Earnings Information Acquisition: The Extensive Margin*

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Abstract

Information sets of investors are difficult to observe yet fundamental to financial markets. Every decision is conditional on some information set. Because information acquisition is costly, many theories posit that information structures throughout an economy should change over time. We investigate temporal changes in the extensive margin of information acquisition. Earnings are prominent information sources about firms and the broader economy. Of the many hundreds of firms announcing earnings each month, how many of these signals does an agent gather? We employ the observable coverage decisions of the *Wall Street Journal* as a proxy for the extensiveness by which other agents are acquiring earnings information. As the WSJ expands and contracts its earnings coverage, we find temporal dynamics that are consistent with other agents' expanding and contracting their information acquisition. Our tests are motivated by, and broadly supported of, theories of endogenous information acquisition. When macroeconomic conditions are weaker and the equity risk premium is higher, the extensiveness of earnings information acquisition is greater. We find that small firms lie at the extensive margin. As information acquisition extends farther, the price informativeness of small firms increases along several dimensions. Post-earnings announcement drift is lower; earnings response coefficients are lower; return dispersion is greater. Moreover, mutual fund performance within the small-stock universe is stronger.

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Information drives financial markets. Every decision that agents make is conditional on some information set. Since information gathering is costly, agents must make choices about which information they will acquire, or ignore. How these choices influence their subjective beliefs, and ultimately market prices, are seemingly important interactions to understand. While there are rich theoretical literatures on information acquisition and information asymmetry across agents in financial markets (i.e., information structures), empirics lag behind the theoretical work because information sets are unobservable. In this study, we measure one dimension of information acquisition activity for a prominent agent and examine how temporal variation in information acquisition relates to economic conditions and to the informativeness of stock prices.

Earnings releases are widely viewed as important information events for firms. Moreover, "earnings seasons" are opportunities to learn more about the economic state of particular industries and the state of the economy overall. Hundreds, sometimes thousands, of firms release their earnings information each month. How do agents filter these batches of information? Specifically, does the number of firm-earnings signals observed change across months?

It seems reasonable to assume that agents seek to condense a given month's information set into the fewest number of signals (firms) that is sufficient to capture the information content. Peng and Xiong (2006) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) represent information with a factor structure, i.e., macroeconomic, industry, and firm-specific components, and show that more information-processing capacity should be devoted to learning about the more pervasive common components of payoffs rather than the more idiosyncratic ones. Common components are more beneficial to know. This view seems to match the common practice of paying more attention to "bellwether" firms whose earnings provide broader information about their own industries and the economy at large.[1]

[1]Beyond the anecdotes of bellwether firms, many studies find that information at earnings announcements spills over to the prices of related firms. For example, see the studies of Hameed et al. (2015), Savor and Wilson (2016), and Patton and Verardo (2012), and the references therein.

Recent studies show that endogenous information acquisition should vary countercyclically to the economy, increasing with the uncertainty of asset payoffs and with the price of risk (Bansal and Shaliastovich (2011), Andrei and Hasler (2015), and Kacperczyk et al. (2016)). We investigate this prediction by employing the observable decisions of *The Wall Street Journal* (WSJ) to report, or not, on each earnings release in a given month. Admittedly, the WSJ is one agent amongst many market participants, but we believe that observing this particular agent offers unique advantages (beyond just observability). First, the WSJ is a prominent and prestigious information agent. Second, the WSJ is tasked with filtering the flow of financial information for its subscribers, and hence, must be attuned to the financial marketplace. Like other agents in the market, the WSJ must select how many firm-earnings signals to extract from a batch of earnings releases. Third, by observing one agent over twenty years, rather than aggregating decisions over multiple agents, we are seemingly relying on a more stationary process of information acquisition.

To isolate the temporal dynamics in the extensiveness of the WSJ's earnings coverage, we employ a logit model to remove the static components of the WSJ's decision to cover an earnings article. Since some firms and some earnings releases have a greater likelihood than others of being covered, such as larger firms and firms with earnings surprises, we estimate the probability of the WSJ's covering each earnings report based on a variety of firm and earnings characteristics. Given a batch of earnings releases in a given month, we predict the number of firm-earnings events that we expect will receive WSJ coverage that month.[2] We measure the deviation of the actual number of earnings reports receiving WSJ coverage from the predicted number, as a fraction of the predicted number. This residual percentage of earnings coverage is our measure of the monthly adjustments the WSJ makes to the extensiveness of its earnings coverage. Additionally, we are careful to distinguish the extent of the WSJ's earnings coverage from the monthly linguistic tone of its coverage, as tone has been shown to covary with stock returns. That is, we separate the

[2] Fang and Peress (2009), Solomon (2012), Ahern and Sosyura (2014), and others find newspaper coverage to be biased toward larger firms, and Solomon and Soltes (2012) find coverage to be biased toward earnings surprises. We control for other firm and earnings characteristics as well, such as industry, analyst coverage, dispersion of analysts' forecasts, recent stock returns, etc.

WSJ's decision to gather earnings information from the outcome of the WSJ's processing of that information.[3]

For perspective, note that the variation in the extent of coverage that we are identifying is small compared to the total number of firms that release earnings each month. In our sample, the number of firms per month that release earnings is 915 on average, while one standard deviation of residual monthly coverage is 29 firms (with 96 firms per month, or about 10%, receiving WSJ coverage on average). The vast majority of firms do not receive WSJ coverage of their earnings releases. Again, the perspective we take is that the residual monthly coverage is the marginal determination of the number of firm-earnings signals selected to convey the information in a given month's batch of earnings.

One dimension of the information filtering that the WSJ employs is based on firm size, consistent with larger firms providing more informative signals about common components of payoffs than smaller firms do. While the actual number of earnings releases covered by the WSJ is roughly split between firms having the largest 20% of equity size and the remaining 80% of firms, the vast majority of residual coverage occurs outside the largest stocks. That is, smaller stocks are the marginal firms for earnings coverage.

With a measure in hand of the monthly variation in the WSJ's extensiveness of earnings-information acquisition, we examine how this measure of information acquisition covaries with macroeconomic conditions. Indeed, we find that the extensiveness of earnings coverage by the WSJ is greater when the consumption-wealth ratio of Lettau and Ludvigson (2001) is higher, when output gap (detrended industrial production) is lower, and during NBER recessions. The traction between our measure of the earnings-information state and these macroeconomic measures is striking. For example, the correlation with the consumption-wealth ratio is 0.48, and the correlation with output gap is -0.27. Further support for the extent of information acquisition being countercyclical comes from the fact that the measure covaries positively with the equity risk premium. A one standard

[3] Tetlock (2007), Tetlock et al. (2008), Solomon (2012), Gurun and Butler (2012), and others find that the tone (positive/negative) of media coverage covaries with future stock returns. We control for the aggregate monthly tone of the WSJ articles by employing a multinomial logit model to estimate the probabilities of negative and of non-negative tone. The monthly residual tone of coverage is positively correlated with the residual extent of coverage. Residual tone is found to be unrelated to the return dynamics we examine.

deviation increase in extensiveness is associated with a roughly 2% increase in the excess stock market return over the next six months. In sum, the extent of the WSJ's coverage of earnings behaves as we expect investors' demand for payoff-relevant information should behave, varying countercyclically.

We then turn our attention to how the extensiveness of earnings coverage covaries with the information content of the stock prices of the smallest quintile of firms. For these small firms, earnings coverage in the WSJ is rare. Additionally, many asset-pricing anomalies are well-documented to be stronger for small firms.[4] Focusing on the pricing of earnings information, we find that post-earnings announcement drift (PEAD) in the returns of small stocks is decreasing in the extensiveness of earnings coverage. A long-short strategy in months with the greatest extent of coverage averages an abnormal return nearly 6% over 60 days, while a long-short strategy in the months with the least extent of coverage averages below 2%. To the extent that PEAD is an underreaction to earnings surprises, this is consistent with a greater extensiveness in earnings coverage identifying months when prices are better impounding firm-level earnings surprises.[5]

However, these PEAD findings are not a simple information diffusion story that the firm-level studies of attention to earnings support (e.g., Hirshleifer et al. (2009), and Boulland et al. (2017)). The market-level measure of the extensiveness of earnings coverage captures a different mechanism than the firm-level studies of earnings information acquisition. Importantly, we find that the price reactions to earnings surprises, the earnings response coefficients (ERC), also decline with the extensiveness of coverage. We discuss various interpretations for this result. The one that is most consistent with the set of findings is that, when the WSJ is extending its earnings coverage to more firms, investors are acquiring more private information about small firms ahead of a given earnings announcement date.

[4]For example, see the study of post-earnings announcement drift in returns by Doyle et al. (2006).

[5]Other potential sources of abnormal-return drift following earnings surprises, besides information frictions, have been suggested and are not mutually exclusive, such as the misspecification of expected returns and agents' rational learning about unknown earnings parameters (e.g., Sadka (2006), Liu et al. (2009), Markov and Tamayo (2006)).

In support of this interpretation, we find that return dispersion in small stocks is greater in months when the extent of coverage is greater (despite ERC being lower), where return dispersion is defined as the cross-sectional standard deviation across returns. An increase in one standard deviation of extensiveness is associated with an increase in return dispersion of nearly 2% per month. Return dispersion has been linked both to greater impoundment of information into prices as well as greater volatility in payoffs (e.g., Gomes et al. (2003), Kacperczyk et al. (2016)). Controlling for a broad set of macroeconomic variables does not diminish the relationship between the extensiveness of earnings coverage and return dispersion, suggesting a role for information acquisition that is distinct from the variation in macroeconomic fundamentals or a role for information acquisition in the measuring of the unobservable economic state.

It is useful to note that the stock-price informativeness of large firms does not covary with the information extensiveness measure. Hence, while the largest stocks seem saturated with respect to the variation in earnings information that is measured here, the price informativeness of (more than a thousand) small stocks moves with the expansion and contraction of information acquisition over the smaller deciles of firm size.

To further examine the ability of the WSJ's extensiveness of earnings coverage to serve as a proxy for private-information acquisition activity by investors, we examine the performance of mutual funds. Many investors pay mutual funds to bear the costs of information acquisition and to make portfolio decisions on their behalf (e.g., Kim et al. (2016)). Recognizing that investing skill depends heavily upon information acquisition, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014, 2016) examine the temporal variation in mutual fund performance and find that fund performance changes in a manner that is consistent with underlying shifts in funds' information-acquisition activities. Given the difficulty in measuring information acquisition, they employ economic recessions as a binary proxy for times when information acquisition is greater. Our analysis both complements and extends their work by linking a direct measure of information-acquisition activity to temporal variations in mutual fund performance.[6]

We find that changes in mutual-fund demand for small stocks better predict future returns when the extent of the WSJ's coverage of earnings is greater. The economic magnitude of this covariation is sizable. A portfolio that is long in small-cap stocks with the largest quarterly increases in the number of mutual funds holding them, and short in small-cap stocks with the smallest increases, produces a mean abnormal return of 60 basis points per month when the extensiveness of earnings coverage is above its median. When the extent of coverage is below its median, the mean abnormal return falls to negative 45 basis points.[7]

In a seemingly related study, Pastor, Stambaugh, and Taylor (2017) use temporal variation in the turnover of a fund's portfolio to detect the investing skill of mutual funds. One of their takeaways is that investment opportunities vary over time, and these opportunities reside mostly within small stocks. The findings here suggest that information structures within a market play an important role in identifying investment opportunities, not just in the identification of a potential mispricing but perhaps in investors' coordination of the resolution of the price dislocation (e.g., Allen, Morris, and Shin (2006); Hellwig and Veldkamp (2009)). Future work on information structures should consider temporal variation in public versus private information acquisition and in the arbitrage strategies of the more informed agents.[8]

[6] Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) focus on the relative capacity allocated to acquiring common information versus firm-specific information. This is not a distinction we pursue. Their model predicts greater overall capacity allocated to acquiring (both common and firm-specific) payoff-relevant information when uncertainty in payoffs is higher or when the risk premium is higher.

[7] Edelen, Ince, and Kadlec (2016) prefer to measure changes in mutual-fund demand for stocks using changes in the number of institutions that hold a stock, since this measure aggregates signals equally across mutual funds. Nevertheless, we find similar results for changes in the fraction of shares outstanding that is held by mutual funds in aggregate.

[8] As Pastor, Stambaugh, and Taylor (2017) and Kacperczyk et al. (2016) note, there is a vast literature on the performance of mutual funds, with most studies finding that mean fund alpha net of fees and operational costs is zero at best. Yet there is mounting evidence that at least some mutual funds have investing skill. Given the size and importance of the mutual fund industry, economists and regulators continue to seek a better understanding of the economic rents that mutual funds command. Temporal variation in information acquisition and in the perceived investing skill of fund managers are hence important topics.

The paper proceeds as follows. The next section details the data sources and measure of the extensiveness of the WSJ's coverage of earnings. We then examine how the extent of coverage covaries with the macroeconomic state in section 2. An analysis of the adjustments that are made along the extensive margin are pursued in section 3. How the extent of earnings coverage covaries with the information content of stock prices and with mutual-fund investing skill is investigated in section 4. Section 5 provides concluding thoughts.

1 Methodology and Data

1.1 Corporate earnings events

Our sample of quarterly earnings reports includes 233,348 firm-earnings events from I/B/E/S, covering the period from October 1984 to December 2005. The base data set of earnings and *The Wall Street Journal* (WSJ) articles to be described below were collected and used by Gaa (2008).[9]

To model the probability of each firm-earnings release's being covered by the WSJ, we gather data from I/B/E/S, CRSP, and Compustat on firm-level characteristics, such as size, analyst coverage, recent stock performance, book-to-market ratio of equity (BE/ME), and industry, as well as earnings-specific characteristics, such as earnings surprise and pre-announcement forecast dispersion. Additionally, we omit earnings reports from firms with a negative BE/ME or with a closing stock price less than $1 two days prior to the earnings announcement date. The complete set of variables and their sources is provided in Appendix A.1.

1.2 WSJ coverage of earnings

Our measure of the extent to which the WSJ covers earnings is based on how many firm-earnings releases are selected by the WSJ to receive a news article that covers the event.

[9] Twenty-one years is a large sample relative to typical studies of media coverage. How the information structure measured here might have changed after 2005 due to News Corp's acquisition of the WSJ in 2007, Regulation Fair Disclosure, Sarbanes Oxley, and the rise of social media is an interesting question for subsequent studies.

We begin with 68,102 "earnings" news articles from Factiva (code: c151) having at least 100 words. The words requirement filters more substantial coverage from terse blurbs. The computational linguistics program Rainbow by McCallum (1996) is then used to identify the articles which are about a specific firm's quarterly earnings release, as some of these earnings articles flagged by Factive are about industry-level earnings trends, regulatory changes, restatements, accounting scandals, etc. The Naive-Bayesian text categorization is trained on a set of 500 articles and uses a unigram and bigram "bag of words" approach. Only articles with a posterior probability greater than 0.5 of being about a firm's earnings release remain in the sample of 49,113 articles.

Although the tone of the WSJ articles is not of primary concern in this study, we want to distinguish the decision to cover a given firm-earnings release from the outcome of the WSJ's processing of the earnings information. These distinct aspects may be correlated, and evidence suggests that tone has explanatory power for stock returns (e.g., Tetlock (2007), Tetlock et al. (2008), Solomon (2012), and Gurun and Butler (2012)). To control for tone, we apply another round of text categorization to disambiguate "negative" and "nonnegative" articles, again trained on a set of 500 articles. We classify articles to be negative if the posterior probability of being negative is greater than 0.5, while all other articles are classified as nonnegative.[10]

Finally, for each of the earnings reports, we search for a related news article published in the WSJ within two days on either side of the I/B/E/S announcement date. If at least one article corresponding to a given earnings report is found within this 5-day window, that earnings report is considered to be "covered". We observe coverage for approximately 11% of the announcements in our sample, implying that the typical firm's quarterly earnings release is ignored by the WSJ.

[10] We test Rainbow's classification accuracy by randomly excluding 100 articles from the training set, re-estimating the model, and then checking accuracy for the excluded articles. Across 100 trials, the average accuracy is 88.5% for the first-stage classification ("earnings/not-earnings") and 83.4% for the second-stage ("negative/non-negative").

1.3 Measuring the extensiveness of earnings coverage

Our goal is to measure monthly changes in the extent of the WSJ's coverage of earnings releases. To begin, let's get a sense of what typical earnings coverage looks like. Table 1 provides summary statistics. On average, 11% of earnings reports released in a given month are covered by the WSJ (97 articles out of 915 events).The monthly number of earnings reports that receive coverage has a mean of 97 with a relatively large standard deviation of 80, which is largely driven by the monthly changes in the volume of earnings reports released each month. While normalizing the number of firms receiving earnings coverage by the number of earnings releases in that month can account for the volume changes, such a normalization implicitly assumes that each earnings report is equally likely to receive coverage in the WSJ. However, this is clearly not the case. Newspaper coverage is biased toward larger firms, certain industries, and firms with earnings surprises (e.g., Fang and Peress (2009), Solomon (2012), Solomon and Soltes (2012), and Ahern and Sosyura (2014)). To identify temporal changes in earnings coverage unrelated to these biases, we want to control for the characteristics of the firms that release earnings and the characteristics of the earnings information in that month.[11]

To filter the monthly flow of earnings releases, we employ a multinomial logistic regression where the three responses are: negative coverage, nonnegative coverage, and no coverage. Classifications of each article as negative or nonnegative are done using the Rainbow program discussed in section 1.2. The set of firm and earnings characteristics we use as determinants are detailed in the Appendix section A.1. Output of the multinomial logit is shown in Appendix A.2. Using this model, we estimate the probability of coverage for each firm-earnings report. In short, firm and earnings characteristics provide a good deal of information about the probability of WSJ coverage. The (McFadden) pseudo R^2 is 0.27. The primary determinants of WSJ coverage are firm size, industry, and the number of analysts covering the firm. These three variables alone account for a pseudo R^2 of

[11] Normalizing the number of firms that receive coverage in a given month by the number of firms that report earnings in that month produces a time series that does not covary with most of the return dynamics we examine in later sections. Hence, adjusting for static biases in the WSJ's coverage is necessary to increase the signal-to-noise ratio of the WSJ's coverage decisions.

0.22. We say more on the determinants of explained and unexplained coverage in the next section.

We measure temporal changes in the extensiveness of the WSJ's earnings coverage as the percentage deviation of the actual number of firm-earnings events that receive coverage from the predicted number to receive coverage each month. We label this percentage residual as EEC, for the "extent of earnings coverage".

$$EEC_t = \frac{\sum_{k=1}^{K_t}(C_k - \hat{C}_k)}{\sum_{k=1}^{K_t}\hat{C}_k} \tag{1}$$

where K_t is the total number of earnings releases observed in month t, C_k is an indicator variable equal to one if earnings report k is associated with a WSJ article and zero if no coverage is observed, and $\hat{C}_k$ is the sum of the predicted probabilities of negative and nonnegative coverage respectively over the earnings releases in month t.

For some perspective, in 1985, the first full year of our sample, the mean monthly number of earnings releases is 410; the mean number of releases receiving WSJ coverage is 43 per month and the predicted number is 40. In 2005, the last year of our sample, the mean monthly number of earnings reports released is 1099, while the mean number of releases receiving WSJ coverage is 104 per month and the predicted number is 155. In Table 1, we see that the mean monthly value of EEC is close to zero at 0.03, but EEC varies a good deal as indicated by its monthly standard deviation of 0.26.

Figure 1 plots EEC (along with CAY). We can visually see the variability in EEC, and we can also see that EEC displays some persistence. The AR(1) coefficient of EEC is 0.62. This is far below the near unit-root behaviors of the macroeconomic variables shown in Table 1, except one. Many studies raise concerns about spurious predictability of stock returns based on such highly persistent measures (e.g., Boudoukh et al. (2008)). We address these concerns by conducting Monte Carlo simulations to assess potential size distortions in our test statistics arising from examining a variable with an AR(1) coefficient of 0.62.

To control for the tone of the WSJ's coverage of earnings, i.e. the outcome of the WSJ's information processing beyond the earnings characteristics that we can observe, we form a residual measure of tone as:

$$NetEEC_t = \frac{\sum_{k=1}^{K_t}(C_k^{NNeg} - \hat{C}_k^{NNeg}) - \sum_{k=1}^{K_t}(C_k^{Neg} - \hat{C}_k^{Neg})}{\sum_{k=1}^{K_t}\hat{C}_k} \tag{2}$$

where C_k^{NNeg} is a dummy variable equal to one if earnings report k is associated with a nonnegative article, and zero otherwise, while C_k^{Neg} is a dummy variable equal to one if earnings report k is associated with a negative article and zero otherwise. Since each article is characterized to be either negative or nonnegative, $C_k = \left(C_k^{NNeg} + C_k^{Neg}\right)$. The predicted number of firms to receive either negative or non-negative WSJ coverage each month is labeled with a "hat". $NetEEC$ declines as the percentage residual tone of coverage in month t becomes more negative.

EEC has a 0.30 correlation with $NetEEC$. Why the extensiveness of earnings coverage is positively correlated with the tone is unclear. For the purposes of this study, we simply wish to disentangle the decision to acquire information from the outcome of processing that information (beyond the earnings-level characteristics we control for in the logit). In all regression tests, we include both EEC and $NetEEC$. In any single-variable exercises, such as the figures, we examine EEC orthogonalized with respect to $NetEEC$. The orthogonalized version of EEC is represented with an additional superscript as $EEC^{\perp}$.

2 Extent of Coverage and Macro Conditions

Table 2 shows that the extent of earnings coverage is correlated with several measures of macroeconomic conditions (defined in section A.1.2 of the Appendix). These correlations indicate that the extent of information acquisition is greater when economic conditions are poorer. Specifically, $EEC^{\perp}$ is higher during recessions, when CAY is higher, and when output gap is lower. The magnitudes of these correlations are striking, 0.26, 0.48, and −0.27, respectively. Note that there are only two brief recessionary periods during our sample according to NBER, July 1990 to March 1991 and March 2001 to November 2001. The plots of $EEC^{\perp}$ against CAY and against output gap are shown in Figures 1 and 2 (along with NBER recessions). The comovement of EEC with these macroeconomic measures is impressive. Consistent with the endogenous-information models of Bansal and Shaliastovich (2011), Andrei and Hasler (2015), and Kacperczyk et al. (2016), information acquisition moves countercyclically to the economy.

To better understand the covariance structure, we regress $EEC^{\perp}$ on a set of macro variables. These variables are purported in prior studies to explain a portion of the equity premium. Given the high persistence of these variables, we form p-values which adjust for spurious rejection rates of the null hypothesis due to the high serial autocorrelations in the covariates and residuals. To do so, we turn to Monte Carlo simulations. We form 10,000 simulated samples of an independently and normally distributed random variable with an AR(1) coefficient that matches that of the dependent variable. We regress our simulated dependent variable on the actual sample of macro variables from Table 3. We then calculate the frequency of observing Newey-West t-statistics with six lags that are greater than a given t-statistic found in the actual sample (or less than a given t-statistic that is negative). We multiply the frequency by two to arrive at a simulated p-value for a two-tailed test.

In Table 3, we see that CAY and output gap robustly covary with EEC, while the sentiment and recession variables relations fall away in the presence of this large set of macro variables. The signs of the coefficients on CAY and output gap remain consistent with a countercyclical movement in EEC. However, once the other variables are controlled for, the sign of dividend yield switches from a positive partial correlation to a negative regression coefficient. What exactly to make of this is unclear. Perhaps this indicates a role for dislocations of stock prices from fundamental values in driving information demand. However, this is just one variable in a set of twelve somewhat multicollinear variables, so some caution is warranted. The set of macro variables captures sizable variation in the WSJ's extent of coverage, with an impressive R-squared of 0.41.

To examine how the extent of coverage covaries with asset pricing, we investigate whether EEC tracks the equity risk premium, which is expected to increase both with the uncertainty in payoffs as well as the price of risk. We regress various windows of the log of future returns of the CRSP VW stock index in excess of the T-bill rate over months $[t + J, t + K]$ on EEC from month t. Table 4 finds that EEC tracks the equity premium. EEC is significant over months (+1,+6) at the ten-percent level and over months (+1,+12) at the five-percent level (using simulated p-values that are adjusted for spurious rejection rates). Examining the explanatory power of EEC jointly across multiple horizons provides a more powerful, and more stringent, test (Boudoukh et al. (2008)). Panel B of Table 4 shows the simulated p-value testing the null hypothesis that the coefficients on EEC are jointly zero over months (+1,+6) and (+1,+12) to be 2.9%. Hence, EEC covaries positively with the equity risk premium.

The economic magnitude of this relation is impressive. The reported coefficients in Table 4 are with respect to standardized coefficients and can be easily interpreted. A one standard deviation increase in EEC is associated with an increase in excess stock returns of 1.89% over the following six months and 3.66% over the following twelve months. Figure 3 plots means of excess stock returns across quintiles of $EEC^{\perp}$. The explanatory power of $EEC^{\perp}$ for future stock returns over months (+1,+6) and (+1,+12) is visible across the full range of quintiles. Six-month returns vary from about 2% to 7%, and twelve-month returns vary from about 2% to 14%.

Given the sizable explanatory power of the set of macro variables for EEC, we also examine if EEC provides incremental information on the equity premium above the set of macro variables. To assess this, we rerun the regressions of excess stock market returns on EEC controlling for the set of eleven macroeconomic variables. The right half of Table 4 displays the results of this larger regression for the two horizons. While controlling for the macro variables affects the significance of EEC for the (+1,+12) horizon, the joint test in Panel B remains significant at a 5% level. Constructed solely from information-acquisition activity, EEC offers explanatory power that is not captured by the macro variables, which are constructed from economic and financial data.

In sum, the extensiveness of the WSJ's coverage of earnings moves countercycylically to the state of the economy, and tracks the equity risk premium. These findings are consistent with the predictions for investors' endogenous demand for information in the models of Bansal and Shaliastovich (2011), Andrei and Hasler (2015) and Kacperczyk et al. (2016).

3 Adjustments along the extensive margin

To better understand changes in the WSJ's extent of residual earnings coverage, it seems instructive to note the main drivers of predicted coverage. The predominant determinants of the probability of WSJ coverage in the logit model seem to be firm size, industry, and the number of analysts covering the firm. A reduced multinominal logit model employing only these three variables — size, industry, and analysts' coverage — produces a pseudo R^2 of 0.22, falling from 0.27 when using the full specification shown in the appendix section A.2. These three variables even intuitively seem to reflect a tradeoff between the costs of acquiring information and the benefits of learning from that information. Larger firms are more important to investors in terms of greater weightings in the typical investment portfolios. The scale and scope of large-firm operations makes them more likely to be considered "bellwether" firms. Some industries, whether cyclical or defensive, can be better indicators of the economy's condition. Other industries may contain firms whose performances are more highly correlated and hence require less information acquisition. Lastly, as the observable outcome of sell-side agents' cost-benefit analyses of coverage decisions, the number of sell analysts that cover a firm would seem to reveal the firms that the WSJ also views to be offering a lower cost-benefit ratio for information acquisition.

In the prior section, we examined macroeconomic drivers of the WSJ's decisions on the extent of its earnings coverage. We can also consider firm-level characteristics that drive the WSJ's marginal decisions on how many firm-earnings signals to report to its subscribers. The firm characteristic we explore is size. Given that many asset-pricing anomalies are well-documented to be stronger for small firms, this dimension of the information state seems fruitful to investigate.

To begin, we separate sample months into three bins based on EEC measured across all stocks. Months with EEC above the 75th percentile are labeled "high," months below the 25th percentile are labeled "low," and remaining months are labeled "normal." Each month we recalculate residual coverage intensity at the size-quintile level, rather than across all stocks. That is, we determine the number of firms within a given quintile of size for which the full-specification full-sample multinomial logit predicts coverage, and then form EEC_q which measures the percentage deviation of actual coverage from predicted coverage within size quintile q.

Panel A of Table 5 reports the mean monthly values of EEC_q within the low, normal, and high states of coverage extensiveness. The most striking result is the dramatic increase in the residual coverage of the smaller stocks in high-EEC months. The residual coverage percentage for the smallest stocks in these months balloons to 91%. The residual percentage across the remaining four quintiles falls steadily down to 18% in the largest stocks. Panel B shows the number of firm-earnings reports per month that are actually covered by the WSJ. The smallest firms receive the least amount of actual coverage, with only 10 firms on average in the high state. The coverage of just one additional firm from the smallest quintile, however, is a much larger deviation from the baseline probability of coverage. On the other end, the largest firms receive much greater coverage on average, with the actual number of firms in the highest quintile averaging 45 per month in the high state.

Analogously, in the low state, the residual percentage deviates less from zero for the largest firms and generally deviates more as firm size falls. While the variation across the size quintiles in the low state is not as dramatic as that in the high state, nor monotonic, the residual coverage is again sizably decreasing from largest to smallest stocks. In the low state, the largest firms average negative 19% while the smallest firms average negative 37%.

Also notice from Table 5 that the adjustments in earnings coverage across high-coverage months to low-coverage months is strongly decreasing across the size quintiles. The smallest stocks experience a 91% increase in residual coverage in the high-EEC months and a 37% decrease in the low-EEC months. This spread between high and low states falls monotonically with firm size. Hence, the marginal coverage decisions of the WSJ, expressed as a residual percentage, are essentially driven by the coverage choices outside the largest stocks. The correlation between the full-sample EEC and the residual percentage of coverage within the lower four size quintiles is 0.95, while the correlation between the full-sample EEC and the residual percentage of coverage within the largest quintile is only 0.57. In sum, the adjustments made by the WSJ to the extensiveness of its earnings coverage can be characterized as expanding and contracting over the smaller deciles of firms.

4 Extensive Margin and the Information Content of Prices

Does the expansion and contraction of earnings coverage by the WSJ covary with the informativeness of stock prices? Prices will reflect the information that investors possess. When the mass of investors in the stock market is acquiring less information about earnings, prices will contain less earnings information, all else equal. In this section, we examine how prices react to earnings surprises as the extent of the earnings-information acquisition of the WSJ changes, and then broaden the analysis to consider more general information-acquisition activities.

4.1 Post-earnings announcement drift

One common assessment of how well stock prices impound earnings suprises is post-earnings announcement drift in stock returns (hereafter "PEAD"; Bernard and Thomas (1989)). To the extent that PEAD is due to the market's underreaction to earnings news, we expect the drift to be smaller for earnings announced in months when the extensiveness of earnings coverage is greater.

Each month we sort the firms announcing earnings in that month according to their standardized unexpected earnings (SUE), defined as the announced earnings per share minus the median analyst forecast from thirty days prior to the announcement divided by the pre-announcement stock price. We then form a PEAD strategy by taking a long position in the stocks in the highest decile of SUE and a short position in the stocks in the smallest decile of SUE. Daily abnormal returns to each stock are adjusted for size and book-to-market effects using 5×5 benchmark portfolios, with the quintile breakpoints determined from NYSE stocks only.[12] We then cumulate the abnormal daily returns (CAR) for each stock over a window beginning two days after the announcement and ending sixty days after the announcement. The CAR are then equally weighted within each month's long and short SUE portfolios respectively.

We sort calendar months over the sample period into quintiles based on $EEC^{\perp}$ and then report the mean abnormal profits of the long-minus-short SUE portfolios. The left panel of Figure 4 reveals that the average PEAD profits within the smallest stocks decrease from nearly 6% over the $[+2, +60]$ window for earnings surprises occurring in months with the least extensive coverage to less than 2% for earnings surprises occurring in months with the most extensive coverage. This is impressive traction between the extensiveness of earnings coverage and PEAD. [13]

To assess the statistical significance of this negative relation, we employ monthly regressions. Each month we regress the cross section of cumulative abnormal stock returns over days $[+2, +60]$ on the SUE for each firm announcing earnings in that month. Then, we regress the time series of monthly cross-sectional coefficients from the first-stage regression on EEC and $NetEEC$, with and without macroeconomic controls. Table 6 shows the second-stage results. We see that PEAD profits for small stocks decrease with EEC at a 1% level of significance (using simulated p-values) regardless of whether or not we control

[12] We thank Kenneth French for providing the benchmark data on his website.

[13] The nonlinearity displayed by PEAD profits in quintile 3 is interesting, as it may indicate nonlinearities in the reactions between asset pricing and information acquisition that can be products of endogenizing information choices.

for macroeconomic conditions. In sum, when the extent of earnings coverage is greater, the prices of small stocks better impound their earnings surprises.

The strong comovement of the PEAD of small stocks with the extensiveness of earnings coverage is strikingly different from the nearly flat PEAD plot for large stocks on the right side of Figure 4. Consistent with the prior findings of section 3, the extent of earnings coverage seems to provide insights into the pricing of small stocks but not large stocks, as the expansion and contraction of the WSJ's earnings coverage is essentially over the smaller stocks, not the largest. However, our ability to examine the PEAD of large stocks is a bit hindered by the number of months in which few large stocks release earnings. As a consequence, we examine quintiles of SUE to produce the right side of figure 4, rather than deciles as we do for small stocks on the left side. We also require a minimum of 10 firm-earnings releases each month for the long and short portfolios. This filter reduces the number of usable large-stock sample months from 255 to 170. As figure 4 shows, large-stock PEAD does not temporally covary with the extent of the WSJ's earnings coverage.

We further investigate a relation between large-stock PEAD and EEC using the cross-sectional regression approach. A potential benefit with the regression approach is that we can extract more information when confronted with just a few stocks each month than is possible with the portfolio approach (since long and short stocks are pooled together each month in the regressions). Unfortunately, SUE is closer to zero for large stocks which can produce greater variability in first-stage coefficients. Although the results are not tabulated, we detect no relation between large-stock PEAD and EEC. The failure to detect a covariance between the extensiveness of earnings coverage and the return dynamics of large stocks is a pervasive finding throughout this study. In short, adjustments to the extent of earnings coverage are silent about the temporal dynamics of the returns of large stocks, but they do speak to the pricing of small stocks.

4.2 Earnings Response Coefficients

The preceding findings suggest that the state of information acquisition plays an important role in the pricing of small stocks. To the extent that PEAD is due to the market's underreaction to earnings surprises, the findings for PEAD are consistent with small-stock prices on announcement dates more fully impounding the earnings surprises of a given firm when the extensiveness of earnings coverage increases. However, there are more nuances to the earnings information environment to consider. For example, holding the quality of the information signal constant, PEAD can vary as the diffusion of the information varies. If the extent of the WSJ's coverage of earnings were solely a proxy for the speed of diffusion in that month, then the announcement-day price responses should be greater. This positive covariance between earnings response coefficients (ERC) and information diffusion is evident in the studies of *firm-level* investors' attention and the media's role in the stock market (e.g., Peress (2008); Hirshleifer et al. (2009); DellaVigna and Pollet (2009); Drake et al. (2015); Boulland et al. (2017)).[14]

The fact that we examine information acquisition at the market level suggests that a mechanism different from information diffusion is in play. Recall that only eleven percent of firms that release earnings in a given month are covered on average by the WSJ, and only a handful are from the smallest quintile of firms. Hence, by construction, EEC is not measuring the information diffusion of firm-level earnings. A positive covariance between EEC and ERC would be predicted if an increase in the extent of earnings coverage were due to more unique firm-level information being disclosed. In other words, when the bellwether firms provide marginally weaker signals about other firms, we would expect a greater reliance on the other firm-level earnings releases — all else equal — and a greater price reaction on earnings release dates.

On the other hand, we can envision several information-based mechanisms that may produce a negative covariance between EEC and ERC. For one, greater spillover from bellwether firms' earnings information to other firms's stock prices can result in small-stock

[14]A positive covariance between ERC and media coverage (or firm-level attention) may also be due in part to reverse causality whereby greater price movements draw attention to the news event.

prices that better anticipate small-stock earnings releases. That is, when the extensiveness of earnings coverage is high, investors may be learning more about small-stock valuations from the earnings releases of other firms, and therefore, stock prices respond less at announcement to the firm-level earnings information. This type of cross-earnings learning can reasonably be considered a type of private-information acquisition. Broadening this view beyond earnings spillovers provides a second mechanism. In high-EEC months, investors may be acquiring more private information overall. Since we measure earnings surprises with analysts' forecasts, this is equivalent to investors' relying less on analysts and more on their own information gathering. Such themes of public versus private information, both their complementarity and their substitution effects, have been investigated in many studies (e.g. Allen, Morris, and Shin (2006); Hellwig and Veldkamp (2009)). Lastly, if months when earnings coverage extends farther coincide with the signal-to-noise ratio of earnings information weakening, then investors should place a lower weight on the earnings news in those months; and the announcement-date price reaction would again lessen. The signal strength may weaken as the quality of earnings decreases or the fundamental uncertainty in the economy increases. Investigating each of these mechanisms is beyond the scope of this initial study.

Nevertheless, we can gain some guidance on the information state that EEC is capturing by examining the announcement-date price response to earnings news. We examine how prices react to earnings surprises by regressing the cross section of cumulative abnormal returns for a stock over days $[-1, +1]$ on the stock's SUE (defined in the prior section). The time series of the mean monthly regression coefficients (i.e. the mean of ERC) across the announcements within each month is then regressed on EEC and controls. The right-side of Table 6 reports the results. Price reactions to SUE decrease as EEC increases, at a five-percent level of significance (using simulated p-values). This finding is inconsistent with a pure information diffusion story for the EEC measure. Rather, it suggests either that investors are gathering more private information and relying less on analysts' forecasts or that earnings are less informative about future payoffs in high-EEC months.

Interestingly, controlling for the set of eleven macro variables diminishes this negative relation in Table 6, implying interplay between macroeconomic conditions, the extensiveness of earnings coverage, and earnings response coefficients. This is not the case for PEAD however, where we see that controlling for macro conditions does not affect the relation between EEC and PEAD. This difference may emanate from underlying nonlinearities that are commonplace in models of endogenous information. This may also suggest that the mechanisms driving PEAD differ in some way from those driving ERC. These topics seem potentially fruitful to pursue in further research.

In sum, greater extensiveness in the WSJ's coverage of earnings identifies months when *both* announcement-date price responses to earnings surprises and post-earnings announcement drift in returns are lower. This pair of findings may be due either to earnings quality declining in these months (and being less informative about future payoffs) or to investors' acquiring more payoff information from sources beyond analysts' forecasts of earnings. We try to distinguish between these in the next section.

4.3 Return Dispersion

If investors are relying less on analysts' earnings forecasts to value stocks in months when EEC is greater, and more on other payoff-relevant information, then returns should display greater cross-sectional dispersion. Essentially, more information is being impounded into prices.[15]

To investigate, we begin by sorting months into quintiles based on $EEC^{\perp}$. For each quintile, the left panel of Figure 5 reports the mean monthly standard deviation of the cross section of returns in the smallest quintile of size. We see that return dispersion among small stocks increases notably with $EEC^{\perp}$, from about 19% per month in the months with the lowest EEC to 24% in the months with the greatest EEC.

To assess statistical significance, we regress the monthly time-series of return dispersion on EEC and $NetEEC$. We find in Table 7 that the relation between EEC and return

[15] Note that this prediction of return dispersion increasing with EEC is not obvious given the finding of a negative covariance between EEC and earnings response coefficients in the previous section.

dispersion in small stocks is statistically strong, with p-values below 1% whether the macro variables are included as explanatory variables or not (using simulated p-values). Adding the macro controls suggests that the increased dispersion in returns is more than just an increase in the dispersion of underlying payoff fundamentals during weaker economic conditions (e.g., Gomes et al. (2003)). In short, the increasing return dispersion seems driven by an information mechanism. When EEC is greater, investors seem to be gathering more information about small stocks beyond analysts' forecasts, resulting in price adjustments that are larger than in other months.

For completeness, both Figure 5 and Table 7 show that the return dispersion of large stocks is unaffected by variation in EEC. This is consistent once again with the marginal adjustments of earnings coverage affecting the pricing of smaller stocks only.

4.4 Investing Skill of Mutual Funds

The view emerging from the set of findings in the prior sections is that the WSJ's extent of earnings coverage serves as a useful proxy for investors' information-acquisition activities along the extensive margin (i.e., more or less firms). When the extensive margin expands, small-stock prices rely less on firm-level analysts' forecasts, and seemingly, more on investors' own private information. Studies of information acquisition, heterogeneous beliefs, and coordination strategies across investors address learning about what others know and hence what others will do (Allen et al., 2006; Hellwig and Veldkamp, 2009; Han and Sangiorgi, 2018). This is a rich and complex literature with many structural differences considered. Our intent here is to offer some broad themes and reduced-form empirical testing that can serve as guidance and confirmation of the important role that conditioning on the information state plays in the understanding of asset pricing.

Given the public nature of analysts' forecasts and earnings, some simple observations can be made. When EEC is high, the prior findings suggest that investors in these times are increasing their information acquisition, coordinating less with others (relying less on analysts' forecasts), and producing their own private signals. As a result, the heterogeneity of their beliefs about payoffs increases, leading to greater return dispersion across stocks, but also to greater return dispersion across investors' portfolios. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) make this prediction using a model of informed and uninformed traders and find empirical support within the temporal variation of mutual-fund return performances. Their findings suggest that mutual funds change their information acquisition strategies as the state of the economy changes, employing the economic state (simply recessions or not) as a proxy for the information state. Our analysis in this section complements and extends their work by linking a direct measure of the WSJ's information-acquisition activities to temporal variations in mutual fund performance.[16]

In addition to considering the information-acquisition activities of investors, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) also highlight the joint importance of examining the underlying skill of mutual funds. A long literature seeks to understand what rents are extracted in the money-management industry, particularly when the ability to generate positive alpha for clients seems weak in the historical sample.[17] We contribute to this literature by examining how the investing skill of mutual funds varies with the information state. The performance of mutual funds, like other investors, may depend on their skill at processing payoff-relevant information, the information-acquisition choices they make, and the information-acquisition choices others make. These choices can produce variation in trading opportunities and return performance. If "skill" is defined solely by return performance, as the prior literature has typically done, then "skill" can vary over time as information choices vary over time.

To investigate, we collect data from Thomson Reuters on the quarterly stock holdings of mutual funds. Following Edelen, Ince, and Kadlec (2016), we estimate the change in mutual funds' demand for a given stock as the change in the number of funds that are holding a given stock from last quarter to this quarter. This measure aggregates

[16] Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) focus on the relative capacity that agents allocate to acquiring common information versus firm-specific information. This is not a distinction we pursue. Their model predicts greater overall capacity allocated to acquiring (both common and firm-specific) payoff-relevant information when uncertainty in payoffs is higher or when the risk premium is higher.

[17] For example, see the recent studies by Berk and van Binsbergen (2015) and Pastor, Stambaugh, and Taylor (2017).

across the individual fund-level buy/sell signals, ignoring the sizing of the changes which would otherwise weight the aggregation toward reflecting the large-fund signals. Also, this measure of changes in fund demand captures only entry and exit decisions of funds, which may convey more information than position adjustments. Following their methodology, we scale the quarterly change in the number of funds that hold a given stock by the mean number of mutual funds that are holding the stocks of similarly-sized firms (lowest quintile of stock size in our case). We also examine the change in the fractional share of outstanding equity held by mutual funds, i.e. the change in the percentage of ownership. Each variable is winsorized quarterly at the 1% and 99% values.

We first measure the cross-sectional relation between a given month's stock returns and the most recent calendar quarter's change in the aggregate fund demand for a stock, using measure of fund demand respectively. Since our analysis is at the stock-level, we are focusing on the aggregate skill of mutual funds to allocate capital across small stocks. The time series of monthly first-stage coefficients is then regressed on EEC measured over the prior quarter, contemporaneous with the observed changes in quarterly holdings. That is, this exercise examines the quarter $q+1$ cross-sectional performance of the small-stock buy/sell signals processed by mutual funds in quarter q, conditional on the information state in quarter q.

Table 8 finds that the performance of mutual funds' trading of small stocks increases with EEC, at the five-percent level of significance using changes in the number of funds that hold a stock, and at the ten-percent level using changes in the percentage share of ownership (using simulated p-values). To provide an economic magnitude of this relation, we sort stocks each quarter into quintiles based on changes in mutual fund demand. Stocks in the highest quintile are held long, and stocks in the lowest quintile are held short. Monthly returns of long-short portfolios over each of the next three months are formed, adjusted for size and book-to-market effects using 5×5 matched portfolios. We then separate calendar quarters into high and low states using the median value of $EEC^{\perp}$.The mean monthly abnormal return of this portfolio when formed during quarters with the most (least) extensive coverage is 60 (-45) basis points per month. Running the returns of this long-short portfolio through a four-factor model using Mkt-RF, SMB, HML, and UMD alters these alphas only slightly.[18] In sum, mutual fund performance covaries with the extent of earnings coverage, suggesting that knowledge of the information structure in the marketplace is crucial to a better understanding of mutual fund performance and of money-manager skill.

Notice that controlling for the set of macroeconomic variables in Table 8 mitigates the covariance of mutual-fund performance with EEC. This suggests that macroeconomic variables are capable of capturing some of the mapping between information acquisition along the extensive margin and mutual-fund performance. This supports the use of macroeconomic measures as proxies for information states by Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) in this particular context. However, the aspects of return dynamics that we investigate in previous sections are mostly orthogonal to the macroeconomic controls, meaning that information states and macroeconomic states play distinct roles in asset pricing.

5 Conclusion

Measuring the state of the information structures in the marketplace is an important avenue for future research. In this study, we empirically measure the extensiveness of the WSJ's monthly coverage of earnings, i.e., how many firms in a given month the WSJ chooses to cover out of the many hundreds that release their earnings. This information measure moves countercyclical to the economy and covaries with a number of return dynamics of small stocks. Not only is the measure novel, but the traction this measure gets in both the level and cross-section of stock returns is remarkable.

The set of findings indicates that changes in the WSJ's extent of earnings coverage can serve as a useful proxy for the adjustments of stock investors' information acquisition activities along the extensive margin. When information acquisition extends to more small

[18] We thank Kenneth French for providing these data on his website.

firms, the stock prices of these small firms better reflect earnings information. This is not a simple information-diffusion story though. When the extent of WSJ coverage increases, investors seem to be relying less on sell-side analysts forecasts of earnings and more on their own private signals. The temporal variation in mutual fund investing skill within small stocks is consistent with their acquiring more small-stock private signals.

In sum, conditioning on the information state of the market is an important determinant of asset pricing. Empirical measures of information, however, have long been an obstacle. Using the observable signals of financial agents to empirically measure other dimensions of the information state seems promising.

A Appendix

A.1 Variable definitions

A.1.1 Firm and Earnings Characteristics

Earnings announcement dates, actual earnings, and analysts' forecasts of earnings are from I/B/E/S. Stock prices, returns, and trading volume are from CRSP. Book value of equity is from the CRSP/Compustat Merged Database. Institutional ownership is obtained from Thomson Reuters.

UE *quantiles* are indicator variables. Each quarterly earnings release is assigned to one of 11 quantiles based on its earnings surprise, where the surprise is the announced EPS minus the median analyst earnings forecast 30 days prior to the announcement normalized by the closing stock price two days prior. Quantiles 1 to 5 rank the negative surprise announcements into equal-sized quintiles. Quantile 6 consists of zero-surprise announcements where announced earnings equal the median of analysts' forecasts. Quantiles 7 to 11 rank the positive surprise announcements into equal-sized quintiles. Indicator variables are formed for each quantile other than the zero-surprise quantile 6, which serves as the base case.

Loss is a dummy variable equal to 1 if the announced earnings is negative.

$Stdev(analysts' \ forecasts)$ is the standard deviation of analysts' EPS forecasts observed over the 30 calendar days prior to the announcement, with each forecast normalized by the closing stock price two days prior to the announcement.

$log(analysts' \ coverage)$ is the natural logarithm of one plus the number of distinct analysts' forecasts observed over the 30 calendar days prior to the announcement.

$log(ME)$ is the natural logarithm of the number of shares outstanding multiplied by the firm's closing stock price two days prior to the announcement.

log(*value of trading*) is the natural logarithm of a stock's mean dollar value of daily trading volume over the 60 trading days prior to the announcement.

Beta is the estimated coefficient from a regression of a firm's daily stock return on the S&P 500 return over the 60 days prior to the announcement.

Recent returns is a stock's mean daily return over the 60 trading days prior to the announcement.

Stdev(*recent returns*) is the standard deviation of a stock's daily returns over the 60 trading days prior to the announcement.

BE/ME is the firm's book value of equity from the fiscal year ending in the previous calendar year divided by its market value of equity from December 31 minus the value-weighted average book-to-market ratio of all announcing firms over the rolling three month period ending in the current month.

Distraction is the announcement day's decile rank (in a given calendar quarter) based on the number of earnings announcements released from other firms on the same day. See Hirshleifer et al. (2009).

Institutional ownership is the percentage of shares held by institutions at the end of the previous calendar year obtained from 13F filings.

Seasonality and industry dummies are three indicator variables for month-of-the-year, day-of-the-week, and the 49 Fama-French industries, respectively. Firms are assigned to industries using SIC codes from Compustat.

A.1.2 Macroeconomic Variables

$PDND$ is the value-weighted dividend premium from Baker and Wurgler (2004). (Downloaded from Jeffrey Wurgler's website.)

$log(Div.\ Yield)$ is the natural logarithm of the market dividend yield (aggregate dividends for months t to $t-11$, divided by total market capitalization in month t for NYSE, AMEX, and Nasdaq firms). (Downloaded from Michael Roberts' website.)

$log(Net\ Payout\ Yield)$ is the natural logarithm of the total net payout yield (where the equity issuance yield is aggregate net equity issues for months t to $t-11$, divided by total market capitalization in month t). (See Boudoukh et al. (2007). Downloaded from Michael Roberts' website.)

$Risk\text{-}free\ rate$ is the US 90-day T-Bill rate. (Downloaded from Michael Roberts' website.)

CAY is the estimated quarterly deviation from the long-run log aggregate consumption wealth ratio. (See Lettau and Ludvigson (2001). Downloaded from Sidney Ludvigson's website.)

B/M is the book value of equity divided by its market value for the Dow Jones Industrial Average. (Downloaded from Amit Goyal's website.)

$Default\ Spread$ is the difference between the BAA and AAA corporate bond yields from FRED. (Downloaded from Amit Goyal's website.)

$Term\ Spread$ is the yield on the 10-year Treasury bond minus the yield on the 3-month Treasury bill. (Downloaded from Amit Goyal's website.)

$Equity\ Share\ of\ New\ Issues$ is the dollar amount of equity new issues divided by the dollar amount of total new issues (debt plus equity) described in Baker and Wurgler (2000). (Downloaded from Jeffrey Wurgler's website.)

$Sentiment$ is the sentiment index from Baker and Wurgler (2006), which is based on the principal component of 6 sentiment proxies. (Downloaded from Jeffrey Wurgler's website.)

$Output\ Gap$ is the estimated residual from the quadratic monthly time trend in the natural logarithm of US Industrial Production over the sample period. See Cooper and Priestley (2009).

A.2 Logit Model Results

Table A.1 Predicting WSJ coverage

Below are the estimated coefficients from the multinomial logit regression of $c_{i,t} \in (-1, 0, 1)$ on various explanatory variables, where $c_{i,t}$ equals -1 when the earnings report for firm i in month t receives negative coverage, 1 when it receives nonnegative coverage, and 0 when it receives no coverage (the base case). Variable definitions are in section A.1. t-statistics (in parentheses) are computed using standard errors clustered by firm; * indicates significance at 10%; ** indicates significance at 5%;*** indicates significance at 1%.

	WSJ Coverage	
	-1	1
UE quantile 11	0.805***	0.530***
	(11.12)	(7.52)
UE quantile 10	0.411***	0.336***
	(6.40)	(6.05)
UE quantile 9	0.113*	0.248***
	(1.74)	(4.96)
UE quantile 8	-0.113*	0.137***
	(-1.77)	(3.00)
UE quantile 7	-0.462***	0.00240
	(-6.77)	(0.06)
UE quantile 5	0.112*	-0.0185
	(1.76)	(-0.39)
UE quantile 4	0.603***	-0.000930
	(9.47)	(-0.02)
UE quantile 3	0.916***	0.186***
	(14.22)	(3.04)
UE quantile 2	1.048***	0.260***
	(14.91)	(3.56)
UE quantile 1	1.272***	0.367***
	(16.05)	(3.32)
Loss dummy	1.041***	-1.449***
	(19.01)	(-17.63)
Stdev(analysts' forecasts)	0.0624***	-0.0905**
	(4.75)	(-2.53)
log(analysts' coverage)	0.410***	0.356***
	(10.57)	(8.18)
log(ME)	0.442***	0.598***
	(12.38)	(14.95)
log(value of trading)	0.226***	0.210***
	(7.82)	(6.49)
Beta	-0.0986***	-0.0146
	(-4.16)	(-0.55)

Recent returns	-0.00226***	-0.00177***
	(-4.55)	(-3.47)
Stdev(recent returns)	0.640	-10.01***
	(0.53)	(-6.10)
BE/ME	0.570***	0.339***
	(20.79)	(8.47)
Distraction	-0.0346***	-0.0637***
	(-2.99)	(-5.13)
Seasonality and industry (FF-49) dummies	Yes	Yes
Observations	233348	
Pseudo R^2	0.269	

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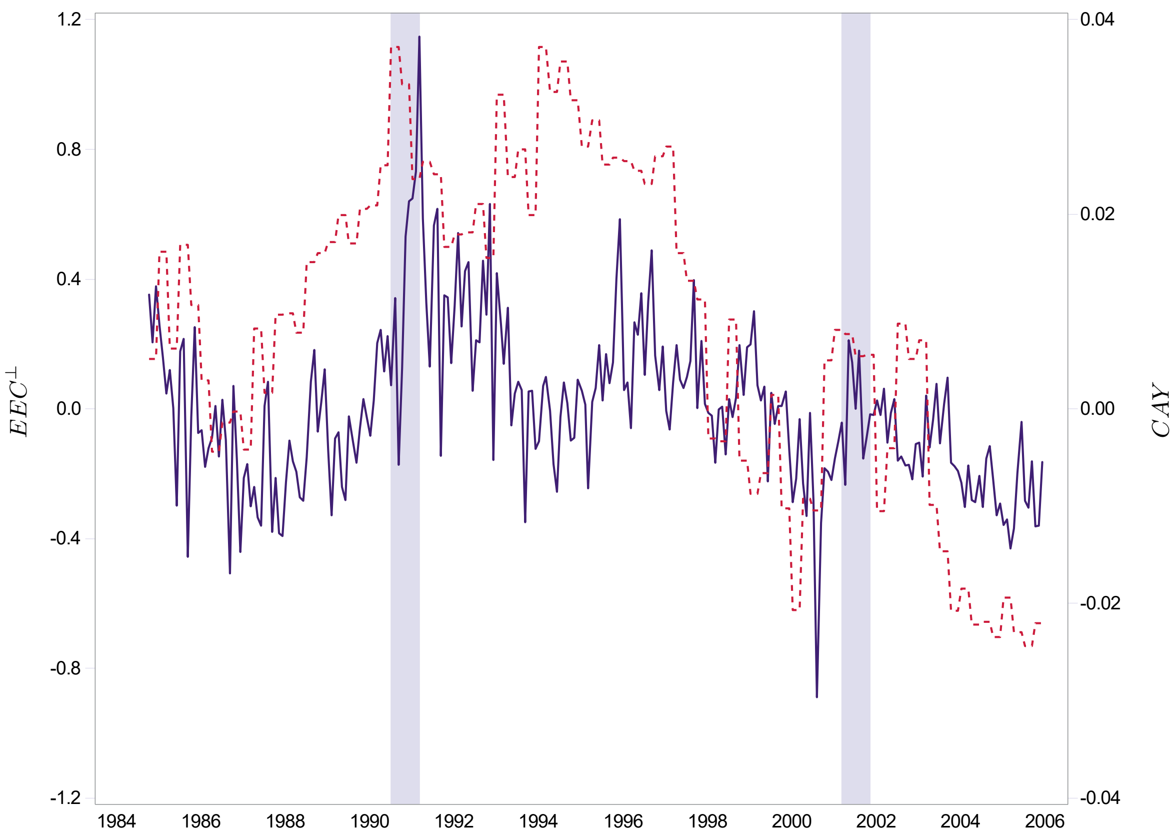

Figure 1: Extent of Coverage Covaries With CAY. The monthly $EEC^{\perp}$ series (solid line) is plotted against the quarterly CAY series (dotted line). CAY is the consumption-wealth ratio of Lettau and Ludvigson (2001). The shaded regions are NBER recession periods.

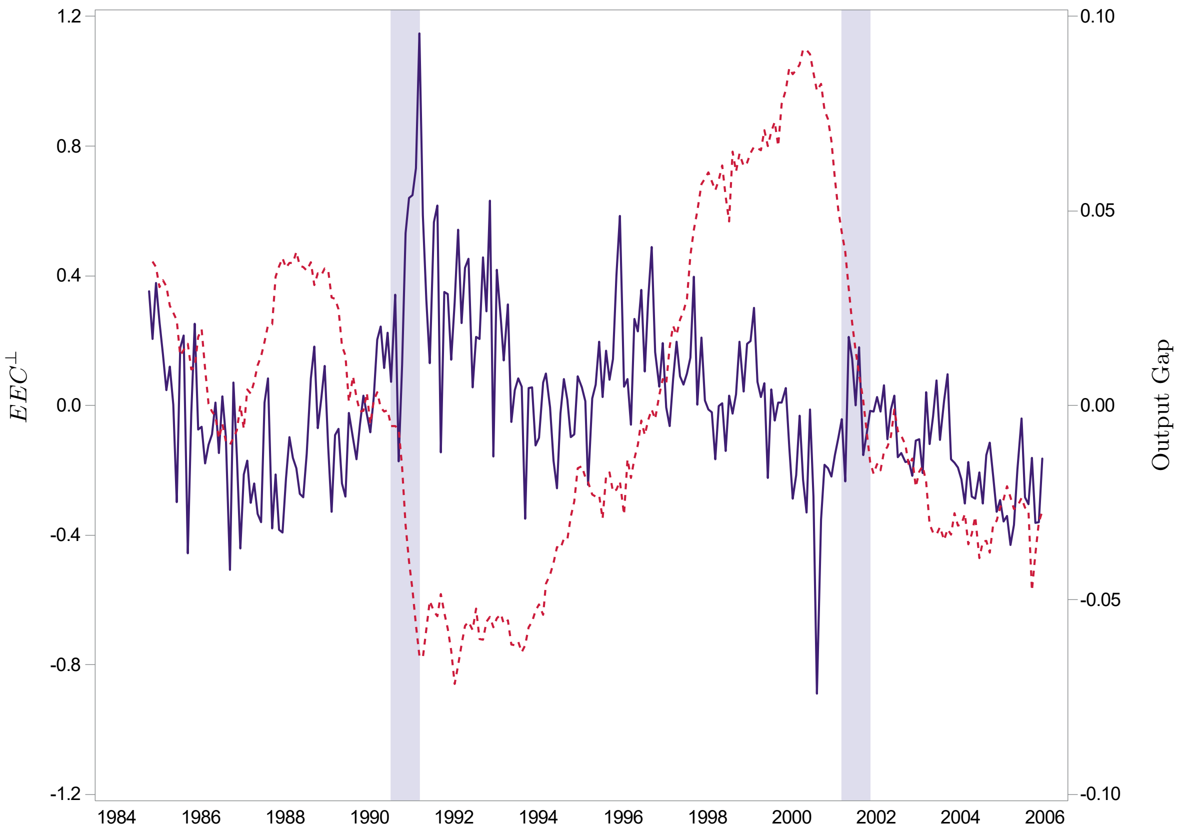

Figure 2: Extent of Coverage Covaries Negatively With Output Gap. The monthly $EEC^{\perp}$ series (solid line) is plotted against the monthly output gap series (dotted line). Output gap is the residual from the quadratic monthly time trend in the natural logarithm of industrial production. The shaded regions are NBER recession periods.

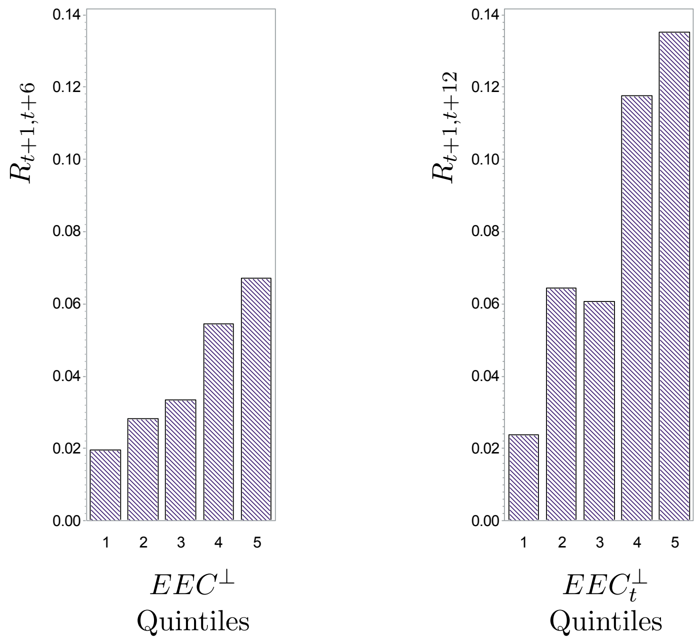

Figure 3: Extent of Coverage and Equity Risk Premium. Months are sorted into quintiles based on $EEC^{\perp}$. Means of excess stock returns within each quintile are plotted for months (+1,+6) in the left panel and for months (+1,+12) in the right panel.

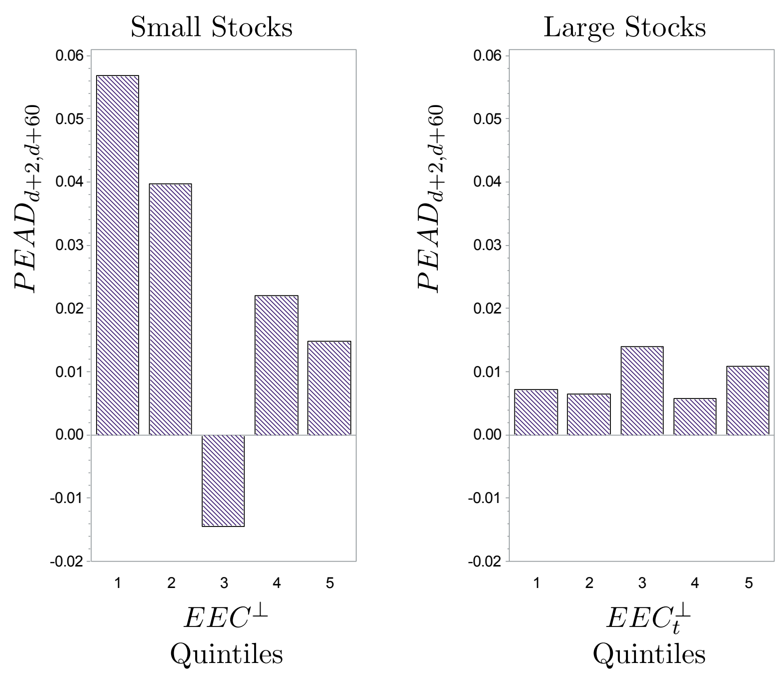

Figure 4: Extent of Coverage and Post-Earnings Announcement Drift in Returns. Months are sorted into quintiles based on $EEC^{\perp}$. Means of PEAD profits are plotted for days (+2,+60) within small stocks in the left panel ($\leq 20^{th}$ percentile using NYSE breakpoints) and within large stocks in the right panel ($> 80^{th}$ percentile using NYSE breakpoints).

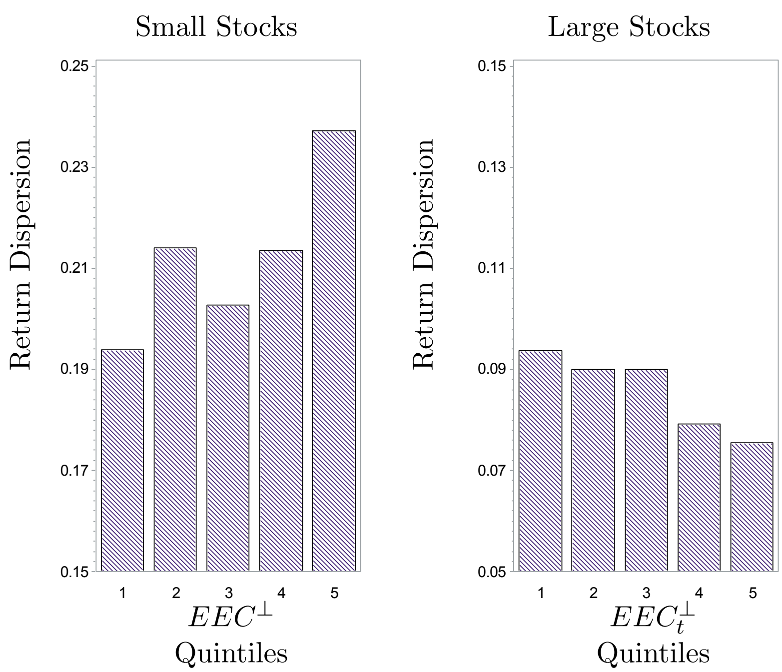

Figure 5: Extent of Coverage and Return Dispersion. Months are sorted into quintiles based on $EEC^{\perp}$. Means of monthly cross-sectional standard deviation of returns within small stocks are plotted in the left panel ($\leq 20^{th}$ percentile of market cap using NYSE breakpoints) and within large stocks in the right panel ($> 80^{th}$ percentile of market cap using NYSE breakpoints). Different axis scales are used for small and large stocks.

Table 1
Summary Statistics

Below are summary statistics for various monthly measures of the WSJ's coverage of earnings and of macroeconomic measures from October 1984 to December 2005. The expected number of nonnegative articles and of negative articles are estimated with a multinomial logit (see section 1.3). *EEC* is the deviation of the actual number of firm-earnings covered in a given month from the expected number to be covered, while *NetEEC* is the deviation of the actual net tone of the coverage from the expected net tone (see equations 1 and 2). Equity premium is the monthly return on the CRSP value-weighted index minus the one-month T-Bill return in percentage terms. The macroeconomic measures in the lower portion are defined in Appendix A.1.

	Mean	Std. Dev.	AR(1)
Number of Earnings Released	915.09	706.12	−0.14
Number of Earnings Covered	96.60	79.56	−0.17
Number of Nonnegative Articles	66.39	59.99	−0.18
Number of Negative Articles	30.22	24.09	0.00
E[Number of Nonnegative Articles]	66.39	60.34	−0.16
E[Number of Negative Articles]	30.22	22.51	−0.01
Extent of Earnings Coverage (EEC)	0.03	0.26	0.62
NetEEC	0.00	0.19	0.43
Equity Premium	0.45	4.38	0.04
PDND	−0.12	0.11	0.93
Dividend Yield	0.02	0.01	0.99
Net Payout Yield	0.10	0.02	0.99
Risk-free rate	0.05	0.02	0.98
CAY	0.01	0.02	0.98
B/M	0.33	0.15	0.98
Default Spread	0.01	0.00	0.95
Term Spread	1.76	1.15	0.97
Equity Share of New Issues	0.12	0.06	0.61
Sentiment	0.10	0.59	0.94
Output Gap	0.00	0.04	0.99

Table 2
Correlations

$EEC^{\perp}$ and $NetEEC^{\perp}$ are respectively EEC and $NetEEC$ orthogonalized with respect to each other. *Recession* is an NBER recession dummy. CAY is the deviation of the consumption-wealth ratio from its long-term trend sampled quarterly (Lettau and Ludvigson (2001)). Output gap is the residual from the quadratic time trend in log U.S. industrial production. Term spread is the month-end 10-year Treasury yield minus the 3-month Treasury yield. Sentiment is from Baker and Wurgler (2006). Standard p-values are listed below each correlation coefficient.

	$EEC^{\perp}$	$NetEEC^{\perp}$	Recession	CAY	Output Gap	Term Spread	log(Div. Yield)	Sentiment
$EEC^{\perp}$	1.000							
$NetEEC^{\perp}$	−0.302	1.000						
	(0.00)							
Recession	0.261	−0.223	1.000					
	(0.00)	(0.00)						
CAY	0.482	−0.054	0.154	1.000				
	(0.00)	(0.39)	(0.01)					
Output Gap	−0.272	0.336	−0.069	−0.271	1.000			
	(0.00)	(0.00)	(0.27)	(0.00)				
Term Spread	0.117	−0.212	0.002	0.058	−0.557	1.000		
	(0.06)	(0.00)	(0.97)	(0.35)	(0.00)			
log(Dividend Yield)	0.197	−0.083	-0.006	0.496	−0.345	0.238	1.000	
	(0.00)	(0.19)	(0.92)	(0.00)	(0.00)	(0.00)		
Sentiment	−0.174	0.049	0.216	−0.156	0.561	−0.084	−0.297	1.000
	(0.01)	(0.44)	(0.00)	(0.01)	(0.00)	(0.15)	(0.00)	

Table 3

Extent of Earnings Coverage and Macro Conditions

$EEC^{\perp}$ is regressed on a set of macroeconomic variables, which are defined in section A.1.2 of the Appendix. The t-statistics (in parentheses) are calculated using Newey-West standard errors with six lags. The p-values shown in brackets are determined using 10,000 randomly generated samples of independent normally distributed variables with first-order serial correlation coefficients of 0.64, representing $EEC^{\perp}$. Asterisks correspond to the simulated p-values, with * indicating significance at 10%,** indicating significance at 5%, and *** indicating significance at 1%.

PDND	0.004	Default Spread	3.709
	(1.80)		(0.37)
	[0.21]		[0.80]
log(Div. Yield)	-0.977^{***}	Term Spread	0.064
	(-4.96)		(1.98)
	[0.00]		[0.15]
log(Net Payout Yield)	-0.052	Equity Share of New Issues	0.435
	(-0.22)		(1.57)
	[0.87]		[0.24]
RF	11.037^{**}	Sentiment	-0.112
	(3.12)		(-1.92)
	[0.02]		[0.21]
CAY	7.523^{***}	Output Gap	-2.959^{**}
	(4.56)		(-2.92)
	[0.00]		[0.04]
B/M	0.927	Recession	0.164
	(2.14)		(1.92)
	[0.16]		[0.26]
Constant	-4.657		
	(-4.85)		
Observations	255		
R^2	0.41		

Table 4

Extent of Earnings Coverage and the Equity Premium

The dependent variable is the log return of the CRSP value-weighted index minus the one-month T-Bill rate across the future six and twelve months respectively. EEC_t and $NetEEC_t$ are the month t measures of the extent of coverage and of the tone of coverage, respectively, defined in equations (1) and (2). Both of these explanatory variables are standardized. The row labeled "Macro Controls" indicates whether or not the set of macroeconomic variables (shown in section A.1.2) are included as regressors. The t-statistics (in parentheses) are calculated using Newey-West standard errors with six lags. The p-values shown in brackets are determined using 10,000 randomly generated samples of independent normally distributed variables with first-order serial correlation coefficients of 0.62 and 0.43, representing EEC and $NetEEC$ respectively. Asterisks correspond to simulated p-values, with * indicating significance at 10%,** significance at 5%, and *** significance at 1%. Panel B reports the simulated p-values of the joint hypothesis that the coefficients on EEC in Panel A are both zero across the six-month and twelve-month horizons.

A. Regressions of Excess Stock Returns				
	(+1,+6)	(+1,+12)	(+1,+6)	(+1,+12)
EEC	0.0189*	0.0366**	0.0214*	0.0208
	(1.97)	(2.51)	(2.36)	(1.63)
	[0.097]	[0.047]	[0.078]	[0.234]
NetEEC	0.0169	0.0109	0.0092	0.0066
	(1.62)	(0.59)	(1.03)	(0.78)
	[0.168]	[0.608]	[0.412]	[0.550]
Macro Controls	No	No	Yes	Yes
Constant	0.035	0.069	0.731	−0.489
	(2.84)	(3.43)	(1.21)	(−0.80)
Observations	255	255	255	255
R^2	0.08	0.08	0.33	0.50

B. Joint-Horizon Tests of Coefficients on EEC

Horizons	Simulated P-Value of Joint Significance
$(+1,+6) \cap (+1,+12)$	0.029
$(+1,+6) \cap (+1,+12)$ with Macro Controls	0.048

Table 5
Extent of Earnings Coverage within Size Quintiles

Months from October 1984 to December 2005 are ranked based on EEC into the lowest 25%, highest 25%, and remaining "normal" months. EEC_q is calculated analogously to EEC but within only size quintile q in a given month, from smallest (quintile 1) to largest (quintile 10). The full-sample logit specification is used to determine the likelihood of coverage. The means of EEC_q and the means of the actual number of earnings reports covered within each decile are shown for the high-EEC, normal-EEC, and low-EEC months.

EEC	(Smallest) 1	2	3	4	(Largest) 5
			Panel A: EEC_q		
Low	−0.37	−0.48	−0.41	−0.25	−0.19
Normal	0.01	−0.07	0.04	0.06	0.02
High	0.91	0.62	0.41	0.32	0.18
			Panel B: Actual Number of Firms Covered per Month		
Low	4.4	5.2	8.5	18.3	44.4
Normal	7.6	9.0	13.2	22.6	46.9
High	10.0	12.4	16.0	23.1	45.3

Table 6

Extent of Earnings Coverage and Price Reactions to Earnings
Within Small Stocks

The left-panel dependent variable is the time-series of monthly coefficients from a cross-sectional regression of small-stock cumulative abnormal returns from day +2 to day +60 (PEAD), relative to each announcement in month t, on standardized unexpected earnings. Regressions of the first-stage coefficients on EEC and $NetEEC$ measured in the contemporaneous month are reported below. Small stocks are defined as those with a percentile of market capitalization less than or equal to the 20^{th} percentile of NYSE stocks. The right panel examines cumulative abnormal returns from day −1 to +1 (ERC) using an analogous method to the left panel. The row labeled "Macro Controls" indicates whether or not the set of macroeconomic variables listed in section A.1.2 are included as regressors. t-statistics (in parentheses) are computed using Newey-West standard errors with three lags. P-values shown in brackets are determined using 10,000 randomly generated samples of independent normally distributed variables with first-order serial correlation coefficients matching those of EEC and $NetEEC$ respectively. Asterisks correspond to the simulated p-values; * indicates significance at 10%,** significance at 5%, and *** significance at 1%.

	PEAD		ERC	
EEC	-0.140^{***}	-0.184^{***}	-0.066^{**}	-0.023
	(-2.96)	(-3.68)	(-2.37)	(-1.12)
	[0.007]	[0.001]	[0.051]	[0.320]
NetEEC	0.050	0.075	0.015	0.017
	(1.33)	(1.52)	(0.70)	(0.71)
	[0.204]	[0.163]	[0.547]	[0.523]
Macro controls	No	Yes	No	Yes
Constant	0.173	-1.038	0.295	0.589
	(3.95)	(-0.36)	(10.52)	(0.46)
Observations	255	255	255	255
R^2	0.04	0.13	0.04	0.36

Table 7

Extent of Earnings Coverage and Return Dispersion

Monthly standard deviation of the cross section of returns is regressed on EEC, $NetEEC$, and macroeconomic controls. Dispersion is measured each month across large and small stocks respectively. Large and small are defined as above the 80^{th} percentile of market capitalization using NYSE breakpoints in the prior month and less than or equal to the 20^{th} percentile, respectively. The row labeled "Macro Controls" indicates whether or not the set of macroeconomic variables listed in section A.1.2 are included as regressors. t-statistics (in parentheses) are computed using Newey-West standard errors with six lags. P-values shown in brackets are determined using 10,000 randomly generated samples of two independent normally distributed variables with first-order serial correlation coefficients matching EEC and $NetEEC$ respectively. Asterisks correspond to simulated p-values. * indicates significance at 10%,** significance at 5%, and *** significance at 1%.

	Return Dispersion Small Stocks		Return Dispersion Large Stocks	
EEC	0.016***	0.019***	−0.007	0.000
	(2.76)	(4.35)	(−1.54)	(0.09)
	[0.007]	[0.000]	[0.203]	[0.949]
NetEEC	−0.008	−0.006	0.008	0.004*
	(−1.72)	(−1.71)	(1.50)	(2.07)
	[0.113]	[0.137]	[0.180]	[0.053]
Macro Controls	No	Yes	No	Yes
Constant	0.212	−0.021	0.086	−0.190
	(37.66)	(−0.11)	(15.67)	(−1.57)
Observations	255	255	255	255
R^2	0.07	0.24	0.04	0.63

Table 8
Extent of Earnings Coverage and Mutual Fund Skill
within Small Stocks

Each month, the cross section of small-stock returns, adjusted for size and book-to-market effects, is regressed on the most recent quarter's change in the mutual-fund demand for a stock. Demand is measured as the number of mutual funds that hold a given stock or the fractional share of the outstanding equity owned by mutual funds. The first-stage coefficients are regressed on EEC and $NetEEC$ measured over the horizon as changes in fund demand. The Newey-West t-statistics use twelve lags. P-values shown in brackets are determined using 10,000 randomly generated samples of two independent normally distributed variables with first-order serial correlation coefficients matching EEC and $NetEEC$ respectively. Asterisks correspond to simulated p-values. * indicates significance at 10%,** significance at 5%, and *** significance at 1%.

	Δ Number of MF		Δ MF Share	
EEC	0.002**	0.001	0.026*	0.024
	(2.65)	(1.35)	(2.17)	(1.25)
	[0.05]	[0.26]	[0.09]	[0.43]
NetEEC	0.000	−0.002	0.0042	−0.014
	(0.46)	(−1.25)	(0.26)	(−0.58)
	[0.74]	[0.29]	[0.83]	[0.96]
Macro controls	No	Yes	No	Yes
Constant	−0.001	0.017	−0.001	−0.247
	(−0.92)	(0.32)	(−0.06)	(−0.23)
Observations	252	252	252	252
R^2	0.03	0.15	0.02	0.06