Time Variation in Attention to Earnings: Through the Lens of the Media*

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Abstract

By observing the decisions of a prominent information agent, *The Wall Street Journal* (WSJ), regarding the number of firms' earnings releases to cover each month, we form a proxy for time variation in the intensity with which investors attend to earnings information. Consistent with recent theories of the rational allocation of limited attention, we find that attention to earnings varies inversely with macroeconomic conditions and positively with the equity premium. We also find evidence that the stock market is processing more firm-specific information when attention to earnings is greater. Specifically, post-earnings announcement drift in stock returns is smaller, cross-sectional return dispersion is greater, and return synchronicity is lower in months when attention to earnings is higher. Lastly, we find that the lead-lag between large stocks' returns and small stocks' returns increases as attention to earnings intensifies, suggesting that greater attention to firm-specific information comes at the expense of investors' processing less systematic information.

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Information is critical to the decision making of investors, and consequently, to the functioning of financial markets. Investors are not endowed with information; information must be acquired. Decisions such as whether and when to acquire information, what subsets of information to acquire, and how to process that information are burgeoning areas of study. In particular, for a trader to become better informed about the intrinsic value of a risky asset, the trader must bear the direct costs of gathering and filtering information as well as the opportunity costs of allocating his or her attention to that asset at that moment. Since the seminal work of Grossman and Stiglitz (1980), economists have understood that the costs for investors to become better informed can potentially constrain the degree of informativeness of security prices.

Because cognitive resources and time are limited and the potential information set to process when valuing stocks is vast, market participants must be selective in allocating their attention. This is the essence of theories featuring limited attention as an informational friction in financial markets. In this study, we seek to empirically measure the attentiveness of market participants to a particular class of information useful for pricing stocks — firms' quarterly earnings reports. Faced with a steady flow of earnings releases from across the marketplace, as well as a myriad of other news items, agents must determine how many earnings releases to devote time and effort to process. We observe the real-time decisions of a prominent information agent, *The Wall Street Journal* (WSJ), regarding the monthly volume of earnings releases receiving coverage in the WSJ. The volume of the WSJ's earnings coverage is a measure of the WSJ's attentiveness to earnings information, which serves as our proxy for the attentiveness of market participants to earnings. We then test several predictions from the limited-attention literature regarding temporal variation in attentiveness to information relevant for valuing risky assets and temporal variation in the informativeness of stock prices.

We examine attentiveness to earnings reports because these are important information events regarding firms' activities, and thus regarding stocks' valuations. Perhaps more importantly, since firms release earnings reports quarterly, we have a steady flow of relatively homogenous and meaningful information events. Agents must continually decide how much time and effort to allocate to this flow of information. Given limits on attention, a rational agent should allocate greater resources to processing earnings information when the net benefits to doing so are greater, relative to the costs of foregoing the processing of other classes of value-relevant information and of foregoing other activities (including leisure). In this vein, Andrei and Hasler (2015), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2015), and Bansal and Shaliastovich (2011) contend that attentiveness to information should vary countercyclically. That is, information about the valuation of risky assets is more beneficial to acquire when uncertainty in payoffs is higher and when the price of risk is higher, and thus agents should pay greater attention to earnings information during weaker economic times.[1]

Following others, we employ the WSJ's coverage decisions as a proxy for the attention of market participants more broadly.[2] The WSJ is an information agent attuned to financial markets and to information of interest to its subscribers, who are participants in financial markets. By design, the WSJ filters the available information for its readers. But more than this, the WSJ is an agent whose own attention must be allocated across the vast information landscape of microeconomic and macroeconomic information flows. The WSJ must determine which items are the most beneficial to cover each day. Reporters interview investment professionals, observe where the attention of market participants is focused, and assess which news items to attend to on behalf of their subscribers. When the earnings information being released throughout the marketplace is more beneficial to process and learn from, the volume of earnings reports receiving WSJ coverage should increase. In

[1]These studies provide empirical support for countercyclical attentiveness to value-relevant information and for other predictions of their models without directly measuring attention. Kacperczyk et al. (2015) use NBER recessions as a proxy for attentiveness to information while Bansal and Shaliastovich (2011) use volatility in consumption expenditures. Andrei and Hasler (2015) define attention to information to be the correlation between the economic fundamental in their model which drives asset payoffs (GDP growth) and an observable signal about that fundamental, and they estimate this correlation from data. We complement these studies by measuring the intensity of attention allocated to a specific type of information, firms' earnings, and we measure this intensity from the WSJ's observable actions.

[2]For example, Barber and Odean (2008), Fang et al. (2014), and Carroll (2003) use media coverage to measure the attention of market participants. While Barber and Odean (2008) and Fang et al. (2014) lean more toward media coverage as an attractor of the attention of an outlet's subscribers, Carroll (2003) highlights the role of the media as both a filtration of the available information set and a conveyor of the filtered information.

this sense, the WSJ's real-time decisions about how much attention to allocate to earnings reports seem a useful proxy for the attentiveness of (at least some) market participants more broadly.

To be confident that we capture temporal variation in the perceived marginal benefits of processing earnings information, we control for firm-specific and earnings-specific determinants of the WSJ's coverage of earnings. Some firms and some earnings releases have a greater likelihood than others of being covered in the media, such as larger firms and firms with earnings surprises. Therefore, we filter the underlying flow of earnings reports to separate the temporal changes in the usefulness of covering earnings from the changes in the underlying characteristics of the firms and earnings reports.[3] For example, months with a greater number of earnings releases by large firms should be adjusted when compared against months with fewer releases by large firms. To do so, we first employ a logit model to estimate the probability of each earnings report's being covered in the WSJ based on a variety of firm and earnings characteristics. Each month, we predict the number of earnings reports we expect will receive WSJ coverage. The percentage deviation of the actual number of earnings reports receiving WSJ coverage in a given month from the predicted number quantifies the atypical attention the WSJ devotes that month to earnings information. This measure is labeled "residual coverage intensity" (RCI), and it captures temporal variation in attentiveness to earnings.

We use this measure to examine whether attentiveness to earnings increases when economic conditions worsen. We also investigate how the informativeness of stock prices varies with attentiveness to earnings. Specifically, when earnings information is being processed more intensely, stock prices should impound more of the reported earnings information if attention constraints bind at the market level, across investors. Furthermore, when market participants increase their attentiveness to one class of information, their attentiveness to

[3] 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.

other information should decrease, and hence, prices should reflect less of this other information. These two inquiries regarding information processing are tenets of the theories of limited attention and empirically address whether constraints on attention bind at the market level.

Using data from October 1984 to December 2005, we find that the WSJ's attentiveness to earnings is greater when economic conditions are weaker, namely, when the consumption-wealth ratio of Lettau and Ludvigson (2001) is higher, when output gap (detrended industrial production) is lower, and during NBER recessions. Hence, attention to earnings information varies countercyclically, consistent with the rational allocation of limited attention.[4] The traction between our measure of attention to earnings and these macroeconomic measures is striking. For example, the correlation between the consumption-wealth ratio and RCI is 0.48, and the correlation between output gap and RCI is -0.27. Further support for countercyclical attention to earnings comes from our finding of a positive relation between attention to earnings and the equity risk premium. A one standard deviation increase in RCI is associated with a roughly 2% increase in the excess stock market return over the next six months.[5]

We also provide some cross-sectional insights on how the measure of attentiveness to earnings is changing over time. Given the substantial role that firm size plays in determining WSJ coverage, we examine how the coverage of large firms' earnings and of small

[4]Some researchers may have predicted the opposite, i.e., lesser attention devoted to earnings when the economy is weaker. By measuring the number of logins to investment accounts, Sicherman et al. (2015) provide evidence of investors' seeking less information about their investments as returns on the stock market decline, possibly because investors want to delay realizing a bad outcome. However, logging into one's account may proxy for attention to one's account balances rather than attention to information useful in the valuation of risky assets. Sicherman et al. (2015) do not observe what investors do during their online sessions.

[5]Tetlock (2007), Tetlock et al. (2008), Solomon (2012), Gurun and Butler (2012), and others find that the linguistic tone (positive/negative) of media coverage explains and even predicts future stock returns, albeit at very short horizons. To ensure that we are identifying a relation between attention to earnings and stock returns rather than an indirect relation between the tone of coverage and returns, we control for the aggregate monthly tone of the WSJ articles similarly to how we measure attention to earnings. Employing a multinomial logit model to estimate the probabilities of negative and of non-negative tone, we find that the aggregate residual tone is positively correlated with aggregate residual coverage, and the orthogonalized component of residual tone displays explanatory power for future stock returns over a window of up to three months. Further research on the aggregate residual tone of coverage is potentially fruitful.

firms' earnings vary. When attention to earnings is high, we find that most of the increased attention is directed toward smaller stocks. Consistent with the idea that greater earnings coverage occurs at times when the benefits of processing earnings information are greater, we find that the WSJ digs more deeply into the earnings landscape and reports on a broader set of stocks than it would typically cover. That is, when the benefits of learning from earnings information is greater, the WSJ chooses to bear greater costs to gather and process the earnings information of smaller firms. Since the time variation in the attention to small-stocks' earnings is much greater than the time variation in the attention to large-stocks' earnings, we expect that the informativeness of small-stock prices will vary more strongly over time if attention constraints indeed bind on the price-setting process.

We investigate how the informativeness of stock prices varies with attentiveness to earnings in several ways. First, to the extent that the well-known drift in stock returns following earnings surprises is due to investors' insufficient attention to earnings, i.e., to an underreaction to earnings news, we should find that the return drift following earnings surprises diminishes when attention to earnings is greater. We indeed find this to be true for small stocks. This evidence provides new support for underreactions to earnings surprises as a reason for post-earnings announcement drift in returns, and for limits on attention as the mechanism for the underreaction. Hirshleifer et al. (2009) and DellaVigna and Pollet (2009) provide evidence at the firm-event level, documenting that concurrent distractions to a given earnings announcement draw attention away from a given announcement and impede the market's ability to fully process the earnings information contained in that given announcement. In contrast, the evidence here is at the market level. Our method identifies calendar months when investors are broadly paying greater attention to earnings information in the marketplace, and we find that investors appear to impound more earnings news into stock prices in these months.[6]

[6]Other potential sources of abnormal-return drift following earnings surprises, besides underreaction, 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)).

Continuing the investigation of how the impounding of information into stock prices varies with attentiveness to earnings, we also examine the cross-sectional dispersion of stock returns. We find that return dispersion increases for small stocks in months when attentiveness to earnings is higher, consistent with more firm-specific information being impounded into stock prices. We also find that return synchronicity (correlation) between small stocks and the value-weighted market index is lower when attention to earnings is higher, again echoing that more firm-specific news is being processed when attentiveness to earnings is high.

Lastly, we examine the processing of firm-specific information versus systematic information. Assuming attention is limited, Peng and Xiong (2006) and Kacperczyk et al. (2015) consider investors' decisions to attend to systematic information common to many assets versus firm-specific information. Motivated by their research questions, and given our findings that attentiveness to earnings seems mostly about acquiring and processing firm-level information, we investigate whether increasing attentiveness to earnings comes at the expense of lowering attentiveness to systematic information. The well documented lead-lag relation between large stocks' returns and small stocks' returns provides a useful testing ground (Lo and MacKinlay (1990)). One reason why large stocks lead small stocks is that small stocks' prices seem slow to fully incorporate the systematic news reflected in large stocks' returns (Hou (2007)).[7] We find that the lag between large and small stocks amplifies when attentiveness to earnings is greater. This is consistent with the prices of small stocks impounding less systematic information as market participants' divert their attention toward firm-specific information. This finding is markedly new evidence supporting an underreaction interpretation of the lead-lag effect across large and small stocks' returns. Moreover, the underreactions in the stock market are at least partially attributable to limits on attention.

[7] The role of nonsynchronous trading in this lead-lag relation at the daily horizon is heavily debated; see Ahn et al. (2002). We examine lead-lags at monthly intervals using value-weighted portfolios and arguably eliminate this concern. We also control for time variation in the expected returns of small stocks by including small stocks' own lagged return.

Overall, our findings suggest that constraints on information acquisition and processing bind at the market level and that further research on such constraints seem fruitful avenues to a better understanding of the price setting process. Our findings complement a growing literature which proposes limited attention to be a source of other curious features of the marketplace besides underreactions to news, such as excess covariance in asset returns (Veldkamp (2006), Mondria (2010)), jumps in asset prices (Bansal and Shaliastovich (2011)), under-diversification in investment portfolios (Van Nieuwerburgh and Veldkamp (2009, 2010)), and the slow adjustment of consumption to investors' wealth shocks (Peng (2005), Luo (2010)).

The next section details the data and methods for estimating attention to earnings and discusses several aspects of the time variation in the measure. Section 2 shows the empirical link between attention and the equity risk premium. Section 3 examines the relation between attention to earnings and the processing of information by the stock market. We conclude in section 4.

1 Methodology and Data

1.1 Corporate earnings events

Our sample of quarterly earnings reports includes 233,379 firm-earnings events from I/B/E/S, covering the period from October 1984 to December 2005. To model the probability of each earnings release's being covered by *The Wall Street Journal* (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 release 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 intensity with which the WSJ covers earnings is based on the number of WSJ articles that cover earnings releases. 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 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 covering an earnings release — paying attention — from the tone of the coverage which reflects an outcome of the processing of the earnings information. These distinct aspects may be correlated, and evidence suggests that tone explains 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.[8]

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.

[8] 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 Measurement of coverage intensity

Our goal is to measure whether the WSJ's coverage of firms' quarterly earnings reports is more intense in say March 1990 than in November 2002. One simple measure of coverage intensity is the proportion of earnings released in a given month that receive WSJ coverage. We define this raw measure of coverage intensity (CI) in month t to be:

$$CI_t = \frac{\sum_{k=1}^{K_t} C_k}{K_t} \tag{1}$$

where K_t is the total number of earnings releases observed in month t, and 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.

Table 1 provides summary statistics for CI and other measures of the WSJ's coverage of earnings. On average, 11% of earnings reports released in a given month are covered by the WSJ. The monthly number of earnings reports that receive coverage has a mean of 97 with a relatively large standard deviation of 80. The relatively low standard deviation of 3% for CI indicates that the primary driver of the time-series variation in the WSJ's raw coverage of earnings is the flow of earnings reports released each month. This observation motivates the need to control for time variation in the flow of earnings releases so that we isolate changes in the WSJ's perception of the marginal benefits of covering earnings.

The raw measure of coverage intensity (CI) implicitly assumes that each earnings report is equally likely to receive coverage in the WSJ. However, this is clearly not the case. For example, 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)). In addition, the number of firms that release earnings in a given month varies over the sample period. Given the characteristics of the firms that release earnings each month and the characteristics of those earnings, the WSJ chooses how much attention to allocate to earnings announcements. To determine the level of atypical coverage in any month, 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 each earnings report's being covered. 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 0.22. We say more on these determinants in the next section.

Months in which the number of WSJ articles on earnings is greater than predicted are the months in which the WSJ's assessment of the marginal benefits of covering earnings information is greater. We measure time variation in marginal benefits of coverage as the percentage deviation of the actual number of articles from the predicted number of articles each month, which we label "residual coverage intensity" (RCI). The predicted number of articles each month ($\hat{C}_k$) is the sum of the predicted probabilities of a negative article and the predicted probabilities of a nonnegative article aggregated across all earnings releases. Then,

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

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

Figure 1 plots RCI (along with CAY). We can visually see the variability in RCI, and we can also see that RCI displays some persistence. The AR(1) coefficient of RCI

is 0.62. This is far below the near unit-root behaviors of all the macroeconomic variables shown in Table 1, save 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, we first form a raw measure of the net tone of the coverage as:

$$NetCI_t = \frac{\sum_{k=1}^{K_t}(C_k^{NNeg} - C_k^{Neg})}{K_t} \tag{3}$$

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, $C_k = \left(C_k^{NNeg} + C_k^{Neg}\right)$. Once again, we adjust the raw measure for the characteristics of the underlying flow of earnings reports. The residual measure of tone is defined to be:

$$NetRCI_t = \frac{\sum_{k=1}^{K_t}(C_k^{NNeg} - \hat{C}_k^{NNeg}) - \sum_{k=1}^{K_t}(C_k^{Neg} - \hat{C}_k^{Neg})}{\sum_{k=1}^{K_t}\hat{C}_k} \tag{4}$$

As the residual tone of coverage in month t becomes more negative, $NetRCI$ declines.

Table 2 shows that RCI has a 0.30 correlation with $NetRCI$. Why the residual coverage of earnings is positively correlated with the residual tone is unclear. For the purposes of this study, we simply wish to disentangle attention from tone. Whereas RCI captures the intensity of the WSJ's attention to earnings, $NetRCI$ reflects the outcome of the WSJ's processing of the earnings information. We control for $NetRCI$ in our tests.

We introduce two new variables $RCI^{\perp}$ and $NetRCI^{\perp}$, which are RCI orthogonalized with respect to $NetRCI$ and vice versa, respectively. Table 3 shows that $RCI^{\perp}$ is also correlated with several measures of macroeconomic conditions indicating that attentiveness to earnings is higher when economic conditions are poorer. Specifically, $RCI^{\perp}$ is higher during recessions, when CAY is higher, and when output gap is lower. The magnitudes of these respective correlations are striking, 0.26, 0.48 and -0.27. Note that there are only two brief recessionary periods during our sample according to NBER, July 1990 – March 1991 and March 2001 – November 2001. The plots of RCI against CAY and output gap are shown in Figures 1 and 2 (along with NBER recessions). The comovement of the WSJ's attention to earnings with these macroeconomic measures is impressive. As the economy weakens, attention to earnings increases, implying that the WSJ views the marginal benefits of gathering and processing earnings information to be increasing as economic conditions decline.

Lastly, it is important to note that the variation in residual coverage intensity is strongly correlated with the variation in raw coverage intensity. That is, the correlation between $RCI^{\perp}$ and $CI^{\perp}$ is 0.63, as shown in Table 3. However, $CI^{\perp}$ behaves differently than $RCI^{\perp}$. Namely, $CI^{\perp}$ is uncorrelated with CAY and with the Baker-Wurgler measure of sentiment and is *negatively* correlated with dividend yield. This is consistent with raw coverage intensity's being a noisier measure of the dynamics in attention to earnings. We see this same message again when we observe that raw coverage intensity fails to track the equity premium (not tabulated). Hence, it is important to filter the underlying flow of earnings reports each month, as the residual measure of coverage intensity does.

1.4 Some insights about residual coverage intensity

To better understand the informativeness of RCI, it is 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. These variables even intuitively seem to capture useful dimensions of attention. That is, larger firms are more important to investors in terms of greater weightings in the typical investment portfolios; certain industries can be better indicators of the economy's condition; and the number of analysts following a firm is a coarse measure of attention to that 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 using the full specification. Forming residual coverage intensity using the reduced model preserves much of the behaviors we note for the larger specification. Namely, the reduced-model estimates of RCI display similar correlations with CAY, output gap, and recessions to those in Table 3, and the reduced-model's measure of the residual coverage intensity of earnings tracks the equity premium, post-earnings announcement drift, and return dispersion, as the full model is shown to do in later sections.

The important point here is that the temporal deviations from the WSJ's typical coverage of earnings covaries negatively with economic conditions. The WSJ's actions presumably reveal months when the perceived marginal benefits of gathering and processing earnings information are larger, and months when the perceived benefits are smaller. To further support this view, we examine how the WSJ changes the composition of the firms it covers.

Since less information is generally publicly available regarding smaller firms, gathering and processing information about smaller firms tends to be costlier. Therefore, we examine how the WSJ's coverage differs between small and large stocks as RCI changes. To do so, we separate months into three bins based on RCI. Months with RCI 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-decile level, rather than across all stocks. That is, we determine the number of earnings reports of firms within a given decile of size which the full-specification multinomial logit predicts will be covered, and then form RCI^{size} which measures the percentage deviation of actual coverage from predicted coverage within each respective size decile. Panel A of Table 4 reports the mean monthly values of RCI^{size}. The most striking result is the dramatically greater attention to smaller stocks in high-RCI months. While RCI^{size} increases only to 12% for the stocks in the largest decile during these high-RCI months, the magnitude of atypical coverage for the smallest stocks balloons to 113%. Moreover, the increase in coverage is nearly monotonic from largest to smallest. Panel B shows the number of earnings reports per month that are actually covered. Note that the sum of earnings reports actually covered across the five smallest deciles when attention is high (30 articles) is on par with that of the largest decile (27 articles). Because predicted coverage in general is much lower for these smaller stocks, a given increase in the actual number of articles increases the measure of residual coverage by much greater for these stocks.

We can also see the opposite pattern in the low-RCI months: The WSJ reduces its coverage of stocks in the smallest five deciles more than they reduce their coverage of stocks in decile 10. Interestingly, these changes in attention to smaller stocks do not appear symmetric across high-RCI and low-RCI months. That is, the increase in attention to smaller stocks in weaker economic times is much stronger than the decrease in attention to smaller stocks in better economic times. This suggests that the marginal benefits of small-firm earnings information varies more when going from normal to weaker economies than when going from normal to stronger economies.

The findings in Table 4 are consistent with the WSJ's bearing greater costs in the high-RCI months to gather more information across a broader set of stocks. Moreover, the driver of the time series variation in the WSJ's attention to earnings is the variation in attention to smaller firms, which typically receive far less attention than the largest firms.

2 Attention to Earnings and the Equity Premium

2.1 Tracking the equity premium

In the prior section, we find that the attentiveness of the WSJ to earnings information increases as macroeconomic conditions worsen. This finding is consistent with theories of the rational allocation of attention which predict that the marginal benefits of becoming better informed about the valuations of risky assets will increase during weaker economic times (Andrei and Hasler (2015), Kacperczyk et al. (2015), and Bansal and Shaliastovich

(2011)). During such times, the equity risk premium should also be greater. Therefore, to further establish a link between the state of the economy and attention to earnings, we examine the relation between the equity premium and RCI.

In Table 5, 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 RCI from month t. Given the moderate persistence in RCI, with an autocorrelation of 0.62, and the overlapping of $(K-J)$ months of the dependent variable across adjacent calendar months, we form p-values which adjust for spurious rejection rates of the null hypothesis due to relatively high serial autocorrelations in the residuals. To do so, we turn to Monte Carlo simulations. We form 10,000 simulated samples of two independently and normally distributed random variables with AR(1) coefficients matching those of RCI ($\phi = 0.62$) and $NetRCI$ ($\phi = 0.43$), respectively. We regress our actual sample of log excess stock returns on the simulated samples over the various monthly horizons in Table 5. We then calculate the frequency of observing Newey-West t-statistics with six lags that are greater than a given t-statistic found in Table 5 (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. These simulated p-values are shown in brackets underneath the t-statistics in Panel A of Table 5.

Table 5 finds that RCI tracks the equity premium. RCI is significant over months (+1,+6) at the ten-percent level and over months (+1,+12) at the five-percent level. Moreover, while the t-statistics for each distinct quarter following month t, i.e, $(+1, +3)$, $(+4, +6)$, $(+7, +9)$, and $(+10, +12)$, are not individually very impressive, note that the coefficient estimates on RCI are fairly stable around 0.01. Examining the informativeness of RCI jointly across multiple horizons provides a more powerful, and more stringent, test of the explanatory power of RCI, as opposed to just relying on a potentially spurious result from any single horizon (Boudoukh et al. (2008)). In general, we find that the p-values testing the joint significance of RCI across two or more horizons to be statistically significant. For example, Panel B of Table 5 shows the simulated p-value testing the null hypothesis that the coefficients on RCI are jointly zero over months (+1,+3) and (+4,+6) to be 3.1% despite neither coefficient being individually significant. And RCI is jointly significant at the five-percent level over months $(+1, +6)$ and $(+1, +12)$. Jointly testing all four quarters in the first 12 months is even more impressive with a p-value less than 0.001. In short, the relatively stable coefficients across multiple horizons is strongly evidencing that RCI possesses genuine explanatory power for stock returns during the next year.

The economic magnitude of the relation is also impressive. The reported coefficients in Table 5 are with respect to standardized coefficients and can be easily interpreted. A one standard deviation increase in RCI 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 $RCI^{\perp}$. The explanatory power of $RCI^{\perp}$ 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%.

The explanatory power for the next twelve months of returns is however not as evenly dispersed across the quintiles as the explanatory power for the next six months. This foreshadows the finding in the next section that the explanatory power of RCI is weaker over months (+1,+12) when controlling for measures of the economic state, while RCI remains strongly linked to stock returns over months (+1,+6). Although not shown in the tables, we also find that RCI is unrelated to lagged stock returns over months $(-6, -1)$ and $(-12, -1)$. In sum, RCI captures variation in the equity premium; attention to earnings intensifies when the equity premium is higher.

2.2 RCI provides new information on the equity premium

Recall that RCI is strongly correlated with some macroeconomic measures, such as CAY and output gap. It is therefore interesting to examine whether the explanatory power of RCI for stock returns is more than a redundant repackaging of commonly used macroeconomic measures. To assess this, we rerun the regressions of excess stock market returns on RCI controlling for a set of eleven macroeconomic variables purported to explain variation in the equity premium. These macroeconomic measures are detailed in section A.1.2 of the Appendix and are the log of the dividend yield, log of net payout yield, T-bill rate, CAY, output gap, book-to-market ratio at the market level, default spread, term spread, equity share of new issues, dividend premium, and sentiment.

Interestingly, controlling for the macro variables reveals information in RCI at a shorter horizon than that observed in Table 5. In Table 6, we see that RCI is informative about stock returns over months $(+1, +3)$ and $(+1, +6)$ respectively, with each simulated p-value less than 0.10. In contrast to Table 5, the explanatory power of RCI when controlling for the macro variables is not evident for months (+1,+12). As before, the joint testing of RCI across multiple horizons is strong. The p-values for the joint sets of coefficients on RCI across various combinations of windows over the first six months and the first twelve months respectively are all less than 0.05, as shown in Panel B. Hence, RCI provides explanatory power for the equity premium that is orthogonal to the set of macroeconomic measures.

The fact that the WSJ's coverage of earnings reveals new information about the equity premium is encouraging as it suggests that the observable actions of information agents may reveal to econometricians some aspects of the conditional yet unobservable information structure used by investors. As a preliminary investigation, we reform residual coverage intensity adding the eleven macroeconomic variables as determinants in the multinomial logit and find the resulting recalculated residual measure of coverage to have no explanatory power for future stock returns. By construction then, this contrast in the explanatory power between the recalculated measure and RCI implies that the incremental effect of the macro variables on predicted coverage tracks expected stock returns. That is, the WSJ's coverage decisions seem to filter the information contained in the set of macroeconomic measures in a nonlinear way (through the multinomial logit) that provides incremental information about stock returns. This echoes the messages of Campbell and Thompson (2008) and Rapach et al. (2010) that commonly employed macroeconomic measures contain more information about the equity premium than previously observed.[9]

2.3 Residual tone of coverage

Lastly, although we do not focus on $NetRCI$ in this study, this measure of the residual net tone of coverage displays a short-term ability to forecast stock returns. Table 5 shows a simulated p-value of 0.023 for the coefficient on $NetRCI$ over months $(+1, +3)$. This aggregate tone result seems consistent with the well-known stock-specific continuation in returns following earnings surprises. However, recent studies of aggregate earnings surprises have encountered mixed evidence, with some researchers finding market-level return continuations and other researchers finding return reversals. In particular, Choi et al. (2013) argue that other studies fail to properly measure aggregate earnings surprises, and after making adjustments, they find return continuations. To the extent that our residual imbalance of negative versus nonnegative WSJ coverage of earnings captures investors' true aggregate earnings surprises, our findings for $NetRCI$ in Table 5 support the claims and findings of Choi et al. (2013). Note that $NetRCI$ can be considered an aggregation of earnings news incremental to the tone predicted based upon the earnings surprise (SUE) and other observable earnings-specific information. Moreover, the macroeconomic control variables which we examine in Table 6 dilute the explanatory power of $NetRCI$, indicating that the information in $NetRCI$ which is useful for explaining stock returns is tied to macroeconomic conditions.

3 Information Processing Varies with Attention

The prior sections find that attentiveness to earnings increases when economic conditions are poorer and when the equity risk premium is greater. These findings are consistent

[9] We find that RCI is a more robust determinant of the equity premium than the predicted WSJ coverage using the macro variables, which is presumably because the residual measure does not commit to a specific, yet misspecified model of the effects of the macro variables on WSJ coverage. The residual measure allows the WSJ's actions to reveal macroeconomic information in a more unfettered way.

with the rational allocation of limited attention, whereby more attention is allocated to the earnings news of firms when the marginal benefit of becoming better informed about the valuations of stocks is higher. We now consider whether stock prices in general are more informative about earnings news in months when attention to earnings releases is greater. We examine the information content of stock prices along several dimensions to paint a broad picture of how price informativeness varies with attentiveness to earnings.

3.1 Post-earnings announcement drift

If attention constraints bind on the price setting process, then we should see that earnings news is better impounded into stock prices when attention to earnings news is greater. We examine this hypothesis using the long-standing and anomalous post-earnings announcement drift in abnormal stock returns (hereafter "PEAD"; Bernard and Thomas (1989)). To the extent that PEAD is due to the market's inattentive underreaction to the earnings information, we expect the drift to be smaller for earnings announced in months when the attention to earnings is greater.

Each month we sort firms announcing earnings in that month based on their standardized unexpected earnings (SUE), defined as the announced earnings per share minus the median analyst forecast from the 30 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.[10] We then cumulate the abnormal daily returns for each stock (CARs) over a window beginning two days after the announcement and ending 60 days after the announcement. The CARs are then equally weighted within each month's long and short SUE portfolios respectively.[11]

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

[11] Note that we focus only on a post-event window because it is more easily interpreted. The relation between the event-window $CARs$ and RCI is not straightforward. Should greater attentiveness increase or decrease the price reaction to an earnings surprise? This is unclear. To answer requires a specification

We sort calendar months over the sample period into quintiles based on $RCI^{\perp}$ and then report the mean abnormal profits of the long-minus-short SUE portfolios for small and large stocks respectively. We examine large and small stocks separately because of the finding in section 1.4 that the temporal variation in RCI is driven by the variation in attention to smaller stocks. We define small stocks to be the lowest quintile of market capitalizations at the end of the prior month, based on NYSE breakpoints, and the largest stocks to be the top quintile of market capitalizations. The left panel of Figure 4 reveals that average PEAD profits decrease from nearly 6% over the [+2,+60] window for earnings surprises occurring in months with the least attention to earnings to less than 2% for earnings surprises occurring in months within the greatest attention to earnings.

We employ monthly cross-sectional regressions to examine the statistical significance of the negative relation between small stock PEAD and attention to earnings. Each month we regress the cross section of abnormal stock returns over days $[+2, +60]$ for each announcing firm on its SUE. Then, we regress the time series of monthly cross-sectional coefficients from the first-stage regression on RCI and $NetRCI$, with and without macroeconomics controls. Table 7 shows the second-stage results. We see that PEAD profits for small stocks decrease with RCI at a 1% level of significance (using simulated p-values). So, for smaller stocks where attention is expected to vary the most over time (Peng (2005)), and for which attention is empirically found to vary the most over time in Table 4, we detect a strong inverse relation.

For large stocks, however, we find no evidence that their PEAD profits vary with attention to earnings. Since the time variation in attention we detect is largely driven by variation in the coverage of small stocks' earnings reports, the lack of a relation between PEAD for large stocks and RCI is not that surprising. However, we must note that our ability to examine PEAD of large stocks is a bit hindered by the number of months in

of what items of earnings information are receiving more attention and what the effects of that increased attention on abnormal returns might be, which is beyond the scope of our exercise here. For example, see Hirshleifer et al. (2011) for contrasts between attention to earnings and attention to accruals. In our case, if greater attention to earnings reports leads investors to become less reliant on SUE as a summary number and more reliant on other information in the earnings report, the price reactions to SUE may decrease with attention. In support of this, we find that the cross sectional dispersion of event-window CARs is increasing in RCI, while the mean event-window CAR decreases.

which few large stocks release earnings. As a consequence, we examine quintiles of SUE for large stocks, rather than deciles as we do for small stocks, and we require a minimum of 10 earnings reports each month for the long and short portfolios. This filter reduces the number of usable large-stock sample months from 255 to 170. The right panel of Figure 4 shows that RCI has no explanatory power for PEAD in large stocks. We further investigate a relation using the cross-sectional regression approach. A potential benefit with the regression approach in Table 7 is that we can extract more information when confronted with just a few stocks 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. In short, we detect no relation between large stocks' PEAD and RCI.

Overall, RCI seems to successfully identify months when the prices of small stocks respond more quickly to the information in their earnings surprises. This supports the hypothesis that increases in attentiveness to earnings are associated with increases in the amount of earnings information being impounded into market prices.

Lastly, recall from Table 1 that, on average, only about 11% of earnings releases per month receive WSJ coverage. Indeed, the relation between RCI and small-stock PEAD that is documented in Table 7 is driven by the vast majority of earnings releases which do not receive coverage. Hence, RCI is serving as a proxy for broad attention to earnings news across the marketplace, not just as a proxy of investors' attention to those firms receiving WSJ coverage.

3.2 Processing of firm-specific news

Following further with the notion that more earnings information is impounded into prices when attention to earnings increases, we examine the relation between RCI and the cross-sectional dispersion of stock returns. Since our measure of attention is directly concerned with the aggregated coverage of firm-level earnings, we expect increases in RCI to capture times when more firm-level information is being gathered and processed. Greater processing of firm-level information generates greater dispersion across stock returns as investors update their stock valuations. As noted above, we expect this effect to be most apparent for small stocks.

We begin by sorting months into quintiles based on $RCI^{\perp}$. For each quintile, Figure 5 reports the mean monthly standard deviation of the cross section of returns, across small stocks and large stocks respectively. Again, small stocks are in the lowest quintile of market capitalization using NYSE breakpoints, and large stocks are in the highest quintile. We see that return dispersion among small stocks increases with $RCI^{\perp}$, from about 19% per month in the months with lowest attention to 24% in the months with greatest attention.

To assess statistical significance, we regress the time-series of return dispersion on RCI and $NetRCI$. We find in Table 8 that the relation between RCI and return 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 greater attention is indeed a driver of the increased dispersion in returns, rather than increased return dispersion being solely due to an increase in the dispersion of underlying stock fundamentals during weaker economic conditions (e.g., Gomes et al. (2003)).

For completeness, we report large-stock results in Figure 5 and Table 8. Despite mean return dispersion for large stocks falling slightly as RCI rises, from a little over 9% per month to a little under 8% in Figure 5, RCI is found to be unrelated to the return dispersion of large stocks in the regressions of Table 8, consistent with the lack of a relation between RCI and large-cap PEAD in the prior subsection.

Our analysis of return dispersion suggests that a greater amount of firm-level information is impounded into the prices of small-cap stocks when our measure of attention to earnings is higher. To provide even further evidence, we examine how the return synchronicity between small stocks' returns and the broad market's return changes with our attention measure.

Morck et al. (2000) employ $(1 - R^2)$ from a regression of stock returns on a market index as a measure of the informational efficiency of markets. The idea is that a better functioning, more efficient market impounds more firm-level information which results in stock returns being less synchronous; that is, $(1-R^2)$ increases for the average stock. Since $(1-R^2)$ increases with idiosyncratic volatility and decreases with systematic volatility, this measure can differ across securities for multiple reasons, as Bartram et al. (2012) highlight. For a better overall context, we also estimate the market betas of small stocks as attention to earnings changes.

We regress the value-weighted returns of small stocks on the CRSP value-weighted market index. Table 9 reports the beta and R^2 within quintiles of months based on $RCI^{\perp}$. We estimate beta and R^2 using two methods. The first uses daily betas as instruments for conditional monthly betas, following Carlson et al. (2010). The second simply runs an OLS regression within each quintile's subsample of months separately.

The instrumental variables approach has three steps. Rolling 3-month betas are estimated using daily data and the lag structure in returns employed by Lewellen and Nagel (2006) to accommodate nonsynchronous trading.

$$r_{s,t} = a + b_0 r_{M,t} + b_1 r_{M,t-1} + b_2 \left(\frac{r_{M,t-2} + r_{M,t-3} + r_{M,t-4}}{3} \right) + \epsilon_{s,t} \tag{5}$$

The *daily* beta estimate for small stocks is then $\hat{b}_0 + \hat{b}_1 + \hat{b}_2$.[12] The second step is to use the daily beta estimates from 3 months prior as instruments for this month's daily beta to mitigate measurement error. Carlson et al. (2010) note that the use of a nonoverlapping lag generates a much less biased estimate. The final step is to employ the lagged fitted values of the *daily* beta as an instrument for the *monthly* beta as follows.

$$r_{s,t} = A + B_0 r_{M,t} + B_1 \left(\hat{\beta}_{s,t-1} \cdot r_{M,t} \right) + u_{s,t} \tag{6}$$

where the conditional estimate of beta in month t, which we desire, equals $\hat{B}_0 + \hat{B}_1 \hat{\beta}_{s,t-1}$.

[12] Qualitatively similar results are found when estimating beta with only the contemporaneous term.

Table 9 reports the beta estimates using the instrumental variables method and also using OLS on only the subset of observations within each respective quintile of $RCI^{\perp}$. The corresponding R^2s are also reported. For the IV betas, the R^2 within each quintile is calculated as: $R^2_{IV} = 1 - \frac{\sum(r_{s,t} - \hat{r}_{s,t})^2}{\sum(r_{s,t} - \bar{r}_s)^2}$, where the fitted values are based on the full-sample parameters for the IV beta estimates but the mean return is allowed to vary across quintiles of $RCI^{\perp}$. Thus, the R^2_{IV} decreases when the variance of the residual return in equation 6 increases relative to the total variance of stock returns.

Although there is a bit of a U-shaped pattern in both estimates of small stocks' betas in Table 9, the general tendency is for the beta of small stocks to decrease as attention to earnings increases.[13] To the extent that the fundamental betas of small stocks are independent of attention, these findings suggest that changes in attention can effect beta estimates. The relation between attention and beta warrants future investigation.

However, the more striking pattern is the precipitous decline in R^2 as attention increases. Goyal and Santa-Clara (2003) show that cross-sectional return dispersion is approximately equivalent to the average standard deviation of stock returns. So, with the typical small firm's total risk found to be increasing with attention in Table 8, Table 9 indicates that more firm-specific information is being processed into small-stock prices when attention to earnings increases. More generally, the returns of small stocks decouple from the returns of large stocks when attention to earnings is high.[14]

3.3 Pricing of firm-specific versus systematic information

With evidence in hand that the market's impounding of firm-specific information into small stock prices increases when attention to earnings is higher, we examine whether

[13] Notwithstanding potential nonlinearities, evaluating the statistical significance of the variation in beta and R^2 across quintiles of RCI is not straightforward. We leave further examinations of attention and second moments of returns for future work.

[14] The return variance of the value-weighted portfolio of small stocks seems to decrease with attention to earnings. So, while the volatility in the idiosyncratic component of returns increases, systematic volatility may decrease. This is consistent with diversification benefits increasing as the market processes more firm-level information, thereby reducing return correlations across stocks. This is also consistent with a decline in the processing of systematic news as attention shifts away from systematic information. The return variance of the value-weighted portfolio of large stocks also seems to decline with attention to earnings. A deeper examination of second moments of returns is beyond the scope of this paper.

the market's processing of systematic information varies too. One of the centerpieces of the limited attention literature is the tradeoff between attending to one thing at the expense of not attending to another. Peng and Xiong (2006) and Kacperczyk et al. (2015) highlight the tradeoff between attending to systematic information versus firm-specific information. Given that our attention measure focuses on firm-specific earnings releases, we explore whether the processing of systematic information relates to our measure of attention. Following Lo and MacKinlay (1990), Hou (2007), and many others, we turn to the well-documented finding that returns of large stocks lead the returns of small stocks. One source of this lead-lag relation seems to be a slow diffusion of systematic news into small stock prices. We discuss other interpretations shortly. In this section, we ask whether the lead-lag effect is greater when attention to earnings is greater.

We begin by estimating the cross-serial correlations between the returns of large stocks and small stocks within each quintile of $RCI^{\perp}$ in month t. For the months within each quintile, we regress value-weighted returns of small stocks in month $t+1$ on value-weighted returns of large stocks in month t. Table 10 shows the coefficients. When $RCI^{\perp}$ is lowest, a 1% increase in large stock returns this month implies a 0.195% increase in small stock returns next month. When $RCI^{\perp}$ is highest, the coefficient is 0.515%. To determine statistical significance, we run the regression across all months and include an interaction term between large stock returns and $RCI^{\perp}$. The results are below, with t-statistics in parentheses underneath each coefficient.

$$\begin{aligned} r_{SM,t+1} =& \underset{(1.69)}{0.01} + \underset{(4.48)}{0.37} r_{LG,t} + \underset{(2.20)}{0.20} \left(r_{LG,t} \times RCI_t\right) \\ &- \underset{(-1.16)}{0.00} RCI_t + \underset{(0.07)}{0.00} NetRCI_t + \epsilon_{SM,t+1} \end{aligned} \tag{7}$$

The significantly positive coefficient on the interaction term indicates that the lead-lag relation increases as attention to earnings increases.[15] Adding the set of eleven macroeconomic controls to equation (7) has little effect on the coefficient on large stocks' returns, dropping the coefficient estimate to 0.18 and the t-statistic to 1.99. Hence, the systematic

[15] The observation pairing September 1987 with October 1987 is removed due to its extreme influence on the regression. The t-statistic on the interaction term falls from 2.20 to 1.56 when including this observation.

news contained in large stock returns disseminates more slowly through small stock prices when attention to earnings is higher.

Beyond the slow incorporation of systematic news into small stock prices, nonsynchronous trading and time variation in expected returns have been identified as potential sources of the lead-lag effect between large and small stocks (e.g., see Lo and MacKinlay (1990), Conrad et al. (1991), Ahn et al. (2002)). Our use of value-weighted portfolios and monthly returns should greatly diminish the contributions of nonsynchronous trading to the lead-lag relation. And, consistent with Hou (2007), we find that the lagging of small stocks behind large stocks is orthogonal to the autocorrelation in small stocks' returns, suggesting that delayed reaction to systematic news is the source of the lead-lad effect, not time variation in the expected returns of small stocks. Specifically, the interaction term in equation (7) is nearly unaltered when lagged small stocks' returns are included as an additional determinant, with the coefficient on the interaction becoming 0.21 with a t-statistic of 2.35.[16] The finding that the lead-lag effect between large and small stocks' returns increases during months when attention to earnings is higher implies that the market's processing of systematic news lessens when the processing of firm-specific news greatens. This is novel evidence of underreactions being a source of the lead-lag effect across large stocks' and small stocks' returns, and jointly, of the underreactions being due to limited attention.[17]

[16] We find no evidence that the delay in processing systematic news from month t extends into month $t+2$ for any of the quintiles of $RCI^{\perp}$. To the contrary, the only effect we find is mild evidence of price reversal for the second quintile. The coefficient on large stocks' returns in month t when explaining small stocks' returns in month $t+1$ is 0.36 for the second quintile in Table 10 and significant at the 5% level. The corresponding coefficient when explaining small stocks' returns in month $t+2$ is -0.35 and significant at the 10% level (not tabulated), which is unaffected by controlling for large stocks' returns in month $t+1$.

[17] Our findings are not necessarily inconsistent with the message of Kacperczyk et al. (2015) that agents, during weaker economic times, should allocate greater attention to systematic news rather than to firm-specific news. First, their analysis does not preclude that allocations to both types of news increase in weaker times, e.g., when CAY is higher or when output gap is lower. We do not measure attentiveness to systematic information, so we cannot assess their prediction about a relative change in allocations. Second, the evidence from Table 10 of a tradeoff between firm-level news and systematic news is orthogonal to variation in the business cycle (as measured by the eleven macro variables). So, we are empirically identifying variation in attention to earnings that is not examined by Kacperczyk et al. (2015). Expanding their framework to explore more complex time-series dynamics in information choices may be useful.

4 Conclusion

We construct a measure of the attention that *The Wall Street Journal* pays to earnings reports. Since the WSJ is an information agent, we interpret the WSJ's attentiveness to earnings to be a proxy for investors' attentiveness more broadly. Our empirical findings support several predictions from recent theories of the rational allocation of limited attention towards risky assets. Namely, more attention is allocated to earnings when economic conditions weaken, and when more attention is allocated to earnings, stock prices more fully reflect earnings news. The improvement in the informativeness of stock prices with respect to firm-specific earnings news comes at the expense of stock prices being less reflective of systematic news.

Measuring the attention of a single agent is easier than measuring aggregate attention across many agents in the economy. Our findings imply that the attention of the WSJ is a useful proxy for the attention of other agents in the financial marketplace. This suggests that employing the WSJ as a representative agent can be fruitful for achieving a better understanding of the role of information acquisition in the price setting process. Several potentially interesting questions are raised by the findings in this paper. Such as, how are beta estimates of securities affected by changes in attention to firm-specific news? Why is the aggregated net tone of the WSJ's coverage related to short-term stock market returns? How does systematic volatility vary with attention to firm-level news? These topics are left to future research.

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

A.2.1 Base Model

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	

A.2.2 Base Model with Macro Variables

Table A.2 Predicting WSJ coverage with macroeconomic variables

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 if the announcement receives negative coverage, 1 if it receives nonegative coverage, and 0 if no coverage is received (the base case). Variable definitions are in section A.1. t-statistics (in parentheses) are computed using standard errors clustered by firm; * significant at 10%; ** significant at 5%;*** significant at 1%.

	Media coverage	
	-1	1
PDND$_{t-1}$	0.0123***	0.00242*
	(5.89)	(1.75)
Risk-free rate$_{t-1}$	24.39***	10.17***
	(8.67)	(5.05)
B/M$_{t-1}$	2.546***	1.138***
	(6.24)	(3.65)
log(Div. Yield)$_{t-1}$	-1.730***	-0.424**
	(-8.22)	(-2.57)
Def. Spread(baa-aaa)$_{t-1}$	35.12***	-34.03***
	(4.08)	(-5.21)
log(Net Payout Yield)$_{t-1}$	-0.994***	-0.592***
	(-5.43)	(-4.07)
CAY$_{t-1}$	19.03***	14.01***
	(12.14)	(11.25)
Term Spread$_{t-1}$	0.118***	0.0955***
	(4.73)	(5.36)
Equity Share of New Issues$_{t-1}$	1.160***	0.372
	(3.72)	(1.45)
Sentiment$_{t-1}$	-0.307***	-0.358***
	(-7.42)	(-10.07)

Output Gap$_{t-1}$	-6.818***	1.877***
	(-7.84)	(2.76)
UE quantile 11	0.864***	0.579***
	(11.71)	(8.20)
UE quantile 10	0.466***	0.384***
	(7.20)	(6.90)
UE quantile 9	0.160**	0.290***
	(2.43)	(5.82)
UE quantile 8	-0.0776	0.176***
	(-1.21)	(3.90)
UE quantile 7	-0.445***	0.00157
	(-6.52)	(0.04)
UE quantile 5	0.0864	-0.0449
	(1.35)	(-0.95)
UE quantile 4	0.590***	-0.00720
	(9.20)	(-0.13)
UE quantile 3	0.907***	0.177***
	(13.88)	(2.90)
UE quantile 2	1.036***	0.252***
	(14.67)	(3.43)
UE quantile 1	1.267***	0.355***
	(15.91)	(3.17)
Loss dummy	1.074***	-1.379***
	(19.24)	(-16.76)
stdev(analyst forecasts)	0.0547***	-0.101***
	(4.57)	(-2.72)
log(analyst coverage)	0.370***	0.325***
	(9.56)	(7.47)
log(MVE)	0.387***	0.518***
	(10.60)	(12.51)
log(value of trading)	0.312***	0.325***
	(10.50)	(9.52)
Beta	-0.113***	0.000993
	(-4.75)	(0.04)
Recent returns	-0.00254***	-0.00220***
	(-4.98)	(-4.21)
stdev(Recent returns)	0.355	-12.55***
	(0.26)	(-6.25)
B/M	0.580***	0.376***
	(20.78)	(9.40)
Distraction	-0.0369***	-0.0648***
	(-3.20)	(-5.22)
Seasonality and industry (FF-49) dummies	Yes	Yes
Observations	232585	
Pseudo R^2	0.278	

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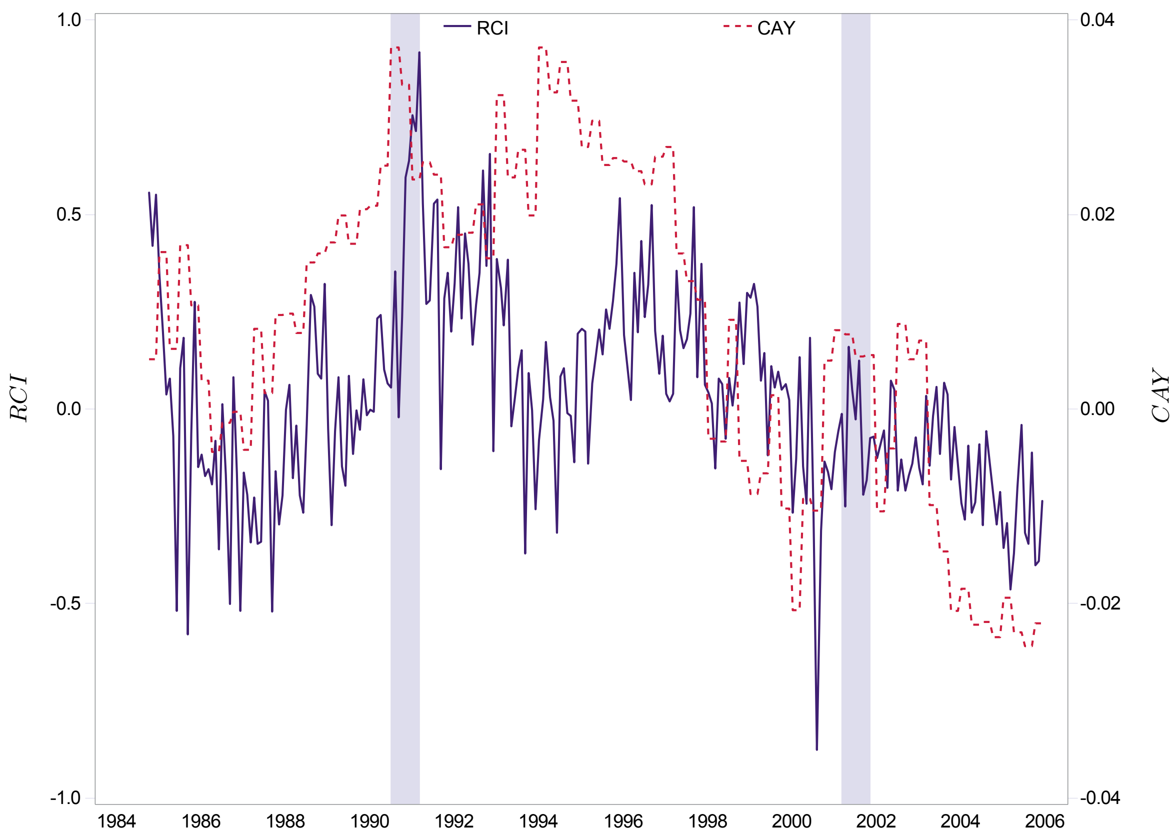

Figure 1: RCI Moves With CAY. The monthly RCI series is plotted against the quarterly CAY series. RCI is defined in equation 2. CAY is the consumption-wealth ratio of Lettau and Ludvigson (2001). The shaded regions are NBER recession periods.

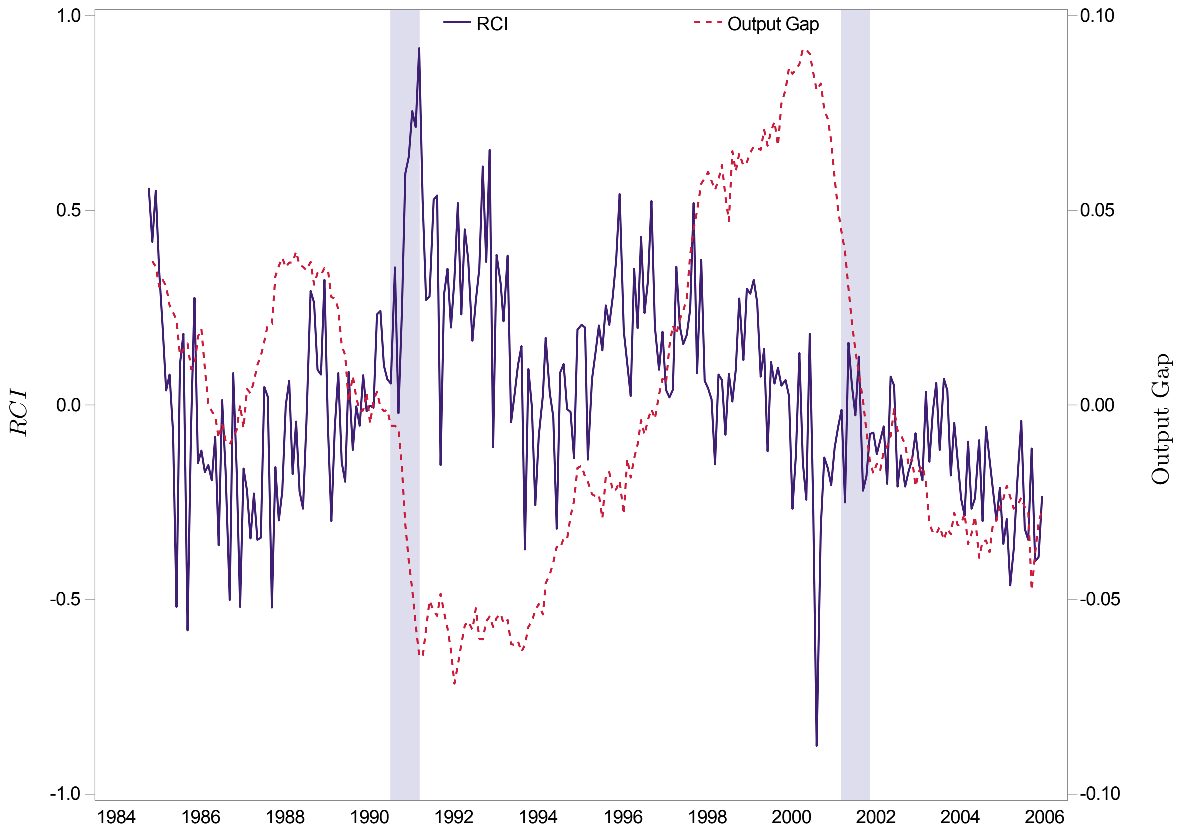

Figure 2: RCI Moves Inversely With Output Gap. The monthly RCI series is plotted against the monthly output gap series. RCI is defined in equation 2. Output gap is the residual from the quadratic monthly time trend in the natural logarithm of Industrial Production as from Cooper and Priestley (2009). The shaded regions are NBER recession periods.

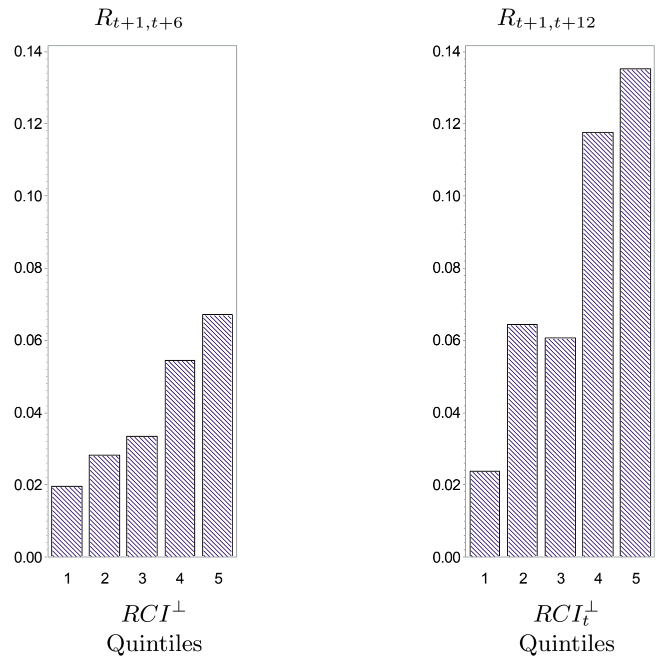

Figure 3: RCI and Equity Premium. Months are sorted into quintiles based on $RCI^{\perp}$. Means of excess stock returns within each quintile are plotted for months (+1,+6) in the left panel and for months (+1,+12) in the right panel.

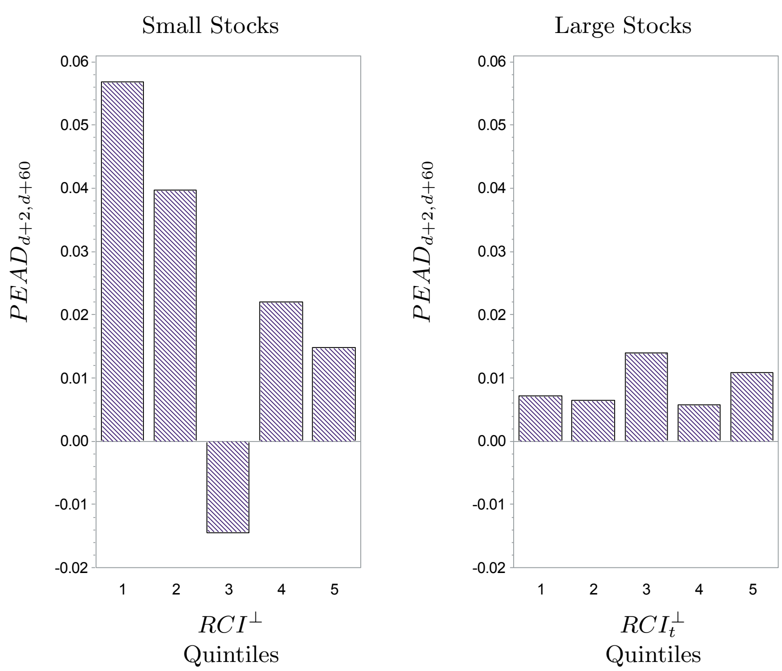

Figure 4: RCI and Post Earnings Announcement Drift. Months are sorted into quintiles based on $RCI^{\perp}$. Means of PEAD profits are plotted for days (+2,+60) within small stocks in the left panel ($\leq 20^{th}$ percentile using NYSE breakpoints) and within large stocks in the right panel ($> 80^{th}$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

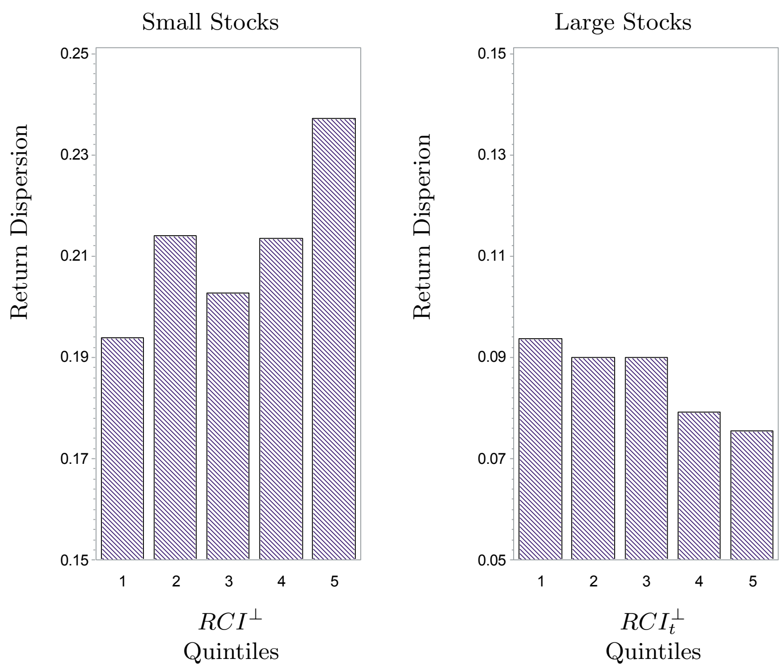

Figure 5: **RCI and Return Dispersion**. Months are sorted into quintiles based on $RCI^{\perp}$. Means of monthly cross-sectional standard deviation of returns are plotted within small stocks in the left panel ($\leq 20^{th}$ percentile of market cap using NYSE breakpoints) and within large stocks in the right panel ($> 80^{th}$ percentile of market cap using NYSE breakpoints). Different scales for return dispersion 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). *Coverage Intensity* (*CI*) is the proportion of earnings releases actually covered. *NetCI* is the number of nonnegative articles minus the number of negative articles divided by the number of earnings released. *RCI* is the deviation of the actual number of earnings covered from the expected number covered, while *NetRCI* is the deviation of the actual net tone of the coverage from the expected net tone (see equations 2 and 4). *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
Coverage Intensity (CI)	0.11	0.03	0.06
NetCI	0.03	0.03	0.26
Residual Coverage Intensity (RCI)	0.03	0.26	0.62
NetRCI	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

Below are monthly correlations from October 1984 to December 2005. RCI and $NetRCI$ are residual coverage intensity and residual coverage tone, respectively, described in equations (2) and (4). The raw measures of coverage intensity and tone are CI and $NetCI$, respectively, defined in equations (1) and (3). P-values are listed below each correlation coefficient; * indicates significance at 10%,** significance at 5%, and *** significance at 1%.

	RCI	NetRCI	# Articles	Net # Articles	# Announcements	Articles/Ann.
RCI	1.000					
NetRCI	0.302	1.000				
	(0.00)					
Number of Earnings Covered	0.125	0.095	1.000			
	(0.05)	(0.13)				
Number of Earnings Released	−0.019	0.068	0.964	0.825	1.000	
	(0.76)	(0.28)	(0.00)	(0.00)		
Coverage Intensity (CI)	0.547	0.180	0.222	0.149	0.032	1.000
	(0.00)	(0.00)	(0.00)	(0.02)	(0.61)	
NetCI	0.079	0.723	0.285	0.560	0.222	0.385
	(0.21)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Table 3
Correlations

$RCI^{\perp}$ and $NetRCI^{\perp}$ are respectively RCI and $NetRCI$ 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 (Lettau and Ludvigson (2001)), sampled quarterly. *OutputGap* is the residual from the quadratic time trend in log U.S. industrial production. *TermSpread* is the month-end 10-year minus 3-month Treasury yield spread. *Sentiment* is from Baker and Wurgler (2006) . $CI^{\perp}$ and $NetCI^{\perp}$ are respectively CI and $NetCI$ orthogonalized with respect to each other. P-values are listed below each correlation coefficient; * indicates significance at 10%,** significance at 5%, and *** significance at 1%.

	RCI$^{\perp}$	NetRCI$^{\perp}$	Recession	CAY	Output Gap	Term Spread	log(Div. Yield)	Sentiment	Articles/Ann.$^{\perp}$
RCI$^{\perp}$	1.000								
NetRCI$^{\perp}$	−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)		
CI$^{\perp}$	0.634	−0.277	0.216	−0.005	−0.228	0.159	−0.155	−0.034	1.000
	(0.00)	(0.00)	(0.00)	(0.94)	(0.00)	(0.01)	(0.01)	(0.59)	
NetCI$^{\perp}$	−0.400	0.812	−0.275	−0.136	0.213	−0.176	−0.093	−0.105	−0.385
	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.14)	(0.09)	(0.00)

Table 4

Earnings Coverage by RCI and Size Groupings

Months from October 1984 to December 2005 are ranked based on RCI into the lowest 25%, highest 25%, and remaining "normal" months. RCI^{size} is calculated analogously to RCI but within each size decile in a given month, from smallest (decile 1) to largest (decile 10). The means of RCI^{size} and the means of the actual number of earnings reports covered within each decile are given across high-RCI, normal-RCI, and low-RCI months.

RCI	(Smallest) 1	2	3	4	5	6	7	8	9	(Largest) 10
Panel A: Mean of RCI^{size}										
Low	−0.30	−0.42	−0.45	−0.52	−0.43	−0.42	−0.31	−0.20	−0.13	−0.21
Normal	0.11	−0.05	−0.09	−0.04	−0.01	0.06	0.06	0.06	0.07	−0.02
High	1.13	0.81	0.76	0.52	0.38	0.43	0.44	0.24	0.27	0.12
Panel B: Mean of Actual Number of Earnings Covered per Month										
Low	1.9	2.1	2.2	2.5	3.7	4.3	6.6	10.4	17.4	24.1
Normal	3.6	3.9	4.1	4.9	5.8	7.3	9.2	13.3	18.7	27.9
High	4.7	5.3	6.1	6.4	7.3	8.9	10.5	12.7	18.3	27.0

Table 5

Residual Coverage Intensity and the Equity Premium

The dependent variable is the log of the return of the CRSP value-weighted index minus the one-month T-Bill rate across various horizons from months $t{+}J$ to $t{+}K$. RCI_t and $NetRCI_t$ are the month t measures of residual coverage intensity and residual tone, respectively, defined in equations (2) and (4). Both explanatory variables are standardized. The t-statistics in parentheses are calculated using Newey-West standard errors with 6 lags. The 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 of 0.62 and 0.43, representing RCI and $NetRCI$ respectively. Asterisks correspond to the simulated p-values. * indicates significance at 10%,** significance at 5%, and *** significance at 1%. Panel B reports the simulated p-values of the given joint hypothesis that the coefficients on RCI in Panel A are zero across the horizons indicated.

A. Regressions of Excess Stock Returns

	(+1,+3)	(+4,+6)	(+7,+9)	(+10,+12)	(+1,+6)	(+7,+12)	(+1,+12)	(+13,+24)
RCI	0.00775	0.0111	0.00907*	0.00863	0.0189*	0.0177*	0.0366**	0.0147
	(1.26)	(1.81)	(1.89)	(1.63)	(1.97)	(2.02)	(2.51)	(1.12)
	[0.250]	[0.111]	[0.094]	[0.149]	[0.097]	[0.098]	[0.047]	[0.345]
NetRCI	0.0156**	0.00125	−0.0103	0.00439	0.0169	−0.00592	0.0109	−0.0265
	(2.51)	(0.18)	(−1.42)	(0.84)	(1.62)	(−0.52)	(0.59)	(−1.66)
	[0.023]	[0.853]	[0.203]	[0.443]	[0.168]	[0.084]	[0.608]	[0.147]
Constant	0.0181	0.0170	0.0166	0.0175	0.0350	0.0341	0.0691	0.0644
	(2.60)	(2.43)	(2.32)	(2.44)	(2.84)	(2.68)	(3.43)	(3.15)
Observations	255	255	255	255	255	255	255	255
R^2	0.060	0.022	0.021	0.019	0.077	0.027	0.079	0.033

B. Multiple-Horizon Tests of Coefficients on RCI

Horizons	Simulated P-Value of Joint Significance
$(+1,+3) \cap (+4,+6)$	0.031
$(+1,+6) \cap (+1,+12)$	0.029
$(+1,+3) \cap (+4,+6) \cap (+7,+9) \cap (+10,+12)$	0.000

Table 6

Residual Coverage Intensity, Macroeconomic Measures, and the Equity Premium

The dependent variable is the log of the return of the CRSP value-weighted index minus the one-month T-Bill rate across various horizons $t+J$ to $t+K$. RCI_t and $NetRCI_t$ are the month t measures of residual coverage intensity and residual tone, respectively, defined in equations (2) and (4). 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 6 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 RCI and $NetRCI$ respectively. Asterisks correspond to simulated p-values. * indicates significance at 10%,** significance at 5%, and *** significance at 1%. Panel B reports the simulated p-values of the given joint hypothesis that the coefficients on RCI in Panel A are zero across the horizons indicated.

A. Regressions of Excess Stock Returns

	(+1,+3)	(+1,+6)	(+1,+12)
RCI	0.0150*	0.0214*	0.0208
	(2.07)	(2.36)	(1.63)
	[0.091]	[0.078]	[0.234]
NetRCI	0.0109	0.00918	0.0066
	(1.38)	(1.03)	(0.78)
	[0.252]	[0.412]	[0.550]
Macro Controls	Yes	Yes	Yes
Constant	0.951	0.731	−0.489
	(1.99)	(1.21)	(−0.80)
Observations	255	255	255
R^2	0.211	0.327	0.502

B. Multiple-Horizon Tests of Coefficients on RCI

Horizons	Simulated P-Value of Joint Significance
$(+1,+3)\cap(+1,+6)$	0.036
$(+1,+6)\cap(+1,+12)$	0.048
$(+1,+3)\cap(+1,+6)\cap(+1,+12)$	0.024

Table 7
Residual Coverage Intensity and Post Earnings Announcement Drift

The dependent variable is the time-series of monthly coefficients from a cross-sectional regression of cumulative abnormal returns from day +2 to day +60, relative to each announcement in month t, on standardized unexpected earnings. Regressions of the first-stage coefficients on RCI and $NetRCI$ in the contemporaneous month are reported below. Large and small stocks are defined as those above the 80^{th} percentile of market capitalization using NYSE breakpoints in the prior month and those 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 3 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 RCI and $NetRCI$ respectively. Asterisks correspond to the simulated p-values; * indicates significance at 10%,** significance at 5%, and *** significance at 1%.

	Small Stocks		Large Stocks	
RCI	−0.140***	−0.165***	−0.195	0.035
	(−2.96)	(−3.10)	(−0.97)	(0.14)
	[0.007]	[0.006]	[0.339]	[0.892]
NetRCI	0.050	0.0670	0.107	−0.163
	(1.33)	(1.40)	(0.51)	(−0.77)
	[0.204]	[0.200]	[0.630]	[0.474]
Macro controls	No	Yes	No	Yes
Constant	0.173	−0.547	0.520	5.763
	(3.95)	(−0.19)	(3.14)	(0.55)
Observations	255	255	170	170
R^2	0.04	0.14	0.01	0.08

Table 8
Residual Coverage Intensity and Return Dispersion

Monthly standard deviation of the cross section of returns is regressed on RCI, $NetRCI$, 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 6 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 RCI and $NetRCI$ 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	
RCI	0.016***	0.019***	−0.007	0.000
	(2.76)	(4.35)	(−1.54)	(0.09)
	[0.007]	[0.000]	[0.203]	[0.949]
NetRCI	−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 9

Small Stocks and Systematic Risk

For stocks with market capitalizations less than or equal to the 20^{th} percentile using NYSE breakpoints, we estimate betas and R^2 with respect to the CRSP value-weighted index. The IV method is a three-stage procedure employing daily betas as instruments for monthly betas. Means of betas and R^2 are reported for months within each quintile of $RCI^{\perp}$. The subsamples method regresses returns of a value-weighted portfolio of small stocks on the returns of the CRSP value-weighted index using only the monthly observations within each quintile of $RCI^{\perp}$ respectively.

Quintile of $RCI^{\perp}$	IV Method		Subsamples	
	β	R^2	β	R^2
1 (Low)	1.12	0.74	1.13	0.75
2	1.09	0.61	1.10	0.60
3	1.02	0.69	1.04	0.67
4	1.03	0.29	0.72	0.40
5 (High)	1.05	0.38	0.94	0.34

Table 10

Large Stocks' Leading of Small Stocks

Months are sorted into quintiles based on $RCI_t^{\perp}$. Within each quintile, returns of small stocks in month $t+1$ are regressed on returns of large stocks in month t. Coefficients and t statistics (in parentheses) are reported below. Large and small stocks are defined as above the 80^{th} percentile of market capitalization using NYSE breakpoints and less than or equal to the 20^{th} percentile, respectively. The observation pairing September 1987 with October 1987 is excluded (see footnote 15). t-statistics are in parentheses; * indicates significance at 10%,** significance at 5%, and *** significance at 1%.

Quintile of $RCI^{\perp}$	Coefficient on Large Stocks
1 (Low)	0.195
	(1.15)
2	0.363**
	(2.19)
3	0.274
	1.48)
4	0.450**
	(2.54)
5 (High)	0.515**
	(2.34)