeth regression coefficients and t-statistics. At each quarter, I run cross-sectional regression of EAR on explanatory variables. The reported coefficients are the time-series average of quarterly cross-section regression coefficients. I report regression coefficients and their t-statistics (in parenthesis), calculated using Newey-West (1987) standard errors. The sample spans from the first quarter of 1986 to the third quarter of 2020. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. *(continued)*

Variables	1	2	3	4	1	2	3	4
adjR2	0.004	0.015	0.093	0.096	0.004	0.016	0.093	0.096
N	228744	228744	228744	228744	228744	228744	228744	228744

$$EAR_{i,t} = \beta_0+\beta_1 \cdot FEP_{i,t} \cdot IUlow_{i,t}+\beta_2 \cdot FEP_{i,t} \cdot IUhigh_{i,t}+\beta_3 \cdot IUlow_{i,t}+\sum_{k=1}^{K}\beta_k \cdot Control_{k,i,t}+\epsilon_{i,t}$$

Table 5: **The effect of information uncertainty on announcement returns, conditional on stocks' mispricing levels.**. This table analyzes the effect of information uncertainty (IU) on earnings announcement returns (EAR), conditional on mispricing levels indicated by investors' expectational errors proxied by analysts' forecasts to price ratio (FEP). The dependent variable is EAR. All regressions are predictive regressions. The IU proxy is PCA1 or PLS1, as indicated on the top of the table. The Appendix provides the variable definitions. The table reports Fama-Macbeth regression coefficients and t-statistics. At each quarter, I run cross-sectional regression of EAR on explanatory variables. The reported coefficients are the time-series average of quarterly cross-section regression coefficients. I report regression coefficients and their t-statistics (in parenthesis), calculated using Newey-West (1987) standard errors. The sample spans from the first quarter of 1986 to the third quarter of 2020. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	PCA1				PLS1			
Variables	1	2	3	4	1	2	3	4
IU	-0.070***	-0.048*			-0.033***	-0.022**		
IU	(-2.935)	(-1.896)			(-3.206)	(-2.008)		
IU_FEPlow			-0.104***	-0.075**			-0.050***	-0.035**
IU_FEPlow			(-3.142)	(-2.228)			(-3.494)	(-2.407)
IU_FEPhigh			0.073**	0.080**			0.025**	0.029**
IU_FEPhigh			(2.078)	(2.455)			(2.079)	(2.359)
FEPlow			-0.179**	-0.127**			-0.164**	-0.130**
FEPlow			(-2.598)	(-2.300)			(-2.493)	(-2.369)
FEPhigh			0.155***	0.208***			0.160***	0.216***
FEPhigh			(2.828)	(4.272)			(2.745)	(4.218)
AGR		-0.225***		-0.262***		-0.221***		-0.260***
AGR		(-2.722)		(-3.304)		(-2.668)		(-3.247)
BETA		0.227***		0.224***		0.229***		0.220***
BETA		(2.715)		(2.876)		(2.792)		(2.814)
BM		0.219*		0.066		0.211*		0.066
BM		(1.948)		(0.587)		(1.850)		(0.580)
GMA		2.426***		2.029***		2.490***		2.060***
GMA		(5.725)		(4.936)		(5.867)		(4.980)
MOM		0.356***		0.362***		0.354***		0.363***
MOM		(2.739)		(2.846)		(2.747)		(2.832)
PAR1		-0.071***		-0.072***		-0.071***		-0.072***
PAR1		(-7.585)		(-7.679)		(-7.600)		(-7.708)
TURN		-0.161***		-0.162***		-0.148***		-0.156***
TURN		(-3.326)		(-3.384)		(-3.036)		(-3.265)
(Intercept)	0.199***	-0.168*	0.244***	-0.052	0.198***	-0.186*	0.244***	-0.056
(Intercept)	(4.283)	(-1.689)	(5.462)	(-0.517)	(4.225)	(-1.848)	(5.462)	(-0.549)
adjR2	0.002	0.014	0.004	0.015	0.003	0.015	0.004	0.016
N	228744	228744	228744	228744	228744	228744	228744	228744

$$\begin{aligned} EAR_{i,t} =& \beta_0 + \beta_1 \cdot IU_{i,t} \cdot FEPlow_{i,t} + \beta_2 \cdot IU_{i,t} \cdot FEPhigh_{i,t} + \beta_3 \cdot FEPlow_{i,t} + \beta_4 \cdot FEPhigh_{i,t} + \\ & \sum_{k=1}^{K} \beta_k \cdot Control_{k,i,t} + \epsilon_{i,t} \end{aligned} \tag{7}$$

Table 6: **Robustness test, sub-sample split by time**. This table analyzes the level of investors' expectations relative to analysts' estimates around the earnings announcements for different levels of information uncertainty. I run similar regressions with table 4 but split the sample into two parts. The first half of the sample spans from the first quarter of 1986 to the first quarter of 2003. The second half of the sample spans from the second quarter of 2003 to the third quarter of 2020 . ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	First half				Second half			
Variables	PCA1	PCA1	PLS1	PLS1	PCA1	PCA1	PLS1	PLS1
FEP_IUlow	0.048	-0.001	0.036	-0.005	0.099***	-0.046	0.094**	-0.044
FEP_IUlow	(1.194)	(-0.035)	(0.963)	(-0.157)	(2.837)	(-1.182)	(2.364)	(-1.035)
FEP_IUhigh	0.070***	0.101***	0.072***	0.102***	0.146***	0.188***	0.148***	0.189***
FEP_IUhigh	(4.039)	(5.527)	(3.907)	(5.380)	(5.749)	(7.828)	(5.689)	(7.656)
IUlow	-0.044	0.064	-0.004	0.084	0.025	0.202	0.022	0.209*
IUlow	(-0.569)	(0.812)	(-0.053)	(0.993)	(0.191)	(1.656)	(0.170)	(1.740)
AFEND		-0.096		-0.092		-0.237		-0.241
AFEND		(-0.704)		(-0.661)		(-1.621)		(-1.632)
AFENLN		0.020***		0.020***		0.030***		0.030***
AFENLN		(10.366)		(10.092)		(10.602)		(10.796)
AFENLP		0.042***		0.042***		0.068***		0.068***
AFENLP		(9.923)		(9.908)		(24.894)		(24.013)
AFEPD		-0.202		-0.201		0.167		0.162
AFEPD		(-1.541)		(-1.552)		(1.373)		(1.280)
AGR	-0.370***	-0.311**	-0.367***	-0.308**	-0.209**	-0.019	-0.214**	-0.020
AGR	(-2.807)	(-2.427)	(-2.779)	(-2.423)	(-2.110)	(-0.235)	(-2.160)	(-0.252)
BETA	0.186*	0.137	0.183*	0.136	0.305**	0.161	0.297**	0.159
BETA	(1.754)	(1.303)	(1.806)	(1.340)	(2.532)	(1.391)	(2.478)	(1.389)
BM	0.257*	0.066	0.270*	0.072	-0.150	-0.373**	-0.152	-0.374**
BM	(1.752)	(0.411)	(1.878)	(0.451)	(-0.945)	(-2.480)	(-0.962)	(-2.505)
GMA	2.405***	2.362***	2.420***	2.361***	1.167**	-0.289	1.150**	-0.306
GMA	(3.994)	(4.095)	(3.955)	(4.108)	(2.334)	(-0.503)	(2.320)	(-0.540)
MOM	0.542***	-0.798***	0.535***	-0.800***	0.066	-0.894***	0.062	-0.893***
MOM	(3.650)	(-5.571)	(3.585)	(-5.561)	(0.352)	(-4.125)	(0.332)	(-4.097)
PAR1	-0.098***	-0.124***	-0.098***	-0.124***	-0.045***	-0.076***	-0.045***	-0.076***
PAR1	(-13.669)	(-16.834)	(-13.761)	(-16.958)	(-3.279)	(-5.223)	(-3.274)	(-5.222)
TURN	-0.115	-0.098	-0.120	-0.107	-0.200***	-0.250***	-0.198***	-0.251***
TURN	(-1.488)	(-1.337)	(-1.539)	(-1.445)	(-3.326)	(-4.220)	(-3.284)	(-4.190)
(Intercept)	-0.162	-0.460**	-0.172	-0.463**	-0.095	-1.151***	-0.079	-1.149***
(Intercept)	(-1.092)	(-2.575)	(-1.208)	(-2.521)	(-0.681)	(-6.528)	(-0.583)	(-6.793)
adjR2	0.019	0.074	0.019	0.074	0.012	0.118	0.012	0.118
N	90936	90936	90936	90936	137808	137808	137808	137808

Table 7: **Robustness test, excluding microcaps**. This table analyzes the level of investors' expectations relative to analysts' estimates around the earnings announcements for different levels of information uncertainty. I run similar regressions with table 4 but exclude firms with market values less than the 20th NYSE percentile. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	PCA1				PLS1			
Variables	1	2	3	4	1	2	3	4
FEP_IUlow	0.018	0.049	-0.039	-0.060*	0.020	0.051**	-0.036	-0.059**
FEP_IUlow	(0.550)	(1.535)	(-1.162)	(-1.707)	(0.782)	(1.987)	(-1.296)	(-2.015)
FEP_IUhigh	0.139***	0.141***	0.097***	0.121***	0.142***	0.143***	0.097***	0.123***
FEP_IUhigh	(5.031)	(5.837)	(4.141)	(5.102)	(5.085)	(5.755)	(4.107)	(5.076)
IUlow	0.086	0.009	-0.034	0.170**	0.042	-0.028	-0.054	0.138**
IUlow	(1.332)	(0.131)	(-0.474)	(2.438)	(0.618)	(-0.417)	(-0.802)	(2.078)
AFEND				-0.228**				-0.220**
AFEND				(-2.275)				(-2.142)
AFENL			0.040***				0.040***	
AFENL			(14.387)				(14.398)	
AFENLN				0.022***				0.022***
AFENLN				(9.915)				(9.713)
AFENLP				0.051***				0.051***
AFENLP				(14.400)				(14.415)
AFEPD				0.238**				0.248**
AFEPD				(2.363)				(2.464)
AGR		-0.162**	-0.124	-0.066		-0.162**	-0.122	-0.065
AGR		(-2.013)	(-1.654)	(-0.859)		(-2.013)	(-1.626)	(-0.844)
BETA		0.281***	0.212**	0.176*		0.266***	0.201**	0.170*
BETA		(3.148)	(2.364)	(1.963)		(3.028)	(2.300)	(1.936)
BM		-0.096	-0.064	-0.464***		-0.103	-0.058	-0.468***
BM		(-0.769)	(-0.488)	(-3.422)		(-0.832)	(-0.451)	(-3.481)
GMA		1.446***	0.033	0.499		1.408***	0.001	0.461
GMA		(3.433)	(0.064)	(1.007)		(3.319)	(0.003)	(0.930)
MOM		0.210	-0.943***	-0.885***		0.216	-0.933***	-0.879***
MOM		(1.357)	(-5.246)	(-4.862)		(1.400)	(-5.216)	(-4.854)
PAR1		-0.073***	-0.102***	-0.103***		-0.073***	-0.102***	-0.103***
PAR1		(-7.166)	(-10.232)	(-10.254)		(-7.166)	(-10.239)	(-10.270)
TURN		-0.116**	-0.096*	-0.153***		-0.126**	-0.111**	-0.163***
TURN		(-2.161)	(-1.868)	(-2.920)		(-2.348)	(-2.166)	(-3.132)
(Intercept)	0.127**	-0.128	-0.238***	-0.783***	0.149**	-0.076	-0.201**	-0.747***
(Intercept)	(1.992)	(-1.388)	(-2.832)	(-5.995)	(2.135)	(-0.814)	(-2.429)	(-5.701)
adjR2	0.003	0.016	0.091	0.095	0.004	0.016	0.091	0.095
N	173651	173651	173651	173651	173651	173651	173651	173651

Table 8: **Robustness test, including more control variables**. This table analyzes the level of investors' expectations relative to analysts' estimates around the earnings announcements for different levels of information uncertainty. I run similar regressions with table 4 but include more control variables. The additional control variables are EPL1, EPL4, FS, PESSC, DLOWTURN, and EMI. The sample is from the first quarter of 1986 to the fourth quarter of 2014 since I sourced the EMI variable, which is available until 2014. The Appendix provides the variable definitions. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	PCA1				PLS1			
Variables	1	2	3	4	1	2	3	4
FEP_IUlow	0.061*	0.106***	0.093***	0.079**	0.051*	0.092***	0.088***	0.074**
FEP_IUlow	(1.964)	(3.515)	(3.016)	(2.419)	(1.691)	(3.157)	(2.989)	(2.376)
FEP_IUhigh	0.133***	0.155***	0.207***	0.224***	0.136***	0.159***	0.209***	0.226***
FEP_IUhigh	(6.843)	(8.536)	(11.083)	(11.768)	(6.817)	(8.509)	(10.942)	(11.663)
IUlow	0.115	0.064	0.047	0.243***	0.130*	0.069	0.048	0.234***
IUlow	(1.589)	(0.852)	(0.623)	(2.897)	(1.760)	(0.994)	(0.681)	(3.108)
AFEND				-0.120				-0.112
AFEND				(-0.922)				(-0.856)
AFENL			0.041***				0.041***	
AFENL			(13.251)				(13.226)	
AFENLN				0.026***				0.026***
AFENLN				(11.502)				(11.320)
AFENLP				0.052***				0.052***
AFENLP				(13.013)				(13.049)
AFEPD				0.152				0.160
AFEPD				(1.308)				(1.370)
AGR		-0.294***	-0.154	-0.110		-0.296***	-0.157*	-0.112
AGR		(-2.876)	(-1.658)	(-1.157)		(-2.898)	(-1.698)	(-1.177)
BETA		0.205**	0.156*	0.156*		0.192**	0.140*	0.145*
BETA		(2.474)	(1.841)	(1.817)		(2.365)	(1.698)	(1.722)
BM		0.172	0.067	-0.260*		0.167	0.063	-0.270*
BM		(1.229)	(0.447)	(-1.696)		(1.187)	(0.416)	(-1.748)
DLOWTURN		-0.267**	-0.312***	-0.302***		-0.269**	-0.316***	-0.306***
DLOWTURN		(-2.523)	(-3.089)	(-3.005)		(-2.533)	(-3.106)	(-3.040)
EMI		0.113***	0.089***	0.104***		0.113***	0.089***	0.105***
EMI		(5.537)	(4.404)	(4.994)		(5.498)	(4.349)	(4.987)
EPL1		-0.044***	-0.040***	-0.038***		-0.044***	-0.040***	-0.038***
EPL1		(-4.676)	(-4.607)	(-4.353)		(-4.633)	(-4.532)	(-4.295)
EPL4		-0.031***	-0.032***	-0.031***		-0.030***	-0.032***	-0.030***
EPL4		(-2.922)	(-2.935)	(-2.767)		(-2.826)	(-2.849)	(-2.675)
FS		0.047	0.158***	0.123***		0.046	0.156***	0.122***
FS		(1.623)	(5.236)	(4.115)		(1.601)	(5.204)	(4.073)
GMA		2.111***	1.963***	2.059***		2.097***	1.953***	2.031***
GMA		(4.519)	(4.117)	(4.254)		(4.449)	(4.072)	(4.170)
MOM		0.265*	-1.003***	-0.974***		0.256*	-1.011***	-0.983***
MOM		(1.807)	(-6.530)	(-6.410)		(1.744)	(-6.585)	(-6.473)
PAR1		-0.102***	-0.134***	-0.134***		-0.102***	-0.134***	-0.134***
PAR1		(-14.868)	(-20.305)	(-20.367)		(-14.937)	(-20.398)	(-20.486)
PESSC		0.325***	-1.245***	-1.065***		0.330***	-1.246***	-1.061***
PESSC		(3.447)	(-6.703)	(-6.226)		(3.504)	(-6.765)	(-6.281)
TURN		-0.188***	-0.164**	-0.211***		-0.187***	-0.169**	-0.209***
TURN		(-2.848)	(-2.459)	(-3.082)		(-2.883)	(-2.566)	(-3.093)
(Intercept)	0.081	-0.099	1.703***	0.690**	0.081	-0.085	1.711***	0.700**
(Intercept)	(1.027)	(-0.337)	(5.018)	(1.986)	(1.028)	(-0.288)	(5.076)	(2.023)
adjR2	0.004	0.022	0.103	0.106	0.005	0.022	0.103	0.106
N	184401	145005	145005	145005	184401	145005	145005	145005

8.2 Figures

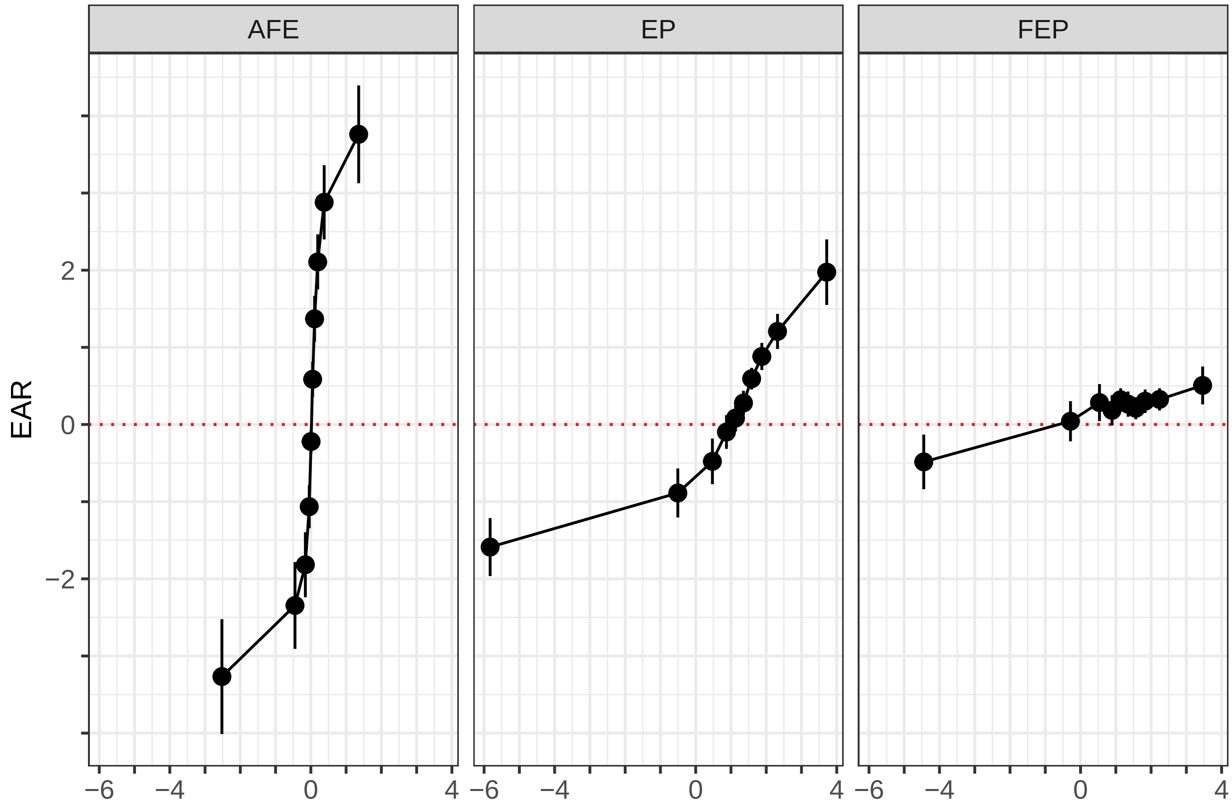

Figure 1: Portfolios sorted on analysts' forecast errors, actual earnings, and forecasted earning. This figure presents the univariate sort of earnings announcement returns (EAR) on analysts' forecast errors (AFE), actual earning to price ratio (EP), and forecasted earnings to price ratio (FEP). I form equal-weighted portfolios for each calendar quarter by sorting stocks based on decile ranks of AFE, EP, or FEP. The cutoff values for the decile ranks are based on all stocks in the calendar quarter. The reported returns are the time-series average of quarterly mean of EAR. I adjust the standard errors of the portfolios' time-series average returns using Newey-West (1987) with four lags and plot the 99% confidence interval. I show the univariate sort in three different panels. Within each panel, I plot the time-series average of the cross-sectional average of the sorting variable in the x-axis. The data has 228,744 firm-quarter observations and spans from the first quarter of 1986 to the third quarter of 2020.

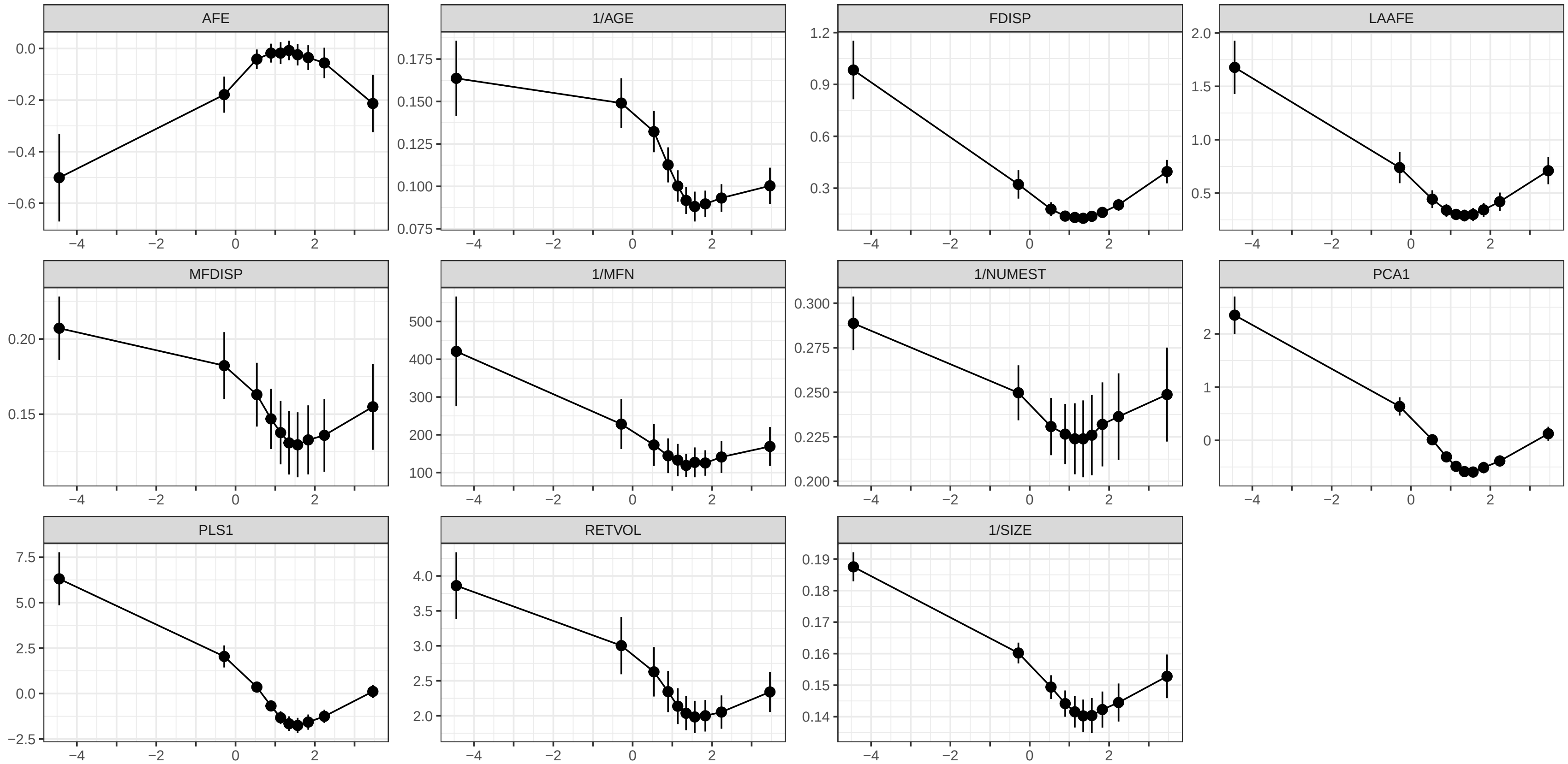

Figure 2: Characteristics of portfolio sorted by forecasted earnings. This figure presents the characteristics of portfolios sorted by forecasted earnings to price ratio (FEP). The characteristics are analysts' forecast errors (AFE) and proxies for information uncertainty. The Appendix provides the variable definitions. At each calendar quarter, I assigned stocks to decile portfolios based on FEP value. The cutoff used for the portfolio assignment is based on all stocks in the calendar quarter. The reported number is the time-series average of quarterly equal-weighted characteristics for each decile portfolio. Each point represents the characteristic's time series mean and its 99% confidence interval for an FEP portfolio. The standard error for the confidence interval is calculated using Newey-West (1987) with four lags. Within each panel, I plot the time-series average of the cross-sectional average of the FEP portfolios in the x-axis. The data has 228,744 firm-quarter observations and spans from the first quarter of 1986 to the third quarter of 2020.

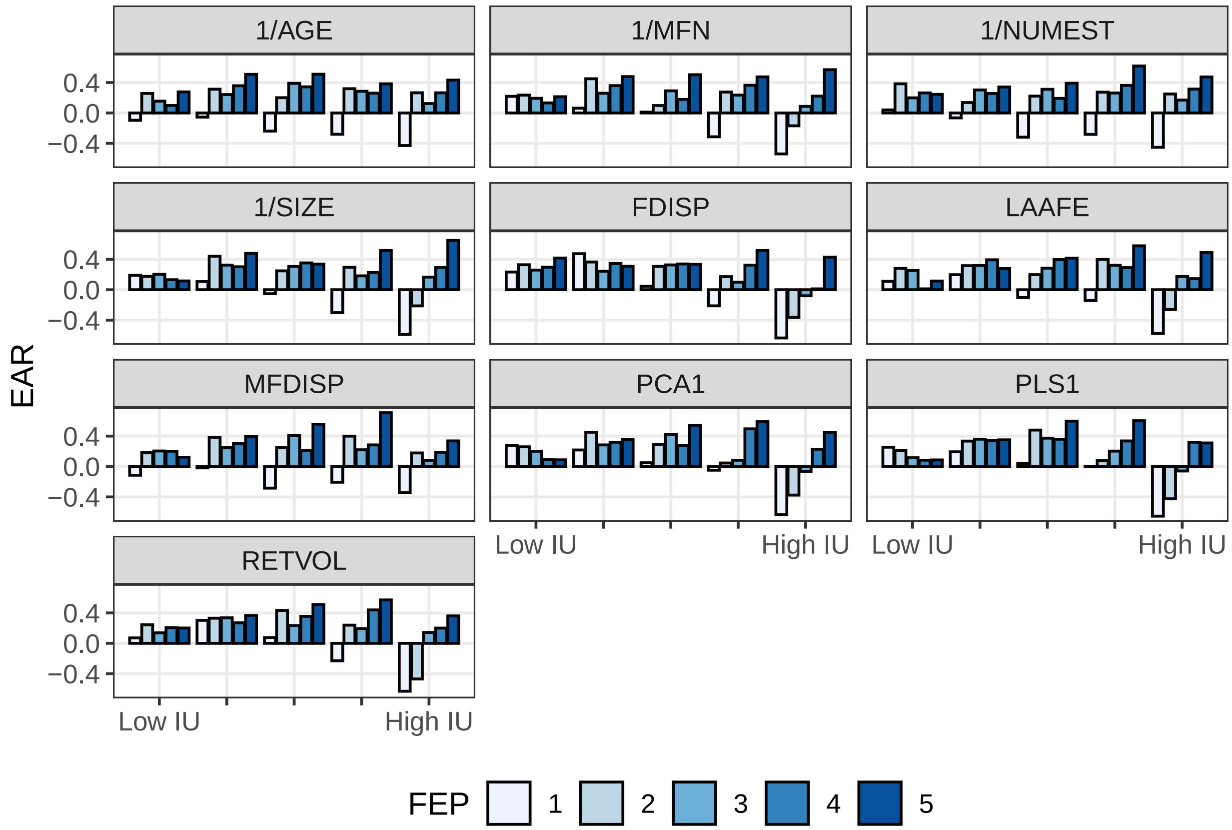

Figure 3: Portfolios of stocks conditionally sorted on information uncertainty and forecasted earnings. This figure presents the conditional double sort of stocks on an information uncertainty (IU) proxy and analysts' forecasts to price ratio (FEP). I form equal-weighted portfolios for each calendar quarter by first sorting stocks based on quantile ranks of an IU proxy, then based on the quantile ranks of the FEP. The cutoff values for the decile ranks are based on all stocks in the calendar quarter. The reported returns are the time-series average of the quarterly mean of earnings announcement returns (EAR). Each panel shows the double sort results based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

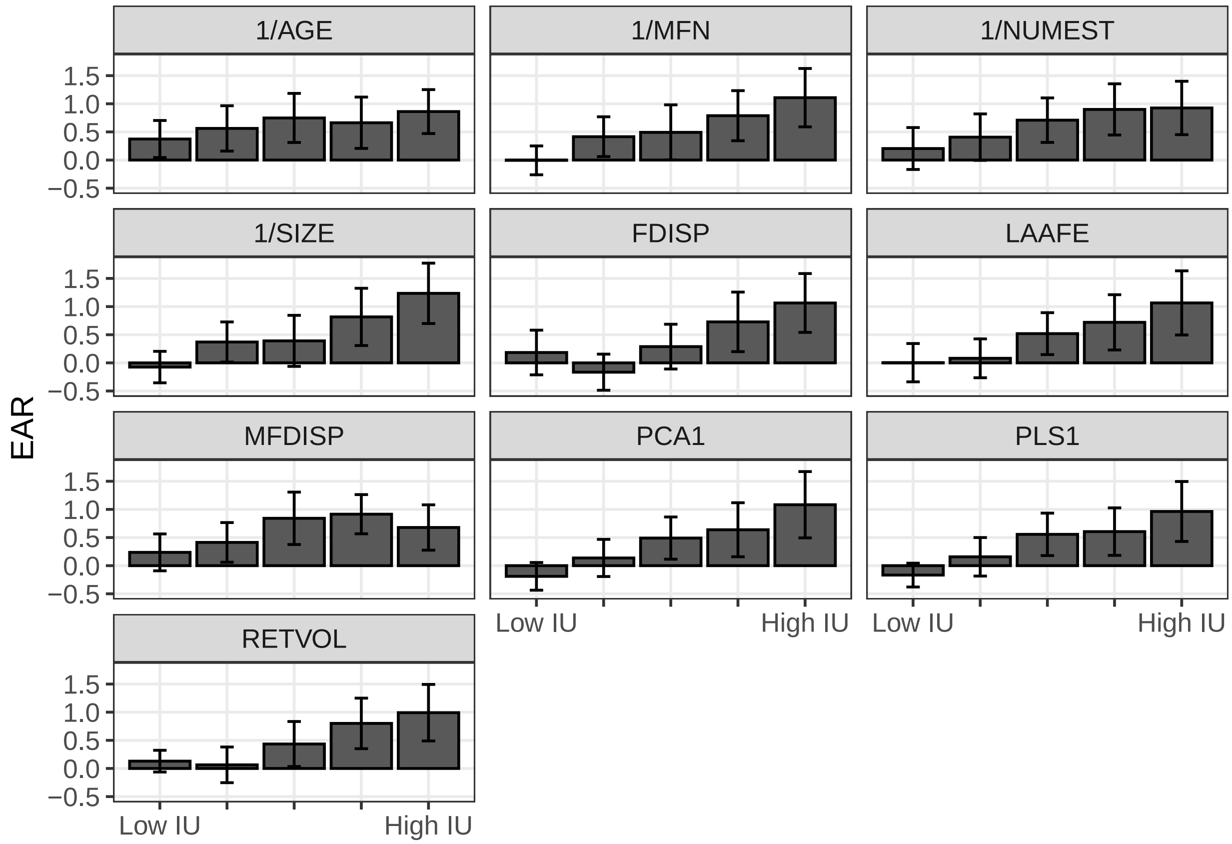

Figure 4: Long-short returns of the conditional double sorted portfolio based on information uncertainty and forecasted earnings. This figure presents the equally weighted long-short returns of portfolios that are long stocks in the highest quantile and short stocks in the lowest quantile of forecasted earnings to price ratio (FEP), within a group of information uncertainty (IU). The reported returns are the time-series average of quarterly mean of long-short returns. I adjust the standard errors of the portfolios' time-series average returns using Newey-West (1987) with four lags and plot the 99% confidence interval. Each panel shows the long-short returns for double sort based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

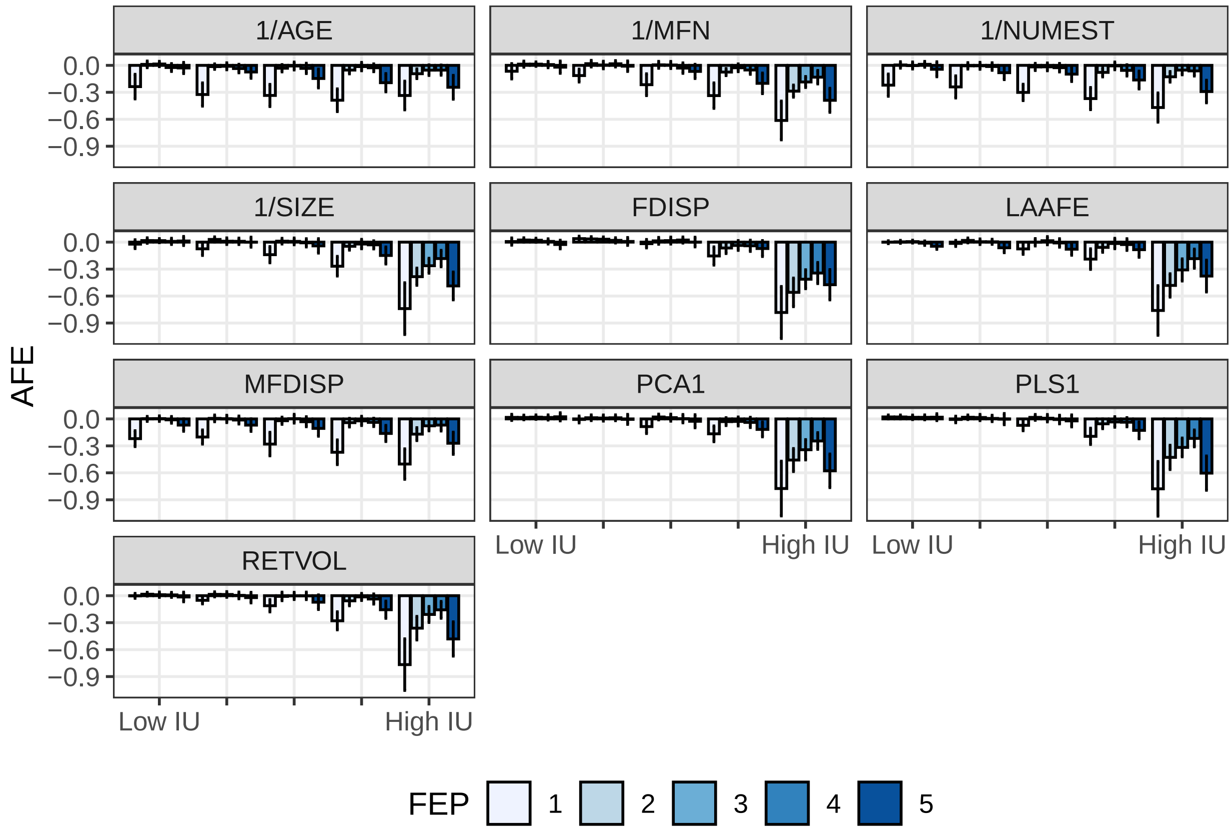

Figure 5: Analysts' forecast errors of the conditional double sort based on information uncertainty and forecasted earnings. This figure presents the equally weighted analysts' forecast errors (AFE) of the portfolios constructed using conditional double sort, first by an information uncertainty proxy, then by forecasted earnings to price ratio (FEP). The reported AFE is the time-series average of the quarterly mean of AFE. I adjust the standard errors of the portfolios' time-series average AFE using Newey-West (1987) with four lags and plot the 99% confidence interval. Each panel shows the AFE for double sort based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

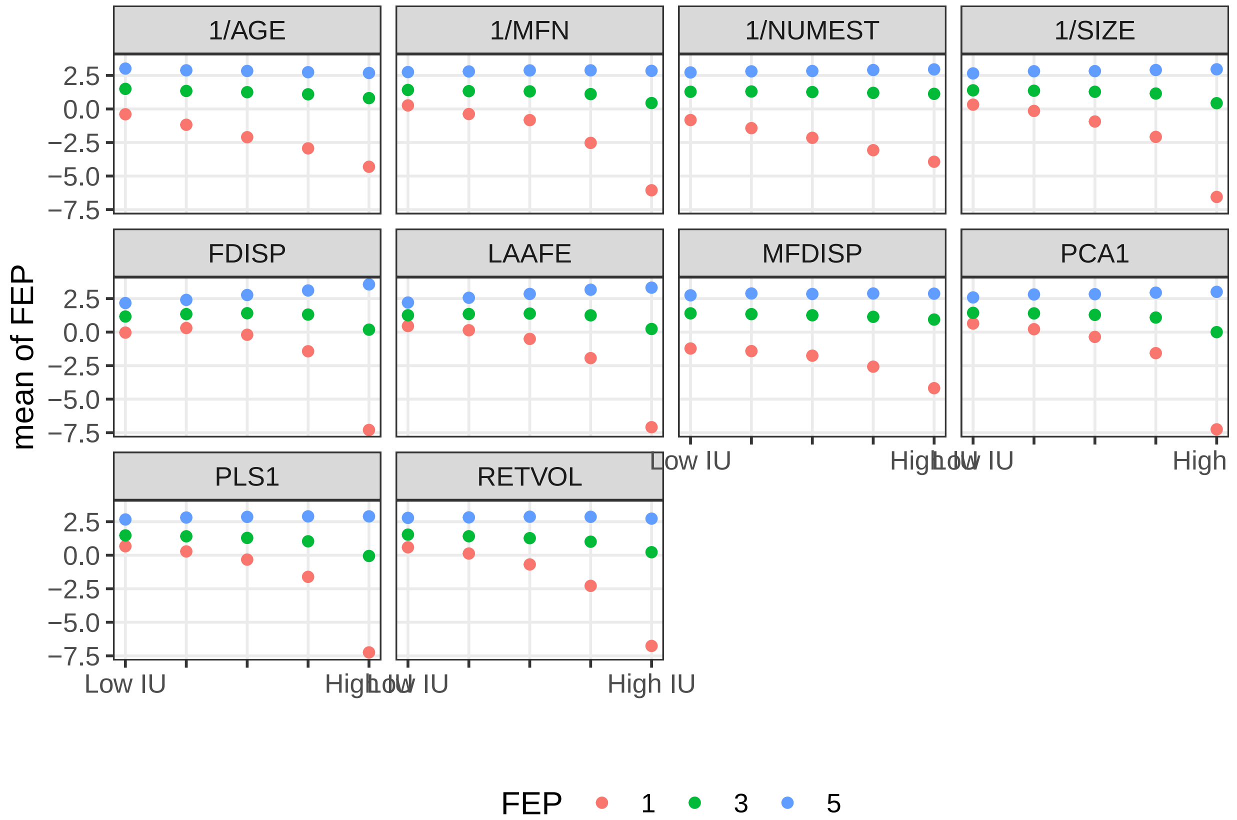

Figure 6: Mean of forecasted earnings of the conditional double sort based on information uncertainty and forecasted earnings. This figure presents the equally weighted analysts' earnings forecasts (FEP) of the portfolios constructed using conditional double sort, first by an information uncertainty proxy, then by forecasted earnings to price ratio (FEP). The reported FEP is the time-series average of the quarterly mean of FEP. Each panel shows the FEP for double sort based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

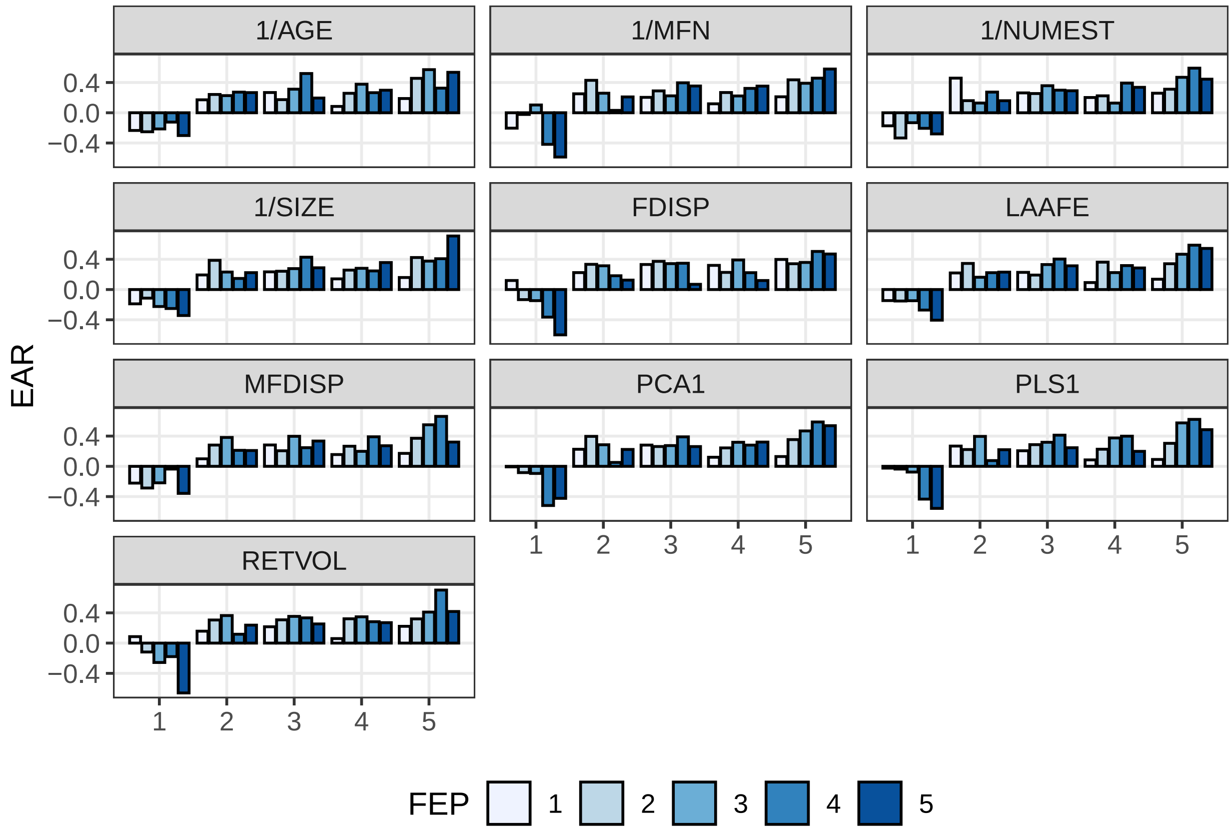

Figure 7: Portfolios of stocks conditionally sorted on forecasted earnings and information uncertainty. This figure presents the conditional double sort of stocks on analysts' forecasts to price ratio (FEP) and an information uncertainty (IU) proxy. I form equal-weighted portfolios for each calendar quarter by first sorting stocks based on quantile ranks of FEP, then based on the quantile ranks of an IU proxy. The cutoff values for the decile ranks are based on all stocks in the calendar quarter. The reported returns are the time-series average of the quarterly mean of earnings announcement returns (EAR). Each panel shows the double sort results based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

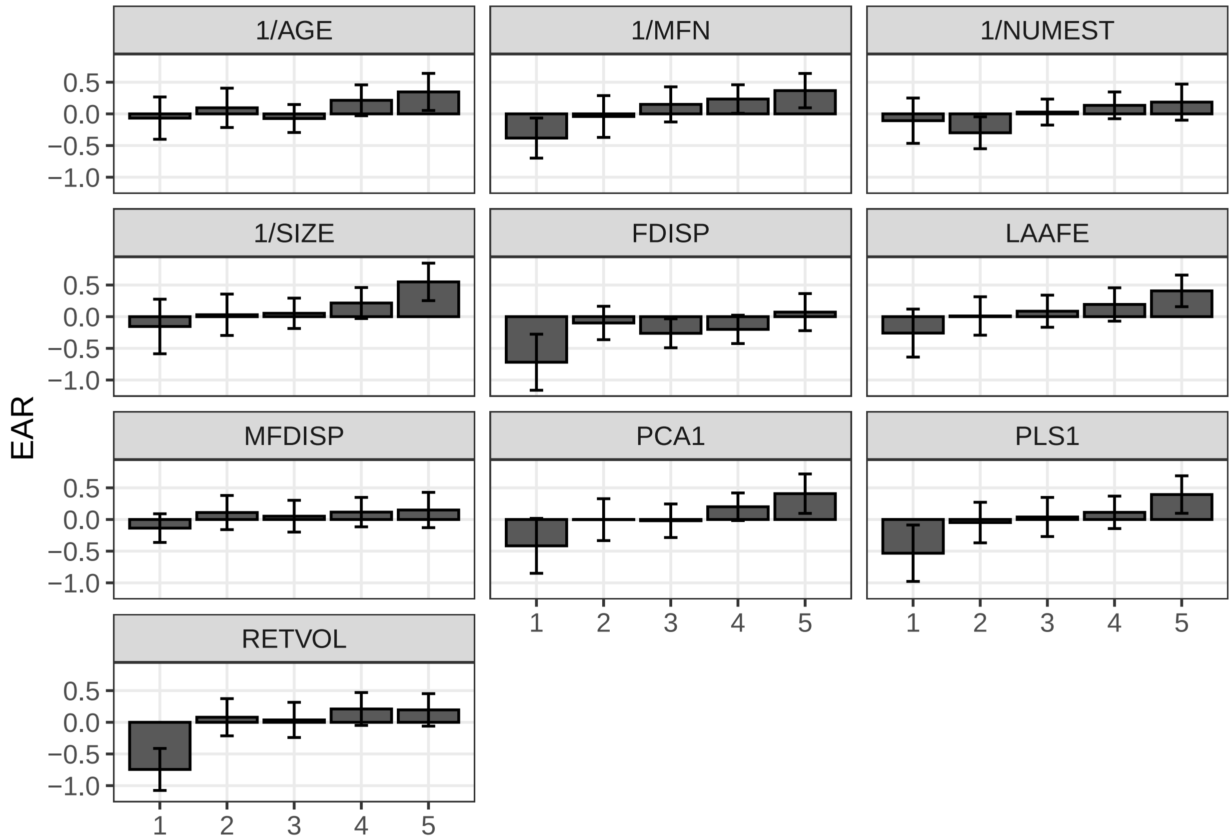

Figure 8: Long-short returns of the conditional double sorted portfolio based on forecasted earnings and information uncertainty. This figure presents the equally weighted long-short returns of portfolios that are long stocks in the highest quantile and short stocks in the lowest quantile of information uncertainty (IU), within a group of forecasted earnings to price ratio (FEP). The reported returns are the time-series average of quarterly mean of long-short returns. I adjust the standard errors of the portfolios' time-series average returns using Newey-West (1987) with four lags and plot the 95% confidence interval. Each panel shows the long-short returns for double sort based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

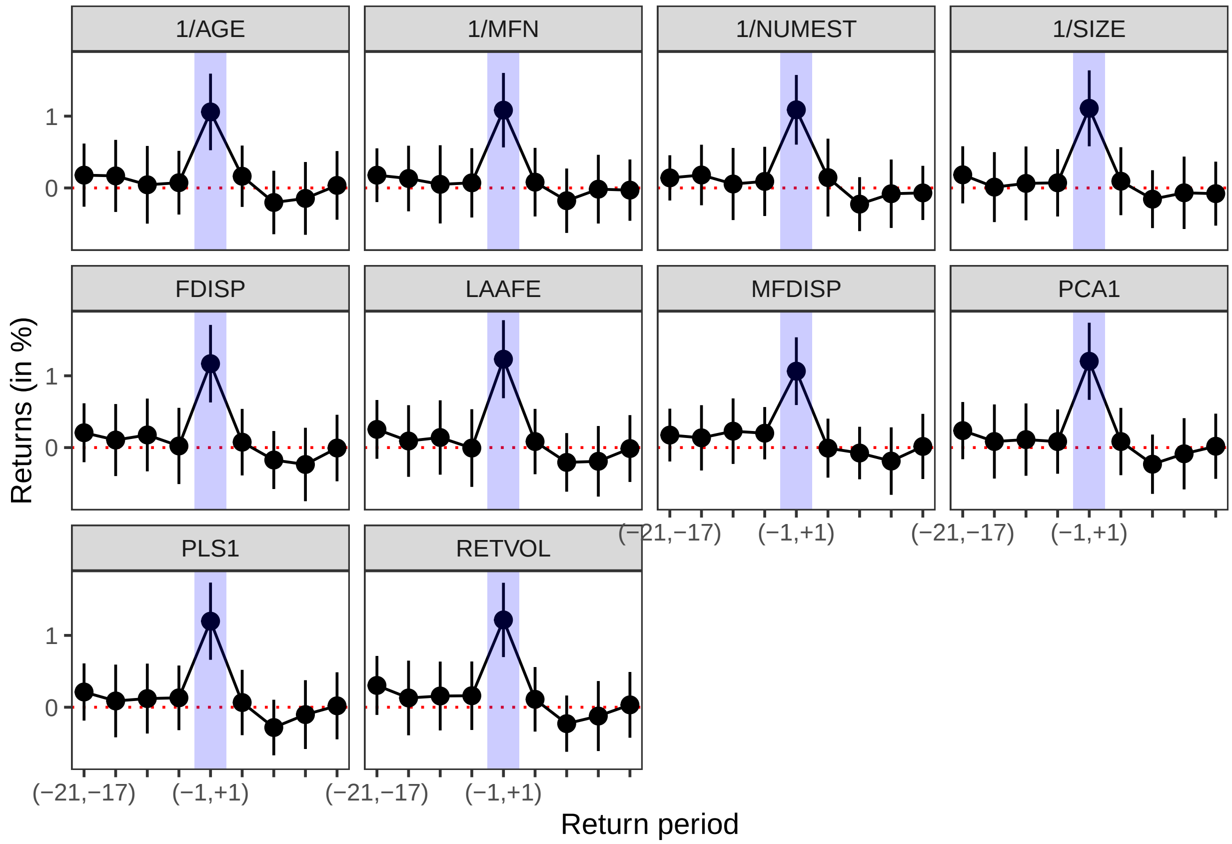

Figure 9: Portfolios sorted on forecasted earnings around earnings announcement periods. This figure presents the long-short portfolio returns of portfolios that are sorted on forecasted earnings to price ratio (FEP). The long-short portfolio strategy takes a long position in high FEP and a short position in low FEP stock. At each quarter, I include stocks with information uncertainty values higher than or equal to the median value. I form equal-weighted portfolios for each calendar quarter by sorting stocks based on decile ranks of the FEP. The cutoff values for the decile ranks are based on all stocks in the calendar quarter. The reported returns are the time-series average of the quarterly mean of returns. I adjust the standard errors of the portfolios' time-series average returns using Newey-West (1987) with four lags and plot the 99% confidence interval. The returns are calculated for nine different periods around the earnings announcement. The shaded area corresponds to the three days around the earnings announcement. Each panel shows the portfolio sort results of stocks filtered by information uncertainty indicated on the panel. The Appendix provides the variable definitions.

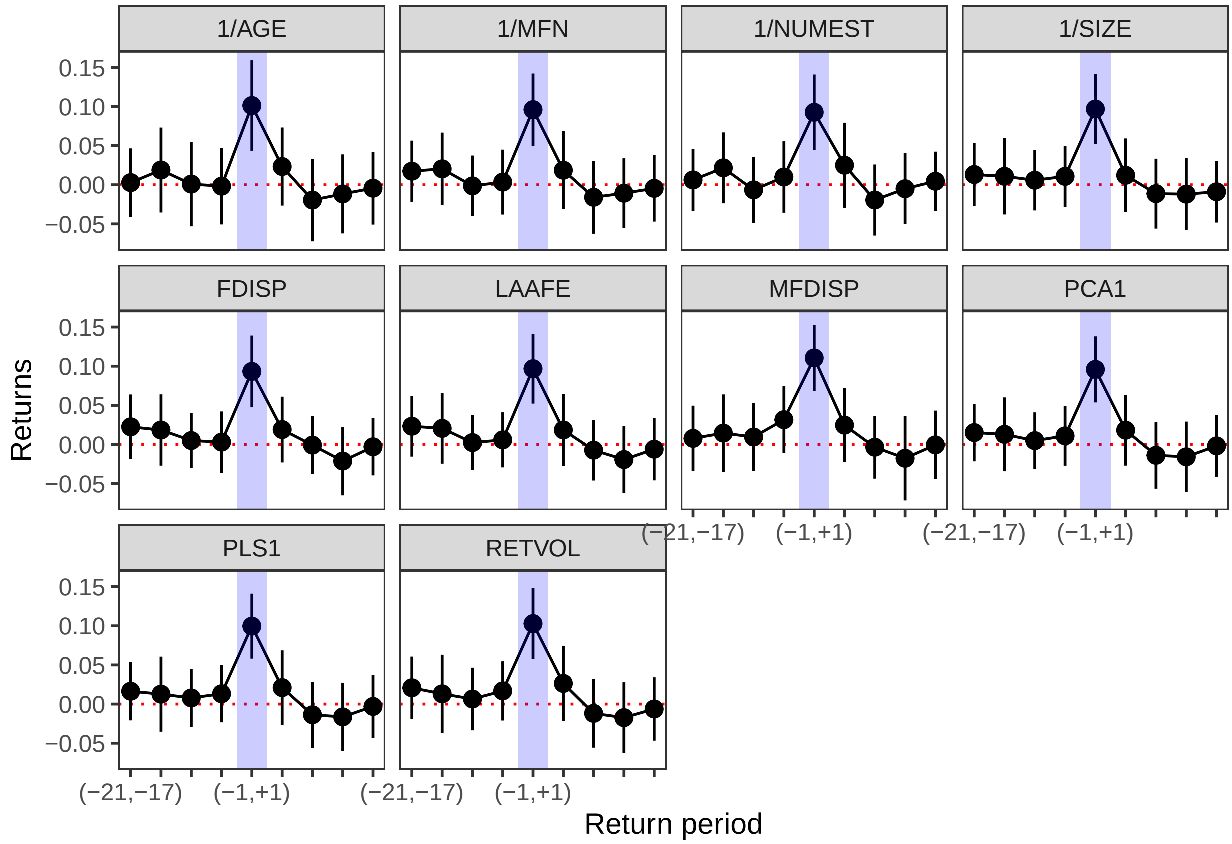

Figure 10: Coefficient of regression of returns around earnings announcement on forecasted earnings. This figure presents the forecasted earnings to price ratio (FEP) coefficient in predictive regressions of returns on FEP and some control variables. The dependent variable is the returns for nine different periods around earnings announcements. I run nine different regressions for different periods around the earnings announcements. The figure shows Fama-Macbeth regression coefficients of FEP and the corresponding confidence intervals. I include stocks with information uncertainty value higher than or equal to the median value of information uncertainty at each quarter. At each quarter, I run cross-sectional regression of excess returns on explanatory variables. The excess returns are the stock's holding period returns for the periods around earnings announcement, minus the corresponding holding period value-weighted CRSP index returns. The reported coefficients are the time-series average of quarterly cross-section regression coefficients. I adjust the standard errors of the regression coefficients using Newey-West (1987) with four lags and plot the 99% confidence interval. The regressions include RETVOL, MOM, TURN, BETA, SIZE, BM, AGR, and GMA as control variables. Furthermore, I control for the stock return in the previous period. For example, when regressing the stock returns in $(t-6, t-2)$, I include the stock returns in $(t-11, t-7)$ as a control variable. Where t is the earnings announcement day. The shaded area corresponds to the three days around the earnings announcement. Each panel shows the coefficient of FEP for regression analysis with sample stocks filtered by information uncertainty indicated on the panel. The sample spans from the first quarter of 1986 to the third quarter of 2020. The Appendix provides the variable definitions.

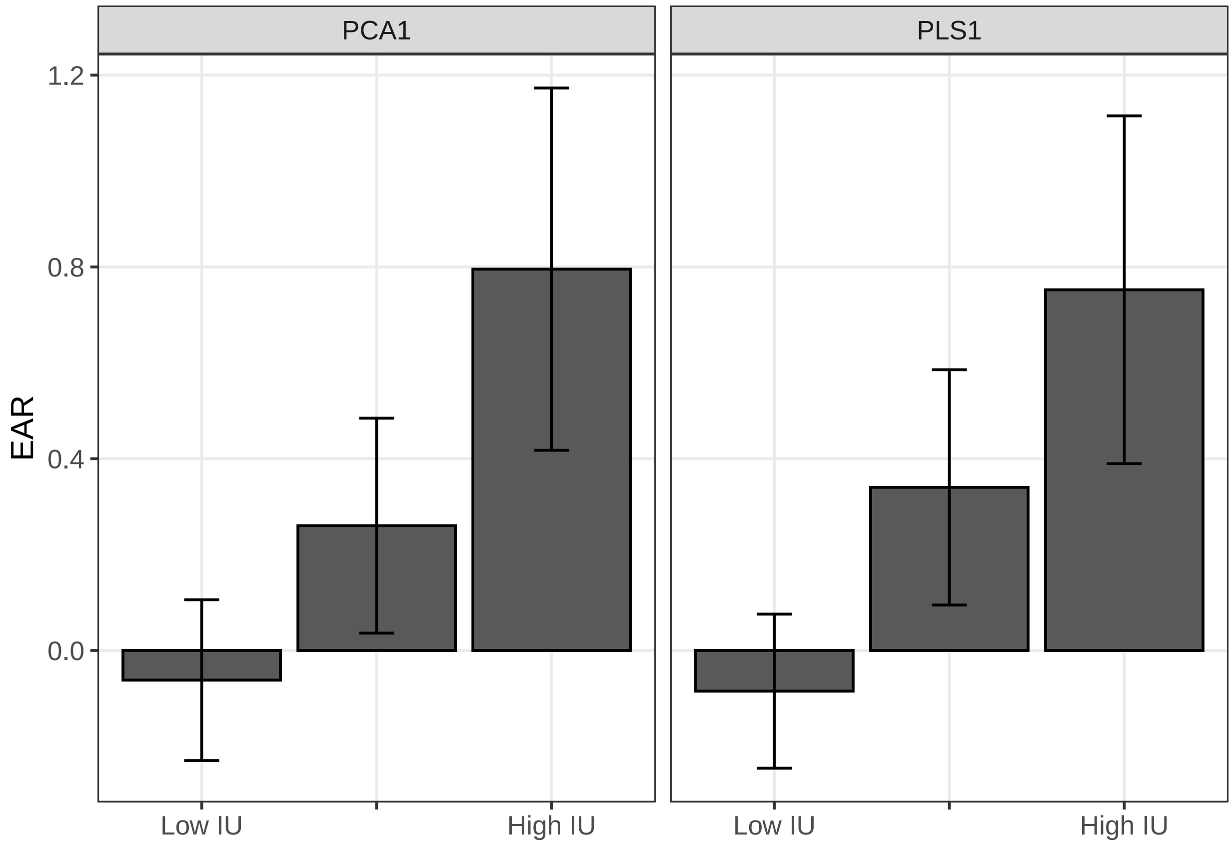

Figure 11: Robustness test for out-of-sample portfolio cutoffs. This figure presents the equally weighted long-short returns of portfolios that are long stocks in the highest group and short stocks in the lowest group of forecasted earnings to price ratio (FEP), within a group of information uncertainty (IU). The cutoffs value is calculated at the end of the month before the stocks' earnings announcement months. For example, if a firm's earnings announcement date is on the 10th of June 2010. I calculate the cutoff based on the other firms' information uncertainty and FEP values for 90 days ending on 31st of May 2010. The cutoffs are conditional cutoffs, first based on an information uncertainty proxy, then based on FEP. The reported returns are the time-series average of quarterly mean of long-short returns. I adjust the standard errors of the portfolios' time-series average returns using Newey-West (1987) with four lags and plot the 99% confidence interval. Each panel shows the long-short returns for double sort based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

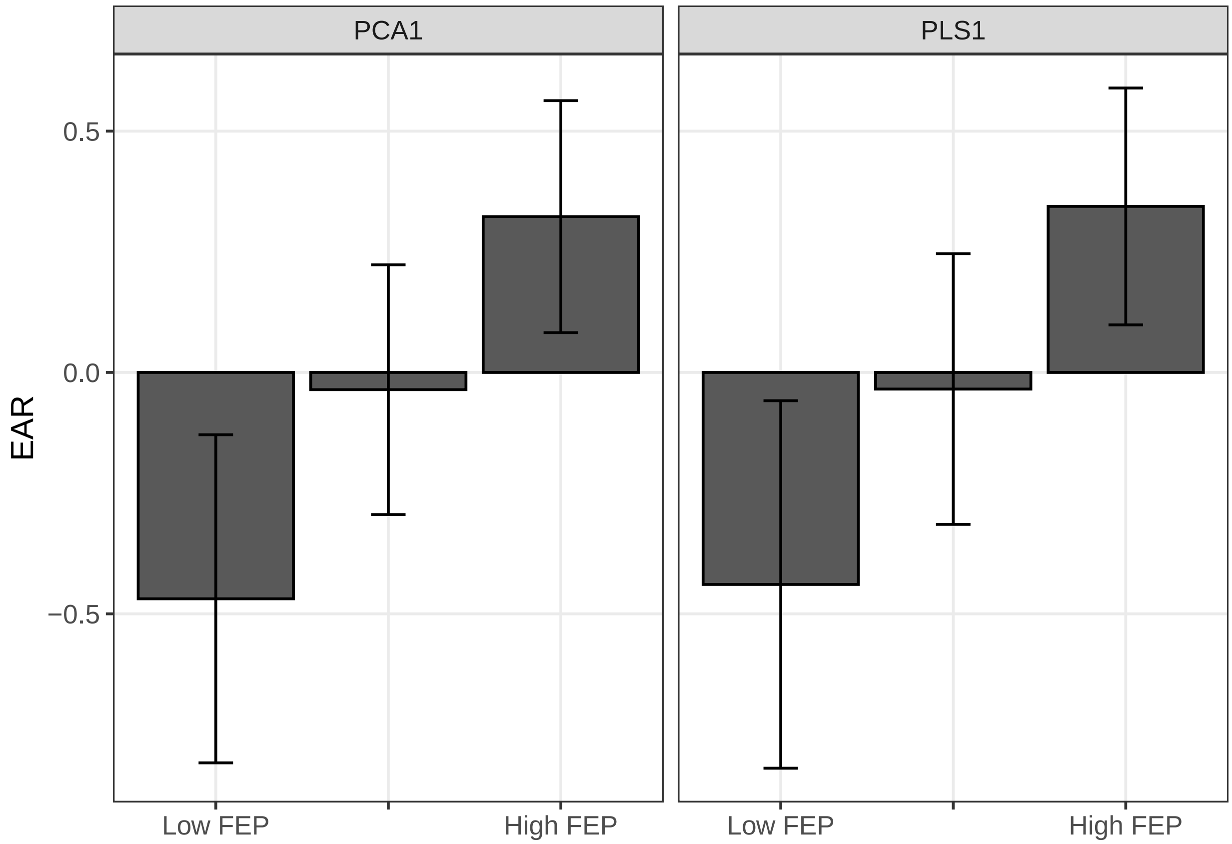

Figure 12: Robustness test for out-of-sample portfolio cutoffs. This figure presents the conditional double-sort analysis similar to figure 11, but sort the stocks first based on forecasted earnings to price ratio (FEP), then based on information uncertainty (IU). The reported returns are the time-series average of quarterly mean of long-short returns. I adjust the standard errors of the portfolios' time-series average returns using Newey-West (1987) with four lags and plot the 99% confidence interval. Each panel shows the long-short returns for double sort based on an information uncertainty proxy indicated on the panel. The Appendix provides the variable definitions.

Appendix

Table A1: **Variable definitions**.

Acronym	Variables	Definition
AFE	Analyst forecast errors	Difference between actual EPS and median of analyst EPS forecast, divided with stock price at 22 trading days before earnings announcement.
AFENL	Analyst forecast errors, non linear	AFENL is transformed value of AFE, by assigning the absolute value of AFE into 100 group ranks based on its quarterly value, then multiplying the rank with minus one if the original AFE is negative.
AFENLP	Analyst forecast errors, non linear positive	AFENLP is AFENL times AFEPD.
AFENLN	Analyst forecast errors, non linear negative	AFENLN is AFENL times AFEND.
AFEPD	Analyst forecast errors, positive dummy	AFPD is a dummy variable that equals to one if AFE is positive.
AFEPN	Analyst forecast error, negative dummy	AFPD is a dummy variable that equals to one if AFE is negative.
AGE	Age of firm	AGE is the number of years since a firm was first included in CRSP database.
AGRA	Asset growth rate, annual	Asset growth rate from previous five quarters to previous quarter.
BETA	Market beta	CAPM market beta estimated over the 252 days period ending on 22 days before earnings announcement..
BM	Book to market	Log one plus previous quarter book to market ratio.
DLOWTURN	Dummy of low turnover	Equals to one if average of daily turnover at t-6 to t-2 is smaller than 20th percentile of daily turnover between t-61 to t-12. Where t is earnings announcement day.
EMI	Expectation Management Incentives	Sourced from Johnson et al. (2020).
EP	Actual earnings to price ratio	Actual quarterly EPS of a firm, reported in IBES, divided by its stock price at 22 days before earnings announcement. EP is in percentage.
FEP	Analysts' forecasted earnings to price ratio	Median of analyst earnings per share (EPS) forecast for current quarter, FPI = 6 in IBES, of a firm divided by its stock price on 22 days before earnings announcements. Median of EPS estimate is calculated over the 90 days period ending on 22 days before earnings announcements. FEP is in percentage.
EPL1	Earnings to price, previous quarter	Earnings to price (EP) ratio from previous quarter. EP is epspxq/prccq*100.
EPL4	Earnings to price, previous 4 quarter	Earnings to price (EP) ratio from previous four quarter. EP is epspxq/prccq*100.
FDISP	Analysts' forecast dispersion	FDISP is standard deviation of analysts' EPS forecast for the current quarter scaled with the stock price at 22 days before earnings announcements.

Table A1: **Variable definitions**. *(continued)*

Acronym	Variables	Definition
LAAFE	Mean of lagged absolute analysts' forecast errors	LAAFE is the average of absolute analysts' forecast errors, AFE, in the previous four quarters.
MFN	Number of mutual fund investing in a firm	MFN is the number of mutual funds that hold a stock scaled with the number of existing funds at the time.
MFDISP	Mutual fund dispersion	MFDISP is the standard deviation of the net change in mutual fund holding of a stock scaled with the number of shares outstanding of the firm.
MOM	Momentum	Momentum is calculated over 126 days period ending at 22 days before earnings announcement. Momentum is holding period return of a stock minus the cumulative market return over the same period.
NUMEST	Number of analysts' estimates	NUMEST is the number of analysts following a firm.
PAR1	Pre-announcement return	Pre-earnings announcement return is calculated as holding period return of a stock from t-6 to t-2 minus the corresponding holding period return of CRSP index, where t is earnings announcement day.
PCA1	The first direction of PCA	PCA1 is the first direction of Principal Component Analysis (PCA). I aggregate eight individual information uncertainty proxies using PCA. Then, I use the first direction of PCA as a composite information uncertainty proxy. To calculate the PCA1 value for firms with earnings announcements in month t, I use training data that consists of firms with earnings announcements within 90 days period ending on the last day of month t-1.
PESSC	Consensus pessimism	Fraction of consensus analyst forecast that has positive earnings surprise in previous 12 quarterly earnings announcements. The calculation excludes stocks with earning surprise of USD 0.00 per share. Earning surprise is calculated based on actual earnings minus the median of analysts' EPS estimate calculated over the 90 days period ending 22 days before the earnings announcement. The stock should have at least four quarterly earnings announcements.
PLS1	The first direction of PLS	PLS1 is the first direction of Partial Least Squares (PLS). I aggregate eight individual information uncertainty proxies using PLS. Then, I use the first direction of PLS as a composite information uncertainty proxy. To calculate the PLS1 value for firms with earnings announcements in month t, I use training data that consists of firms with earnings announcements within 90 days period ending on the last day of month t-1.
RETVOL	Return volatility	Daily excess return volatility over the 45 days period ending on 22 days before earnings announcement, where the daily excess return is a stock return minus market return.
SIZE	Log market value of equity	Log market equity of a firm, where market equity is in USD million and calculated at 22 days before earnings announcement.
TURN	Turnover	Average of daily turnover, volume divided by number of shares outstanding, over the 45 days period ending on 22 days before earnings announcement.

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