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# Analysts Get SAD Too: The Effect of Seasonal Affective Disorder on Stock Analysts' Earnings Estimates

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Previous research finds that stock analysts exhibit both optimistic and pessimistic biases in their earnings forecasts, with the net result being a consistent but declining overestimation of forecasted earnings. We extend this research by examining the potential effect of seasonal affective disorder (SAD), a documented psychological condition that produces heightened pessimism and risk aversion during the fall and winter months, on stock analysts' earnings estimates. Our results suggest that analysts are generally optimistic in their forecasts but significantly less so during SAD months. We also find this relation to be most pronounced for analysts located in northern states, who should be the ones most impacted by the disorder. We conclude that while the effect of SAD appears to be present, it actually seems to overcome an existing positive bent in earnings forecasts, thereby making estimates more accurate. Our findings add to the existing literature by identifying an additional psychological bias that could potentially influence stock analysts' earnings estimates.

***Keywords:*** Analyst forecasts, Seasonal affective disorder (SAD)

## INTRODUCTION

Stock analysts play a critical role in the financial economy, serving as a primary source of information for many retail and institutional investors. Of particular importance in this regard is analysts' estimation of forecasted earnings. The magnitude of this responsibility is readily apparent in the immediate, and potentially large, reaction of market prices to significant changes in earnings estimates. For example, Bonner, Hugon, and Walther [2006] find that, on average, a downward forecast revision generates a −.59% five-day abnormal return immediately following the revision.

Given their importance, it is encouraging that analyst earnings forecasts have proven (see Brown and Rozeff [1978] and Fried and Givoly [1982]) to be superior relative to simple time series estimates. Unfortunately, the objectivity (and accuracy) of these estimates has also been hotly debated, with researchers documenting both optimistic and pessimistic biases in stock analysts' earnings forecasts. For example, Fried and Givoly [1982], O'Brien [1988], and Debondt and Thaler [1990] all find a positive bias in average analyst earnings forecasts, while more recent studies (e.g., Brown [2001], Richardson, Teoh, and Wysocki [2004]) provide evidence of declining optimism (i.e., increasing pessimism). In both cases, the majority of studies attribute any bias in analyst forecasts to either (1) intentional behavior of financial analysts and/or the firm managers guiding such estimates or (2) psychological/behavioral biases (such as overreaction) embedded in analysts' decision making processes.

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This study adds to the existing research by exploring an additional potential source of pessimistic bias in earnings forecasts that is purely psychological. Specifically, we consider the prospective impact of seasonal affective disorder (SAD), which is a documented (e.g., Molin et al. [1996], Schwartz and Clore [1983]) medical condition that causes depression and heightened risk aversion during the fall and winter months when the amount of daylight is lowest. According to Rosenthal [1998], approximately 10 million Americans are reportedly afflicted with SAD, with another 15 million suffering from a milder form of "winter blues."

While, to our knowledge we are the first to consider the effect of SAD on stock analyst earnings estimates, others have identified impacts in other (related) areas of the financial system. For example, Kamstra, Kramer, and Levi [2003], Garrett, Kamstra, and Kramer [2005], and Dowling and Lucey [2008] all find a significant SAD effect in financial markets worldwide, with overall market returns being lower in the fall and winter. Further, Dolvin and Pyles [2007] examine the potential influences of SAD on initial public offerings (IPOs), finding a significant positive relation between SAD and IPO underpricing, which is consistent with increased pessimism in setting offer prices.

In considering the potential impact of SAD on stock analyst earnings estimates, there are two competing possibilities. First, since analysts are highly trained professionals, they may be less susceptible to the psychological bias associated with SAD (i.e., completely objective). This is the null hypothesis. Second, an opposing view is that analysts, even given the extent of their financial training, are still vulnerable to behavioral disorders, SAD included. Our results suggest the latter is true, as we find a distinct SAD effect on stock analysts' earnings estimates.

Consistent with prior studies, we find that analysts are, on average, optimistic in their earnings estimates. However, for forecasts made during SAD months, we find the measurement error for one-year ahead earnings forecasts is lower (i.e., less optimistic/more pessimistic). In contrast to prior studies, we do not find a consistent asymmetric effect around the winter solstice.

We further study the relative influence of SAD by segmenting our sample in different ways. First, we examine the impact of SAD based on the location of the analyst (i.e., northern states vs. southern states), hypothesizing that the effects of SAD should be most pronounced in the North where the depressive factors associated with SAD would be the greatest. Consistent with our expectation, we find that SAD has a significant impact on those analysts located in the North but not on those located in the South. Second, we segment our sample based on the date of a firm's fiscal year end (i.e., spring/summer vs. fall/winter), which effectively divides firms that employ a typical calendar year from those that do not. We find the effect of SAD is significant across both samples, which adds robustness to our results.

It is well-known that reducing bias generally improves accuracy, so it is somewhat ironic that the bias associated with SAD actually makes estimates more, rather than less, accurate. This, however, results from the pessimistic bias associated with SAD offsetting an existing positive bent in overall earnings forecasts. Thus, there is a net reduction in overall estimate bias, which, as would be expected, improves forecast accuracy.

The remainder of the article proceeds as follows. The second section briefly discusses previous literature. The third section identifies our hypothesis. The fourth section presents data and sample selection. The fifth section provides results and the sixth section concludes.

## PREVIOUS LITERATURE

### Seasonal Affective Disorder

Seasonal affective disorder, or SAD, is a subtype of depression that is characterized by a lack of energy, hypersomnia, overeating, weight gain, and, perhaps most notably, depressed mood. Molin et al. [1996] and Young et al. [1997] document that seasonal depression is explicitly linked to the number of hours of daylight, with declining hours of daylight contributing to increased levels of depression.

Sullivan and Payne [2007] compare seasonal and nonseasonal depression in a sample of college students and find SAD is much more prevalent than other major nonseasonal depressive disorders. However, they find both types of disorders are associated with higher reports of cognitive failures relative to those individuals who have no depressive symptoms, which suggests both seasonal and nonseasonal disorders have similar effects on impaired individuals. Bagby et al. [1996] examine seasonal depression relative to other forms of psychological depression and find SAD patients may be a distinct subgroup of depressed patients who are more imaginative, emotionally sensitive, and likely to entertain unconventional ideas.

Whether this description characterizes stock analysts is an open question; however, some existing studies have examined the influence of SAD on general financial market participants. For example, Kamstra, Kramer, and Levi [2003] investigate the role of SAD in the seasonal time-variation of stock market returns. They find that returns are, in fact, significantly affected by the level of daylight throughout the fall and winter months. More specifically, Kamstra, Kramer, and Levi find general market returns are, on average, higher in the fall and winter, but they also find the effect of SAD is not symmetric. Rather, returns tend to be lower in the fall when the amount of daylight is declining, and although winter returns are generally higher than those in spring or summer, they also tend to be higher than those in the fall, which is attributed to a reversal of emotions as days begin to lengthen. In addition, Kamstra, Kramer, and Levi find their results are robust to markets across the globe, including different hemispheres.[1]

Garrett, Kamstra, and Kramer [2005] extend this work by examining SAD in the context of an equilibrium pricing model to determine whether seasonality can be explained using a conditional version of the Capital Asset Pricing Model (CAPM) that allows the price of risk to vary over time. They find the revised model can completely capture the SAD effect, which is consistent with SAD leading to heightened risk aversion, thereby requiring a higher risk premium.

Dolvin and Pyles [2007] examine, also within the Kamstra, Kramer, and Levi [2003] framework, the influence of SAD on IPOs between 1986 and 2000. Since IPOs represent an investment in a firm that is generally smaller and less well-known than the typical public firm, it is likely these investments are associated with increased information uncertainty (i.e., higher risk). Thus, during SAD periods, it is possible that IPOs need to be priced differently than issues going public at other times during the year. Dolvin and Pyles find support for this notion, as issues going public during fall and winter are associated with higher levels of underpricing and a larger degree of offer price revisions.

Other studies extend the potential impact of behavioral disorders such as SAD by examining the relationship between investor mood and the willingness to take on risk, as well as the potential financial ramifications of such a relationship.[2] For example, Carton et al. [1995] conclude depression reduces risk seeking (thereby increasing the general level of pessimism), and, as such, individuals are more reluctant to make decisions that have a greater level of risk or exhibit optimistic thinking.

### Biases in Analyst Estimates

Brown and Rozeff [1978] were the first to document the superior accuracy of analysts' forecasts relative to simple time-series forecasts.[3] However, there is also ample evidence documenting biases (mostly optimistic) in analysts' forecasts. For example, Lim [2001] finds an average optimistic bias of .46% of share price.[4] Although the optimistic bias in analyst forecasts is rather robust in the literature, some recent studies find that the optimistic bias is being progressively offset by increased pessimism (e.g., Brown [1997], Brown [2001], Matsumoto [2002]), particularly after the stock market "crash" in 2000. Further, more recent studies (e.g., Richardson, Teoh, and Wysocki [2004]) find that pessimism has continued into the new century. Nonetheless, the overall result is a consistent, albeit declining, positive bias in earnings estimates.

There are multiple potential explanations for analyst bias. Some fall into the category of incentive based issues (see Kothari [2001] and Ramnath, Rock, and Shane [2008] for reviews). Other explanations revolve around the relationship between analysts and the firms they cover. For example, Degeorge, Patel, and Zechauser [1999] suggest pessimistic bias results from firm managers' desire to beat forecasts. Consistent with this notion, Matsumoto [2002] argues that firm managers guide analysts toward pessimistic targets to then beat the target. Naturally, this creates the possibility for conflicts of interest. Chan, Karceski, and Lakonishok [2003] suggest analysts tend to become pessimistic over time in order for firms to have positive earnings surprises.

There is also a strong line of behavioral explanations for the bias in analyst forecasts. For example, Capstaff, Paudyal, and Rees [2001] and Debondt [1992] hypothesize analysts overreact to information concerning firm earnings and that the overreaction to bad news does not completely offset the overreaction to good news. This is supported by Easterwood and Nutt [1999], who find analysts actually underreact to negative earnings news. Stotz and Nitzsch [2005] also suggest much of the reason behind biases in analysts' estimates is overconfidence, and this overconfidence is more pronounced in earning estimates relative to price estimates. The present study adds to this behavioral line of research by considering an additional psychological explanation for earnings forecast error.

## HYPOTHESIS

We examine the error in stock analyst annual earnings estimates relative to actual earnings over 1998–2004, specifically concentrating on the potential pessimistic bias that is associated with SAD. By focusing on this prospective explanation of estimation errors, we add to the literature on both analyst forecast bias and behavioral finance.

The effect of SAD on the willingness to accept risk suggests that those afflicted with the disorder are more pessimistic, particularly in regards to issues that are uncertain and/or occur in the future. Relating this notion to stock analyst earnings estimates (which are definitely uncertain and forward looking), we expect analysts afflicted by SAD to have a larger pessimistic bias in their estimates. Building on this rationale, we examine the following primary hypothesis.

> Earnings estimates made during SAD times (i.e., fall and winter months) will be associated with a pessimistic bias relative to estimates made during other times of the year.

## DATA AND SAMPLE SELECTION

### Data Sources

We employ the Institutional Brokers Estimate System (I/B/E/S) Forecast database as our primary source of individual analyst's one-year-ahead forecasts of annual earnings per share (EPS), and we concentrate on the 1998–2004 time period.[5] We obtain per share stock prices and book values from the Center for Research in Security Prices (CRSP) and Compustat databases, respectively. Institutional ownership data are obtained from 13f in Thomson Financial.

I/B/E/S (Detail History-Forecasts) provides an entry for each earnings forecast made by an individual analyst. Important variables in the file include the identity of the underlying security, the (dollar) earnings forecast, the forecast date, the forecast period, an analyst code, and a brokerage firm code. Further, I/B/E/S (Summary-Forecast) also identifies the number of analysts following the stock, the standard deviation (at mid-calendar month) of the forecasts for a particular security, and the actual subsequent EPS of the underlying firm. With this last piece, we are able to calculate the one-year ahead forecast error for each estimate relative to the actual earnings value.[6]

For the purposes of our study, we ensure the analysts in our sample are employed in the United States. Typically this screening criterion would be unnecessary; however, since we concentrate on the psychological impact of seasons, analysts located internationally would face different seasonal cycles and therefore be subject to SAD at different times of year. We are unable to identify the working location of each analyst based on information in I/B/E/S, thus we examine each brokerage firm's Web page to determine if they have an international office, subsequently excluding firms that do. We begin with 85 brokerage firms; however, our screening criterion reduces our final working sample to analysts affiliated with 41 brokerage firms, each without an international office.[7]

At the individual security level, we further exclude penny stocks and those stocks with abnormally large negative events. Specifically, we eliminate observations where the share price as of the last day of the calendar quarter before the announcement date of the earnings forecast is less than \$3 per share, as well as those where actual annual earnings are below −\$.10 per share.[8] Since analyst forecasts may be at least partially driven by early access to inside information from company management (see Ivkovic and Jegadeesh [2004]), we exclude forecasts within 14 days of the actual earnings announcements.[9]

## Variable Definitions

To explore the forecast error associated with analysts' estimates, we construct three dependent variables. The first is *PrGap*, which, building upon Qu, Starks, and Yan [2004], is defined as the difference between the actual earnings and the corresponding analyst estimate, divided by the share price of the underlying security and multiplied by a factor of 10,000. Thus, we calculate *PrGap* as follows:

$$PrGap = 10,000 * \frac{Actual\ Earnings - Analyst\ Estimate}{Price} \tag{1}$$

where *Price* is the per share stock price at the end of the quarter preceding the forecast. By definition, a positive value of *PrGap* indicates an analyst has underestimated earnings, while a negative value indicates an overestimation. Thus, any variable with a positive relationship to *PrGap* can be interpreted as increasing the level of underestimation, or pessimism, associated with an analyst's estimate.

Following Bergman and Roychowdhury [2008], the second dependent variable we examine is *RGap1*, defined as the difference between actual earnings and the corresponding analyst estimate, divided by the absolute value of the actual earnings and scaled by a factor of 100. Thus, *RGap1* is calculated as follows:

$$RGap1 = 100 * \frac{Actual\ Earnings - Analyst\ Estimate}{abs(Actual\ Earnings)} \tag{2}$$

To reduce computation issues, we exclude observations with actual earnings exactly equal to zero when examining *RGap1*. Similar to *PrGap*, a positive (negative) value of *RGap1* is indicative of an analyst underestimating (overestimating) earnings.

The third dependent variable is *RGap2*, defined as the difference between actual earnings and the corresponding analyst estimate, divided by the absolute value of the analyst's estimate and multiplied by a factor of 100. Thus, *RGap2* is calculated as follows:

$$RGap2 = 100 * \frac{Actual\ Earnings - Analyst\ Estimate}{abs(Analyst\ Estimate)} \tag{3}$$

In a similar fashion as *RGap1*, we exclude observations with analyst earnings estimates exactly equal to zero when examining *RGap2* as the dependent variable. Consistent with both prior measures, a positive (negative) value of *RGap2* again implies the analyst has underestimated (overestimated) earnings.

We examine summary statistics for each of these variables in Panel A of Table 1. We find the averages for all three dependent variables are negative across the entire sample, which, consistent with prior studies, indicates an optimistic (positively biased) average forecast error. For example, the average of *PrGap* is −19.62, which indicates a .20% positive forecast error relative to actual earnings (as a percentage of stock price). This level is lower than that reported by Lim [2001]; however, it is consistent with recent studies that find a reduction in forecast optimism (i.e., increased pessimism) in current periods.

We also segment the sample into those estimates made during SAD months (i.e., fall and winter) and those made during more "optimistic" times of year (i.e., spring and summer), subsequently testing the difference between these values. For each of the three dependent variables, we find a greater level of pessimism (i.e., lower forecasted earnings) for those estimates made on SAD days relative to non-SAD days, which is consistent with our hypothesis. Interestingly, however, the pessimism does not result in overall estimates that are lower than the actual earnings. Rather, the estimates

TABLE 1
Descriptive Statistics.
This table provides descriptive statistics for the entire sample, as well as subsamples segmented based on estimates made on SAD days. SAD sample observations are those estimates issued from September 21 to March 20 in each respective year, while the Non-SAD sample includes all other estimates. *PrGap*, *RGap1*, and *RGap2* are proxies of measurement error, calculated as the difference between actual earnings and analyst estimate of earnings, scaled by price, the absolute value of earnings estimates, and actual earnings, respectively. *SAD* is calculated as [H – 12] during fall and winter, zero otherwise, where H is the number of hours of night for the given trading day. *FALL* is a dummy variable equal to one if the trading day is in the Fall (i.e., September 21 to December 20). *LGSZ* is the natural log of the firm's market value (in millions of dollars). *NEST* is the number of analyst estimates. *DISP* is the standard deviation of analysts' quarterly earnings forecasts from the month immediately preceding the month of an earning forecast date. *TIO* is the total percentage of institutional ownership of the company at the end of the quarter immediately preceding the forecast. *BM* is the book-to-market ratio of the firm as of the end of the quarter immediately preceding the forecast. *DAY* is the number of calendar days between the forecast date and the corresponding actual earnings announcement date. *TECH* is a dummy variable equal to one if the firm is classified as a technology firm, zero otherwise. *BUB* is a dummy variable equal to one if the estimate was made during the January 1998 to December 2000 period, zero otherwise. The final column reports *p*-values from difference tests calculated assuming either equal or unequal variances, depending on a test of equality of variances. Data are from the I/B/E/S, CRSP, Compustat, and Thomson Financial 13f databases for the period 1998–2004.

| | Total Sample | SAD | Non-SAD | *p*-value |
|---|---|---|---|---|
| N | 117,732 | 51,708 | 66,024 | |
| *Panel A: Dependent Variables* | | | | |
| PrGap | −19.62 | −12.53 | −25.16 | <.0001 |
| RGap1 | −4.14 | −2.75 | −5.23 | <.0001 |
| RGap2 | −2.02 | −.87 | −2.92 | <.0001 |
| *Panel B: Independent Variables* | | | | |
| SAD | .73 | 1.67 | 0 | <.0001 |
| FALL | .28 | .63 | 0 | <.0001 |
| LGSZ | 6.63 | 6.59 | 6.66 | .1000 |
| NEST | 13.41 | 13.41 | 13.41 | .9751 |
| DISP | .09 | .08 | .10 | <.0001 |
| TIO | .61 | .61 | .61 | .5953 |
| BM | 1.64 | 1.70 | 1.59 | <.0001 |
| DAY | 202.02 | 171.47 | 225.95 | <.0001 |
| TECH | .20 | .20 | .20 | .8186 |
| BUB | .40 | .40 | .40 | .2750 |

are simply scaled back and essentially become more reflective of actual earnings. Thus, the pessimism associated with SAD appears to make analyst estimates more accurate in that it offsets an existing positive bias in forecasts.

To further our understanding of the potential determinants of the level (and direction) of forecast error, we examine several independent variables, many of which have been explored in prior studies of either SAD or analyst forecast bias. We report descriptive statistics for these independent variables in Panel B of Table 1.

First, given the primary focus of our study, we define *SAD* as follows:

$$SAD_t = \begin{Bmatrix} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise} \end{Bmatrix} \tag{4}$$

where $H_t$ is the time from sunset to sunrise for the specific trading day. We deduct 12 (the average number of night hours over the entire year) to obtain a measure (i.e., $H_t - 12$) that reflects the length of night relative to an average day. The specification (i.e., modified binary variable) also addresses the medical evidence that suggests SAD only occurs during fall and winter months.[10] Based on our definition, we expect *SAD* to be positively related to *PrGap*, which would indicate an increase in analyst underestimation, or pessimism, during SAD times of year.

Kamstra, Kramer, and Levi [2003] find that SAD is most pronounced during the fall when the amount of daylight is short and declining, but the effect tends to moderate after the winter solstice as the amount of daylight increases. To examine the possibility of an asymmetric effect of SAD around the solstice, we also create a dummy variable, *FALL*, which is equal to one if the forecast is issued between September 21 and December 20 (i.e., fall) of each year, zero otherwise. Beyond *SAD* and *FALL*, we also examine more traditional variables included in the analyst forecast literature. For example, *LGSZ* is the natural log of the underlying stock's market value (in millions of dollars) at the end of the quarter and is included as a typical size control variable. It is well documented in previous literature (e.g., Lee and Liu, [2007]) that increased analyst coverage indicates less uncertainty (i.e., less informational asymmetry) for a covered stock. Therefore, we examine *NEST*, which is the number of analysts following the company during the month immediately preceding the earnings forecast date.

Zhang [2006] finds that an analyst's tendency to underreact to new information is more pronounced in firms with a greater level of uncertainty. Further, Zhang finds greater information uncertainty leads to more positive forecast errors. Following previous studies (e.g., Ajinkya, Atiase, and Gift [1991] and Lobo and Tung [2000]), we calculate *DISP*, defined as the standard deviation of analysts' quarterly earnings forecasts for each particular security from the month immediately preceding the earnings forecast date, scaled by the absolute value of the mean forecast.[11] *DISP* proxies as a measure of analysts' uncertainty regarding the earnings of the covered company.

*TIO* is the total percentage of institutional ownership of the underlying company at the end of the quarter immediately preceding the forecast, and it controls for the effect of institutional holders on analysts' behavior (e.g., Ljungqvist et al. [2007]). *BM* is the book-to-market ratio of the company at the end of the quarter immediately preceding the forecast. We also include *DAY*, which is the number of calendar days between the forecast date and the corresponding actual earnings announcement date. We expect that a longer time period between the forecast and reporting dates increases forecast error (see Richardson, Teoh, and Wysocki [2004]).

Finally, we include two variables to control for the technology boom in the late 1990s. First, *TECH* is a dummy variable equal to one if the firm is classified as a high-tech firm, zero otherwise.[12] Next, we include *BUB*, a dummy variable equal to one if the forecasts are made during the 1998 to 2000 time period (i.e., the Internet "bubble"). Similar to Panel A, we also examine each independent variable on a segmented basis (i.e., SAD versus non-SAD months).

Examining the values presented in Panel B of Table 1, we find the average firm in our sample has a market value of $755 million and there are, on average, 13.4 analysts following each firm. The average total institutional ownership is about 61%. Approximately 20% of forecasts are for firms in the high tech industry, and roughly 40% of forecasts in our sample are made during the bubble period. As we would expect, there is no significant difference in any of these variables in SAD versus non-SAD months.

Surprisingly, we find that analysts appear to be more uncertain during non-SAD periods, which is counter to our expectations. However, this finding may be related to two factors. First, *BM,* the average book-to-market ratio, is higher during SAD months, which may be indicative of firms with less uncertainty. Second, the number of days between the forecast and actual earnings date is lower for SAD forecasts, which may also suggest reduced uncertainty.

We would expect, following the results of prior studies, for firms with lower uncertainty to be associated with a reduced forecast error. Thus, our findings related to our dependent variables (i.e., more accurate (pessimistic) estimates during SAD months) may be driven by underlying firm fundamentals and not necessarily a psychological bias. Therefore, in section V below, we control for these relations in a multiple regression framework.

Simply concentrating on our variables of forecasting error (and the associated univariate results), it would appear that analysts as a whole are influenced by SAD. However, without further segmentation we would be unable to provide evidence of a specific link. Thus, to more completely examine this issue, we segment our sample into estimates that are made by analysts that are located in northern states and those that are located in southern states.[13] Given the differences in the amount of daylight between these regions, we expect that analysts located in northern states would be most significantly influenced by the depressive effects of SAD.

TABLE 2
Descriptive Statistics Segmented by Location of Analyst.
This table provides descriptive statistics for subsamples determined by location of the analyst. Panel A (Panel B) provides descriptive statistics for analysts that are located in a northern (southern) state. The final column presents *p*-values from difference tests calculated assuming either equal or unequal variances, depending on a test of equality of variances. All variables are defined in Table 1. Data are from the I/B/E/S, CRSP, Compustat, and Thomson Financial 13f databases for the period 1998–2004.

| | Total | SAD | Non-SAD | *p*-value |
|---|---|---|---|---|
| | *Panel A: Northern states sample* | | | |
| N | 96,234 | 42,406 | 53,828 | |
| PrGap | −19.54 | −11.91 | −25.56 | <.0001 |
| RGap1 | −.04 | −.03 | −.05 | <.0001 |
| RGap2 | −.02 | −.01 | −.03 | <.0001 |
| SAD | .73 | 1.66 | 0 | <.0001 |
| FALL | .29 | .64 | 0 | <.0001 |
| LGSZ | 6.67 | 6.63 | 6.70 | .0100 |
| NEST | 13.36 | 13.37 | 13.35 | .6944 |
| DISP | .09 | .08 | .10 | <.0001 |
| TIO | .61 | .61 | .62 | .7509 |
| BM | 1.67 | 1.73 | 1.62 | <.0001 |
| DAY | 201.10 | 170.61 | 225.12 | <.0001 |
| TECH | .21 | .21 | .21 | .6671 |
| BUB | .36 | .36 | .37 | .9220 |
| | *Panel B: Southern states sample* | | | |
| N | 21,498 | 9,302 | 12,196 | |
| PrGap | −19.94 | −15.35 | −23.44 | .0059 |
| RGap1 | −.04 | −.03 | −.05 | <.0001 |
| RGap2 | −.02 | −.01 | −.03 | <.0001 |
| SAD | .73 | 1.69 | 0 | <.0001 |
| FALL | .26 | .58 | 0 | <.0001 |
| LGSZ | 6.46 | 6.40 | 6.50 | .0090 |
| NEST | 13.66 | 13.60 | 13.70 | .4158 |
| DISP | .11 | .10 | .12 | .0034 |
| TIO | .60 | .60 | .60 | .0701 |
| BM | 1.51 | 1.59 | 1.45 | <.0001 |
| DAY | 206.16 | 175.39 | 229.63 | <.0001 |
| TECH | .19 | .19 | .19 | .7621 |
| BUB | .57 | .56 | .57 | .1269 |

To measure the potential impact, we first segment the sample based on the location of the analyst, reporting details of analysts located in northern states in Panel A of Table 2 and those located in southern states in Panel B. Similar to Table 1, in each panel we then segment by forecasts made during SAD and non-SAD months.

Given that the major financial centers of New York City and Chicago are located in "the North," there are significantly more observations for this subsample. Nonetheless, the majority of the independent variables (*LGSZ* for example) remain strikingly similar, as does the significance of the difference between these variables in the SAD and non-SAD segments.

Of importance to this study, however, the measures of forecast error reveal an important finding. Specifically, analysts, regardless of location, appear to be influenced by SAD, as forecasts made during SAD months are significantly more pessimistic than those made during non-SAD months. However, the difference between the forecast errors for SAD and non-SAD months is greater in absolute terms for analysts located in the northern region of the United States and this disparity is also reflected in the $p$-values of the difference tests for *PrGap*.

To examine this issue in more depth, in unreported results we also conduct difference tests between the northern and southern samples. Specifically, we examine estimates made in northern states during SAD months versus those made in southern states during the same time of year. We repeat this analysis for non-SAD months as well. We find that estimates made during non-SAD months in northern and southern states (i.e., *PrGap* of −25.560 vs. −23.440, respectively) are insignificantly different from each other. However, estimates made during SAD months by analysts in northern states (i.e., *PrGap* of −11.910 vs. −15.350) are (moderately) lower ($p$-value = .1312) than their southern counterparts. Thus, the univariate results appear to indicate that analysts located in "the North" may be more severely affected by SAD, which is consistent with the reduction in daylight (and the depression it engenders) being more pronounced. However, we reserve judgment until further multivariate analysis is conducted.

Kamstra, Kramer, and Levi [2003] also suggest the depressive impact of SAD will be more pronounced in fall relative to winter, as the amount of daylight, although shorter in both seasons, is declining in the fall and increasing in winter. Thus, people see "the light at the end of the tunnel." To explore this relation, we examine only those estimates made during the SAD period. We segment this subsample into those estimates made during fall and winter and report values for our dependent and independent variables in Table 3.

Consistent with existing literature, we find that estimates are less optimistic (i.e., more pessimistic) during the fall relative to winter. However, similar to our results in Table 1, we find that uncertainty (as proxied by *DISP*, *BM*, and *DAY*) appears to be lower during the fall. Therefore, our results may not be purely psychological. Rather, they may simply be a function of the characteristics of the firms in each sample. We attempt to sort out this issue using the multivariate analyses presented in the following section.

TABLE 3
Descriptive Statistics Segmented by Fall versus Winter.
This table provides descriptive statistics for the SAD subsample (i.e., fall and winter month estimates). The final column presents $p$-values from difference tests assuming either equal or unequal variances, depending on a test of equality of variances. All variables are defined in Table 1. Data are from the I/B/E/S, CRSP, Compustat, and Thomson Financial 13f databases for the period 1998–2004.

| | SAD Sample | Fall | Winter | $p$-value |
|---|---|---|---|---|
| N | 51,708 | 32,383 | 19,325 | |
| PrGap | −12.50 | −8.61 | −19.11 | <.0001 |
| RGap1 | −2.75 | −1.53 | −4.77 | <.0001 |
| RGap2 | −.87 | −.07 | −2.22 | <.0001 |
| SAD | 1.67 | 1.66 | 1.69 | <.0001 |
| FALL | .63 | 1 | 0 | <.0001 |
| LGSZ | 6.59 | 6.58 | 6.60 | .2479 |
| NEST | 13.41 | 13.43 | 13.38 | .4949 |
| DISP | .08 | .07 | .11 | <.0001 |
| TIO | .61 | .62 | .60 | <.0001 |
| BM | 1.70 | 1.75 | 1.62 | <.0001 |
| DAY | 171.47 | 120.51 | 256.87 | <.0001 |
| TECH | .20 | .20 | .21 | <.0001 |
| BUB | .40 | .38 | .42 | <.0001 |

## EMPIRICAL RESULTS

To disentangle these effects, we examine the following multiple regression model:

$$\begin{aligned} Dep_{i,t} = {} & \beta_0 + \beta_1 SAD + \beta_2 FALL + \beta_3 LGSZ + \beta_4 NEST \\ & + \beta_5 DISP + \beta_6 TIO + \beta_7 BM + \beta_8 DAY + \beta_9 TECH \\ & + \beta_{10} BUB + \beta_{Brokerage} + \beta_{Year} + \varepsilon_i \end{aligned} \tag{5}$$

We report the results of this model for the full sample in Table 4. The dependent variable we report is *PrGap*, although in unreported results we also examine *RGap1* and *RGap2*, finding qualitatively similar results to those reported, which would be expected given the outcome of the univariate analysis. $\beta_{Brokerage}$ and $\beta_{Year}$ are vectors of dummy variables for each brokerage firm and year, respectively. We provide estimates from three specifications. In the first two, we control for both the fixed effects of years and brokerage firms. In the third, we only control for the fixed effects of brokerage firms, as we include a dummy variable for the bubble period.[14]

Examining the results, we find that SAD is positively related to *PrGap*, which suggests that SAD results in a larger degree of pessimism, even after controlling for various firm and analyst coverage characteristics. The coefficient on *SAD* in Model 1 is 2.55. To put this number in perspective, consider a stock with a per share price of \$31.95, which is the average price in our sample. For a one standard deviation increase in *SAD*, *PrGap1* will increase by 2.55 * 0.99 * \$31.95/10,000 = \$.0081. Given the positive starting point of analyst estimates relative to actual earnings, this suggests the impact of SAD would decrease forecasted earnings from our average \$1.31 per share to approximately \$1.30 per share, making the estimate more accurate with respect to the average actual earnings of \$1.26 per share.

Considering the control variables, we find that pessimism increases with the number of analysts covering a firm, although this may likely reflect the fact that more analysts following a firm results in a greater amount of accuracy and therefore a more accurate (less optimistic) estimate. *DISP*,

TABLE 4
Regression Results for Full Sample.
This table provides regression results from the following model:

$$PrGap_{i,t} = \beta_0 + \beta_1 SAD + \beta_2 FALL + \beta_3 LGSZ + \beta_4 NEST + \beta_5 DISP + \beta_6 TIO + \beta_7 BM + \beta_8 DAY + \beta_9 TECH + \beta_{10} BUB + \beta_{Brokerage} + \beta_{Year} + \varepsilon_i$$

$\beta_{Brokerage}$ and $\beta_{Year}$ are vectors of dummy variables for each brokerage firm and year, respectively. All other variables are as defined in Table 1. In the first two models we control for fixed effects of brokerage firms and years. In the third model we control for the fixed effects of brokerage firms. To conserve space, intercepts and coefficients for year and brokerage firm dummies are not shown. Two-sided *p*-values are reported in parenthesis. Data are from the I/B/E/S, CRSP, Compustat, and Thomson Financial 13f databases for the period 1998–2004.

| | [1] | [2] | [3] |
|---|---|---|---|
| SAD | 2.55 (<.0001) | 2.20 (.0007) | 3.02 (<.0001) |
| FALL | | 1.79 (.2707) | .35 (.8305) |
| LGSZ | −3.40 (<.0001) | −3.40 (<.0001) | −2.60 (<.0001) |
| NEST | 1.23 (<.0001) | 1.23 (<.0001) | 1.12 (<.0001) |
| DISP | 13.89 (<.0001) | 13.90 (<.0001) | 14.60 (<.0001) |
| TIO | −26.97 (<.0001) | −27.06 (<.0001) | −14.85 (<.0001) |
| BM | −4.45 (<.0001) | −4.46 (<.0001) | −3.80 (<.0001) |
| DAY | −.11 (<.0001)) | −.10 (<.0001) | −.10 (<.0001) |
| TECH | 7.38 (<.0001) | 7.37 (<.0001) | 8.11 (<.0001) |
| BUB | | | −2.53 (.0394) |
| N | 115,071 | 115,071 | 115,071 |
| Adj. $R^2$ | .0256 | .0256 | .0117 |

which may reflect analyst uncertainty, and *TECH* also have positive coefficients, reflecting increased pessimism associated with these characteristics.

The negative coefficient on *LGSZ* suggests that analysts are more optimistic for larger firms. Higher institutional ownership (*TIO*) and a higher book-to-market ratio (*BM*) are negatively related to the degree of analysts' pessimism. The negative coefficient on *DAY* also implies analysts are more optimistic (and possibly less accurate) for forecasts that are made further away from the actual earnings announcement date, which is consistent with the findings of previous studies (e.g., Richardson, Teoh, and Wysocki [2004]).

In columns 2 and 3 we include both *SAD* and *FALL* in the regression. Of particular importance to our study, *SAD* remains positive and significant, suggesting a psychological impact on earnings estimates associated with seasonal depression. However, *FALL* is insignificant, which is in contrast to the asymmetric effect of SAD documented by Kamstra, Kramer, and Levi [2003].[15] The coefficients on the control variables are generally similar to those in column 1. The coefficient on the dummy variable for the bubble period (*BUB*) is negative in column 3, which indicates that during the bubble period analyst estimates tended to be more optimistic (i.e., positively biased).

TABLE 5
Regression Results for Northern and Southern States Samples.
This table provides regression results from the following model:

$$PrGap_{i,t} = \beta_0 + \beta_1 SAD + \beta_2 FALL + \beta_3 LGSZ + \beta_4 NEST + \beta_5 DISP + \beta_6 TIO + \beta_7 BM + \beta_8 DAY + \beta_9 TECH + \beta_{10} BUB + \beta_{Brokerage} + \beta_{Year} + \varepsilon_i$$

The subsamples are determined by location of the analyst. Panel A (Panel B) provides results based on analysts that are located in a northern (southern) state. $\beta_{Brokerage}$ and $\beta_{Year}$ are vectors of dummy variables for each brokerage firm and year, respectively. All other variables are as defined in Table 1. In the first two models we control for fixed effects of brokerage firms and years. In the third model we control for the fixed effects of brokerage firms. To conserve space, intercepts and coefficients for year dummies and brokerage firm dummies are not shown. Two-sided *p*-values are reported in parenthesis. Data are from the I/B/E/S, CRSP, Compustat, and Thomson Financial 13f databases for the period 1998–2004.

| | [1] | [2] | [3] |
|---|---|---|---|
| | | *Panel A: Northern Sample* | |
| SAD | 3.24 (<.0001) | 2.70 (<.0001) | 3.38 (<.0001) |
| FALL | | 2.69 (0.1188) | 1.70 (0.3199) |
| LGSZ | −1.96 (0.0004) | −1.95 (0.0004) | −1.50 (0.0061) |
| NEST | 0.98 (<.0001) | 0.98 (<.0001) | 0.92 (<.0001) |
| DISP | 12.34 (<.0001) | 12.36 (<.0001) | 13.08 (<.0001) |
| TIO | −26.95 (<.0001) | −27.09 (<.0001) | −15.84 (<.0001) |
| BM | −4.40 (<.0001) | −4.41 (<.0001) | −3.91 (<.0001) |
| DAY | −0.11 (<.0001) | −0.10 (<.0001) | −0.10 (<.0001) |
| TECH | 6.61 (<.0001) | 6.59 (<.0001) | 7.30 (<.0001) |
| BUB | | | −7.58 (<.0001) |
| N | 93957 | 93957 | 93957 |
| Adj. $R^2$ | 0.0263 | 0.0263 | 0.0125 |
| | | *Panel B: Southern Sample* | |
| SAD | −.39 (.8025) | .02 (.9923) | .72 (.3220) |
| FALL | | −2.09 (0.6358) | −6.76 (0.1242) |
| LGSZ | −10.14 (<.0001) | −10.14 (<.0001) | −7.16 (<.0001) |
| NEST | 2.36 (<.0001) | 2.36 (<.0001) | 2.00 (<.0001) |
| DISP | 21.50 (<.0001) | 21.47 (<.0001) | 20.82 (<.0001) |
| TIO | −25.77 (.0009) | −25.70 (.0009) | −10.37 (.1798) |
| BM | −4.11 (.0005) | −4.10 (.0005) | −2.66 (.0245) |
| DAY | −0.10 (<.0001) | −0.10 (<.0001) | −0.09 (<.0001) |
| TECH | 13.67 (.0010) | 13.67 (.0010) | 15.06 (.0003) |
| BUB | | | 21.79 (<.0001) |
| N | 21114 | 21114 | 21114 |
| Adj. $R^2$ | 0.0306 | 0.0306 | 0.0146 |

Our results thus far suggest SAD has both a statistically and economically significant effect on analyst forecasting behavior. In conventional Wall Street wisdom (e.g., Kinney, Burgstahhler, and Martin [2002], Skinner and Sloan [2002]), firms are concerned with beating analyst estimates by as little as 1 cent, thus our finding that SAD has anywhere from a .54 to 1.40 cents (based on the dependent variable chosen) impact in the estimate error suggests an economically significant result. However, it is possible the effect is not

TABLE 6
Regression Results for Spring/Summer and Fall/Winter Year-End Samples.
This table provides regression results from the following model:

$$PrGap_{i,t} = \beta_0 + \beta_1 AD + \beta_2 SAD{*}Southern + \beta_3 FALL + \beta_4 LGSZ + \beta_5 NEST + \beta_6 DISP + \beta_7 TIO + \beta_8 BM + \beta_9 DAY + \beta_{10} TECH + \beta_{11} BUB + \beta_{Brokerage} + \beta_{Year} + \varepsilon_i$$

The subsamples are determined by the fiscal year end of the covered firm. Panel A (Panel B) provides results based on spring/summer (fall/winter) year ends. $\beta_{Brokerage}$ and $\beta_{Year}$ are vectors of dummy variables for each brokerage firm and year, respectively. *Southern* is a dummy variable equal to one if the analyst is located in a southern state. All other variables are as defined in Table 1. In the first two models we control for fixed effects of brokerage firms and years. In the third model we control for the fixed effects of brokerage firms. To conserve space, intercepts and coefficients for year dummies and brokerage firm dummies are not shown. Two-sided *p*-values are reported in parenthesis. Data are from the I/B/E/S, CRSP, Compustat, and Thomson Financial 13f databases for the period 1998–2004.

| | [1] | [2] | [3] |
|---|---|---|---|
| | *Panel A: Spring/Summer Sample* | | |
| SAD | 2.75 (0.0590) | 3.47 (0.0281) | 3.85 (0.0152) |
| SAD*Southern | 1.20 (0.6390) | 1.14 (0.6561) | 0.86 (0.7390) |
| FALL | | −3.55 (0.2422) | −2.98 (0.3262) |
| LGSZ | 2.86 (0.0302) | 2.83 (0.0320) | 2.27 (0.0789) |
| NEST | 0.07 (0.7717) | 0.07 (0.7583) | 0.19 (0.4253) |
| DISP | 19.71 (<.0001) | 19.67 (<.0001) | 20.24 (<.0001) |
| TIO | 4.75 (0.4509) | 4.96 (0.4314) | 12.22 (0.0507) |
| BM | −8.11 (<.0001) | −8.10 (<.0001) | −7.81 (<.0001) |
| DAY | −0.12 (<.0001) | −0.12 (<.0001) | −0.11 (<.0001) |
| TECH | 6.28 (0.0598) | 6.27 (0.0600) | 7.66 (0.0220) |
| BUB | | | −4.37 (0.1051) |
| N | 22200 | 22200 | 22200 |
| Adj. $R^2$ | 0.0291 | 0.0291 | 0.0216 |
| | *Panel B: Fall/Winter Sample* | | |
| SAD | 3.65 (<.0001) | 2.42 (0.0031) | 3.81 (<.0001) |
| SAD*Southern | −4.87 (0.0021) | −4.73 (0.0028) | −4. 80 (0.0026) |
| FALL | | 5.70 (0.0043) | 2. 50 (0.2150) |
| LGSZ | −5.92 (<.0001) | −5.89 (<.0001) | −4.93 (<.0001) |
| NEST | 1.60 (<.0001) | 1.59 (<.0001) | 1.45 (<.0001) |
| DISP | 14.12 (<.0001) | 14.14 (<.0001) | 14.80 (<.0001) |
| TIO | −32.40 (<.0001) | −32.62 (<.0001) | −18.24 (<.0001) |
| BM | −4.32 (<.0001) | −4.34 (<.0001) | −3.57 (<.0001) |
| DAY | −0.10 (<.0001) | −0.09 (<.0001) | −0.08 (<.0001) |
| TECH | 5.61 (0.0005) | 5.56 (0.0005) | 5.24 (0.0012) |
| BUB | | | −4.79 (0.0003) |
| N | 92871 | 92871 | 92871 |
| Adj. $R^2$ | 0.0281 | 0.0281 | 0.0099 |

systematically contained in the entire spectrum of forecasts. In other words, the results may be driven by a subset of the forecast population.

Based on our findings from our univariate analysis, we necessarily must control for the location of the analyst, as we would expect that if SAD is truly significant, then its effects would be most pronounced on analysts located in northern states. To address this issue, we examine results for two subsamples, which is similar to our approach in Table 2. Specifically, we segment the sample into forecasts that are made by analysts located in northern states and those that are located in southern states and report the results in Panels A and B, respectively, of Table 5.[16] Consistent with our hypothesis, we find that estimates made by analysts located in northern states are significantly influenced by SAD (i.e., have more pessimistic earnings forecasts), whereas the relation to those analysts located in southern states is insignificant. The control variables in each sample retain the same signs and approximately the same significance levels. These results add validity to our early findings and conclusions; that is, stock analysts are influenced by the depressive effects of SAD.

Since the majority of firms have fiscal year ends in December and since forecasts in the fall may be relatively less pessimistic (e.g., Richardson, Teoh, and Wysocki [2004]), an alternative explanation for our results is the *Fall* dummy picks up a related effect.[17] To examine this issue, we analyze whether our findings are robust to different fiscal year ends. Thus, we repeat our analyses on two additional subsamples: (1) those forecasts based on year ends during fall and winter, which would include December, and (2) those forecasts based on year ends during spring and summer. In addition to the independent variables identified in Equation 5, we also include the interaction between SAD and a dummy variable that identifies the analyst as being located in a southern state. This inclusion follows the findings reported in Tables 2 and 5. We report the results of this analysis in Table 6.

We find the impact of SAD remains significant in both samples and the coefficients and significance levels of the control variables are generally in line with our previous results. We also find the interaction variable included is either insignificant (spring/summer) or of the opposite sign (fall/winter) as SAD, which is consistent with our prior results that indicate the effect is most pronounced on analysts located in the North. Thus, our general conclusions appear robust to different fiscal year ends; that is, analysts' earnings estimates appear to reflect the impact of SAD, particularly in locations where the impact of SAD would be most prominent.

## CONCLUSION

We combine the fields of psychology and finance in examining the influence of seasonal depression on the level of pessimism exhibited in stock analyst earnings estimates. Numerous studies have identified weather-related influences on the stock market, among those Kamstra, Kramer, and Levi [2003], who find a strong influence of SAD on markets worldwide. Their findings suggest the increased level of pessimism displayed by those afflicted with the disorder is significant to the point that total market returns are affected. We extend this line of reasoning by examining earnings estimates made by professional stock analysts.

We find evidence of increased pessimism in analysts' estimates during SAD months (i.e., fall and winter), particularly for those analysts located in states (i.e., the North) that are most likely to be influenced by a reduction in daylight and the depression it engenders. We also find these results are robust to controlling for different fiscal year ends of covered firms. Given that estimates generally exhibit an optimistic bias, our findings suggest that seasonal depression and its associated pessimism actually offset an existing positive bias and makes analyst estimates, as a whole, more accurate.

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## NOTES

1. There are also several climate-oriented studies in the literature. For example, Saunders [1993] and Hirschliefer and Shumway [2003] examine cloud cover; Cao and Wei [2005] consider temperature; and Dichev and Janes [2003] and Yuan, Zheng, and Zhu [2006] study lunar cycles. In a more broad-based study, Dowling and Lucey [2008] examine, in a statistically robust manner, several proxies for investor mood worldwide. They find the only variables that are consistently related to stock market returns worldwide are SAD and low temperature.
2. See Schwarz [1990] and Loewenstein et al. [2001] for theories linking individual mood to decision making. See Etzioni [1987], Romer [2000], Mehra and Sah [2002], and Olson [2006] for studies examining the effect of emotions on economic and financial decisions.
3. Although Imhoff and Pare [1982] and O'Brien [1988] offer contradictory findings, it is generally accepted that analysts' estimates are superior to time series predictions.
4. Hilary and Menzly [2005] document analysts have a tendency to become more overconfident (optimistic) following superior performance, and this leads to inferior future estimates.
5. Since each analyst's forecast could include different items (e.g., extraordinary items), I/B/E/S communicates with analysts in an attempt to ensure that each earnings forecast includes similar items and is therefore comparable.
6. In unreported results, we also examine quarterly forecasts, finding no significant impact from SAD. This, however, is not necessarily inconsistent with our expectations or contrary to our reported findings. First, SAD is most pronounced in areas where uncertainty is the greatest. Thus, quarterly forecasts, which are inherently more predictable, would, in all likelihood, be impacted less (or not at all) by the disorder. Second, it is possible that managers are able to provide better guidance (i.e., more in line with actual results) for quarterly results as opposed to yearly, thereby improving accuracy and reducing volatility. Thus, since the effect of SAD is most pronounced when uncertainty is the greatest, we might expect this result.
7. In unreported results, we compare summary statistics for the firms included in our sample (i.e., purely domestic firms) versus those outside our sample (i.e., firms with an international office) and find no significant differences between the two in relation to the characteristics of securities examined or the resulting forecasts. Although we would like to examine forecasts made in different hemispheres, it is impossible, based on the available data, to determine the exact location of the analyst making the estimate.
8. We exclude "penny stocks" and those with "large" negative earnings since these firms typically have different information disclosure behavior, hence affecting the forecasting behavior of financial analysts. For example, managers tend to preempt bad news to reduce litigation costs (see Skinner [1994] and Skinner [1997]).
9. Our results are robust to different exclusion criterion. For example, restricting the sample to stock prices higher than \$5, earnings larger than \$−.05, and forecast dates outside seven days before actual announcement dates produces similar results to those reported.
10. These values were obtained at Lisa Kramer's Web site, www.chass.utoronto.ca/∼lkramer/. For completeness, we also examine an alternative specification where SAD = (Ht – 12) for the entire year rather than just during the fall and winter. The results are qualitatively similar to those reported.
11. In an alternative specification, we also include a measure of the firm's earnings volatility over the previous three quarters (see Minton and Schrand [1999]); however, our primary results are unchanged.
12. Technology stocks are defined as those in Loughran and Ritter [2004] and Bradley, Jordan, and Ritter [2006].
13. We categorize the following as southern (i.e., "sunshine") states: Louisiana, Georgia, California, Arizona, Texas, Tennessee, and Kansas. The most debatable of these is Kansas, so we repeat our analysis with Kansas classified as a northern state, finding our results to be robust. Other southern states (e.g., New Mexico, Alabama) do not appear in the full sample and are therefore irrelevant to our coding.

14. We report $p$-values based on OLS standard errors. We have also calculated robust standard errors using the usual Huber-White "sandwich" estimator. The robust standard errors produce somewhat larger (less significant) $p$-values, but they have no effect on statistical inferences in our analyses.
15. In the unreported results examining *RGap1* and *RGap2*, we find the coefficients on *FALL* are positive and significant, which is indicative of an asymmetric effect. Thus, this finding in the literature appears dependent on specification and is not generally robust.
16. In unreported regression results (for the full sample), we include an interaction term between SAD and a dummy variable that identifies analysts located in southern states. We find a negative and significant effect, which is consistent with our reported results and the notion that SAD is most influential in northern states.
17. Moreover, the *DAY* variable does not completely mitigate this effect since it is based on a linearity assumption, which is inappropriate at fiscal year end if the "walk-down" (see Richardson, Teoh, and Wysocki [2004]) increases at this time. We thank an anonymous referee for pointing out this potential issue.

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