Depressive Realism and Analyst Forecast Accuracy

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Abstract

Whether a bad mood enhances or hinders problem-solving and financial decision making is an open question. Using the Gallup Analytics survey, we test the depressive realism hypothesis in the earnings forecasts provided by Estimize users. The depressive realism hypothesis states that mild forms of depression improve judgment tasks because of higher attention to detail and slower information processing. We find that a 1-standard-deviation increase in the segment of the U.S. population with depression leads to a 0.25% increase in future forecast accuracy, supporting the hypothesis. This influence is comparable to other determinants of Estimize users' accuracy, like the geographic proximity of users to firms, users' experience, and their professional status. Our result is robust to using an IV analysis, different measures of forecast accuracy and mood, as well as alternative explanations.

Keywords: depressive realism; Estimize; earnings forecast accuracy; negative mood

JEL Classification: G00, G24

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1 Introduction

The emotional state or mood of a person influences her cognitive abilities, and thus her judgments, especially in situations that are less grounded by direct or concrete information (Forgas, 1995). Since financial outcomes such as prices, returns, earnings forecasts, and recommendations are directly influenced by market participants' future expectations of cash flows, the impact of mood is of interest to behavioral finance and economics. Many studies find that indeed, market participants' decisions appear to be influenced by their affective states (Kamstra et al., 2003; Hirshleifer and Shumway, 2003; Dolvin et al., 2009).

At first glance, the psychology literature documents a mood congruency effect, whereby bad (good) material or information is made more salient when an agent is in a bad (good) mood (Forgas and Bower, 1987). However, due to the complex nature of emotions and their impact, it is unclear whether judgments and decisions are enhanced under the influence of a good or bad mood. The situation is made even more complex when accounting for the task at hand, as the conditions of the judgement or decision also impact the extent and direction of how mood will influence the problem solver (Isen, 2008).

In this paper we attempt to resolve this paradox and ask, do negative emotions enhance financial judgements? To answer this question, we rely on a natural laboratory that utilizes a time series of crowd-sourced quarterly earnings forecasts, as well as a representative measure of aggregate mood. Our experiment then entails comparing the accuracy of forecasts made in negative affect environments with those made in positive affect environments.

On the one hand, good moods are associated with more creative problem solving and improved thinking in complex tasks, because of the impact on memory and thought flexibility (Isen, 2008). On the other hand, good moods are also found to disrupt systematic and critical thinking producing sub-optimal decisions, whereas more negative affective states lend themselves to better problem solving through more detailed analysis (Sinclair and Mark, 1995; Isen, 2008). For example, a phenomenon known as depressive realism has been documented by several psychology studies contending that depressive people are better at solving problems (Moore and Fresco, 2012). The mechanism proposed is that bad or sad moods promote a reasoning style that pays greater attention to detail and leads to processing information in smaller increments and at a slower pace (Andrews and Thomson, 2009).

Previous studies examining analysts in finance and accounting find that analysts' forecast accuracy is determined by a number of factors, including their reputation (Hilary and Hsu, 2013), incentives or career concerns (Lin and McNichols, 1998; Womack and Michaely, 1999; Hong and Kubik, 2003), market uncertainty (Grinblatt et al., 2018), as well as the business cycle (Chang and Choi, 2017). Qian (2009) also finds that analyst forecast errors are positively related to investor sentiment. In other words, analyst forecast errors (defined as the difference between consensus and actual earnings per share) are positively biased when investors are more optimistic. Given these findings, we conjecture that the accuracy of quarterly earnings forecast will decrease (increase) as mood improves (degrades).

To test our hypothesis, we use data from Estimize, a platform that allows users to submit their earnings and revenue forecasts for firms listed on the website. We use absolute earnings forecast errors as our measure of judgment because they allow us to compare users' output to a standard and objective benchmark (i.e., the actual earnings of a company). Specifically, we compare a user's earnings forecast to the actual earnings of the company and take the absolute value of the error as our main proxy of inaccuracy. Using Estimize as a source of forecasts provides several advantages. First, users making a submission are not limited to buy- or sell-side analysts that are in the financial industry or connected to financial brokerage firms (as in the I/B/E/S database). Such a feature allows us to ensure that our results are not driven by issues related to Wall Street analyst forecasts such as their conflicting incentives (Lin and McNichols, 1998; Womack and Michaely, 1999; Hong and Kubik, 2003). Second, a feature of the Estimize platform is that the consensus forecasts, either made by other users or Wall Street analysts, are hidden when a user is inputting her own estimates. Therefore, our results should not be affected by known biases, such as anchoring or herding, that may affect accuracy of analysts' forecasts (Da and Huang, 2019).

To measure mood or emotions, we use over 2 million responses by households to a survey on emotions and subjective well-being, collected by Gallup Analytics. We focus on the question "Have depression?" at the national-level for each quarter to construct our variable of interest, *Have Depression*, which is the proportion of the U.S. population that indicates they have depression. Other questions in the survey with yes and no answers attempting to proxy for emotions, such as "Experience sadness/enjoyment/happiness yesterday?" are used for robustness in the later part of the analysis.

The data from Gallup provides a nationally representative sample of individuals across the U.S. which has been used in many studies, among them those examining subjective well-being (e.g., Kahneman and Deaton, 2010; Deaton and Stone, 2013; Deaton, 2018). We rely on the Gallup survey as it provides several advantages in measuring mood. Most importantly, the standard measures of sentiment used in the financial literature tend to rely on market information (e.g., Baker and Wurgler's (2007) sentiment index and Qian's (2009) CBOE put-call ratios), whereas Gallup circumvents the use of market outputs as an emotional proxy by providing a direct measure of respondents' emotional state. Moreover, recent financial studies try to generate other measures of sentiment using alternative sources of information such as Twitter (Yang et al., 2015) and Google trends (Da et al., 2015), to provide a more exogenous proxy of emotion. However, these alternate measures do not reflect a representative sample of emotions since they are taken from user-generated inquiries or tweets. Lastly, the Gallup survey allows us to disentangle and distinguish between various types of mood, from the variety of questions provided.

We begin our analysis by examining whether the analysts in the Estimize database exhibit depressive realism. That is, we test if an analyst's absolute forecast error in a given quarter is affected by the national level of depression in the prior quarter. After controlling for various firm and analyst characteristics, as well as time, analyst and firm fixed effects (FEs), we find that indeed, higher levels of *Have Depression* decrease the absolute forecast errors. In economic terms, a 1-standard-deviation increase in the proportion of the population with depression increases future accuracy of earnings forecasts by 0.25%. This impact is comparable to previously documented determinants of Estimize users' accuracy, like the geographic proximity of users to firms (Nikolic et al., 2016), users' experience, and professional status.

To establish a causal link between depression and improved forecast accuracy, we further perform an instrumental variable (IV) analysis. In this test, we instrument the *Have Depression* variable with the national quarterly change in precipitation. In addition to weather being truly exogenous to earnings forecasts, we also use this instrument as many studies have previously established the link between sunlight and mood (e.g., see Kamstra et al., 2003; Hirshleifer and Shumway, 2003; Dolvin et al., 2009). We perform a two-stage least squares (2-SLS) regression on absolute forecast error of analysts progressively including analyst and firm characteristics, along with time, analyst, and firm FEs. Our IV analysis confirms our finding that indeed higher levels of depression positively affect the forecast accuracy of Estimize users.

According to our hypothesis, a reduction in optimism (i.e., an increase in pessimism), which enhances problem solving, is the mechanism through which depressive realism leads to an increase in accuracy (Dolvin et al., 2009). To examine the channel, we measure whether an analyst is pessimistic, by creating an indicator variable, $Pessimism$, that takes a value of 1 if her forecast is below the management guidance, and 0 otherwise. Subsequently, we interact the $Pessimism$ variable with *Have Depression* and re-estimate our previous analysis including all three variables (i.e., $Pessimism$, *Have Depression*, and the interaction variable). We find that pessimistic analysts during higher levels of depression have more accurate forecasts relative to those with optimistic forecasts, lending support to the idea that the effect of increased accuracy is driven through a reduction of optimism.

To ensure that our results are robust to measurement error, we re-examine our hypothesis using alternative measurements for forecast errors and depressed mood. First of all, forecasts are provided in terms of earnings-per-share, which implies that the forecast error will be in dollar terms. In this way, higher errors may mechanically occur for stocks with higher share prices. Therefore, we follow Malmendier and Shanthikumar (2014) and standardize the accuracy across firms, dividing the absolute forecast errors by the share price two days prior to when the forecast was made. While standardization alleviates one type of measurement error, it introduces another. This method of standardizing is impacted by the price itself. Qian (2009) documents that since price changes over time, it affects inferences by introducing a new source of variation. Despite this concern, our results remain consistent when we use standardized absolute forecast error as our independent variable.

Secondly, we reconstruct our mood variable using other questions in the Gallup survey that proxy for a depressed mood, such as whether the respondents have experienced sadness, lack of enjoyment, or lack of happiness. As explained earlier, these variables measure the proportion of the U.S. population that indicates this feeling in a given quarter. Next, we separately perform the same analysis on each of these variables and find that the results remain robust to all variable definitions. Additionally, using alternative measures of mood provides similar magnitudes for the depressive realism effect.

Subsequently, we perform additional tests to show that our findings are not subject to alternative explanations. We first ensure that our results are not merely capturing previously established findings related to other measures of sentiment, such as Baker and Wurgler's (2007) sentiment index and the consumer confidence index (CCI). To do so, we progressively include these measures into our main regression specification and find a similar outcome as before.

Next, it is possible that a certain analyst or firm, or analyst-firm relationship is driving our results. To rule out this scenario, we aggregate our analysis at the analyst-level and re-examine the impact of depressed mood on forecast accuracy. Again, we find consistent results: a 1-standard-deviation increase in the proportion of depressed individuals predicts a 0.89% increase in the forecast accuracy of an average analyst.

Lastly, several studies document that people with severe depression are affected differently than those with mild forms of it (Moore and Fresco, 2012). Therefore, it is important to disentangle such an impact from our results. Due to data limitations, we proxy for those with severe depression using the answers to the question of "using drugs for relaxation." We think this question is an appropriate proxy for our purpose because a large proportion of people with severe depression are treated, and the use of depression treatments has been increasing over time (Pratt et al., 2017). Unlike our previous results, we find no clear impact of our proxy for severe depression on the forecast accuracy of Estimize users. This result further clarifies the main drivers of our results.

Our findings contribute to the psychology literature on depressive realism. While the hypothesis has been tested in the lab, according to Moore and Fresco (2012), studies lacked a "gold standard of reality with which to compare a participants' perceptions of events." In this regard our paper provides an experimental setup with a judgment task that has a clear, real-world, objective benchmark, facilitating comparisons across individuals and across time.

Moreover, we provide evidence that a bad mood or emotional state may indeed facilitate financial problem solving by tempering overly optimistic expectations. Fear and anxiety have been previously linked to pessimistic financial outcomes (Kaplanski and Levy, 2010; Wang and Young, 2019; Cuculiza et al., 2019). However, these findings have mostly focused on the impact of disasters (e.g., aviation disasters, terrorist attacks, etc.). While related, fear and anxiety are generally associated with imminent threats, unlike the emotions from depression and bad moods (Kemeny and Shestyuk, 2008). Our results contribute by disentangling the impact of depression from anxiety, specifically in determining financial analyst forecast accuracy.

Finally, we contribute to the behavioral financial economics literature by providing more evidence for the role mood plays in processing information, especially when judgements about an uncertain future are being made. This relates to previous studies such as, Da et al. (2015) and Engelberg and Parsons (2016) that uncover correlations between market sentiment, uncertainty, and psychological outcomes. Unlike these studies, we do not rely on market prices as our financial outcomes and instead examine direct outcomes of a task with a standardized benchmark for all participants (i.e., analyst forecasts).

The balance of this paper is organized as follows. Section 2 describes the data and variables used in the study. Section 3 and Section 4 describe the empirical methodology and results, while Section 5 provides additional checks. We conclude the paper in Section 6.

2 Data and Methods

This section provides information about the data sets and main variables used in the empirical analyses. Table A1 shows detailed information about the definition and sources of each variable.

2.1 Data Sources

We obtain information about individual forecasts and households' mood from Estimize and Gallup Analytics, respectively. In what follows, we describe these databases in detail.

2.1.1 Estimize

Estimize is a private company that crowd-sources quarterly earnings and revenue forecasts on its online platform.[1] Unlike in the I/B/E/S database – a commonly used database for analyst earnings forecasts– the contributors of Estimize are not limited to buy- or sell-side analysts. This diversity has shown to positively affect the overall forecast accuracy of Estimize users compared with Wall Street consensus (Jame et al., 2016; Adebambo et al., 2019).

Following previous studies (e.g., Jame et al., 2016), we exclude all duplicate observations which may come from erroneous data input. Given that our focus is on users' earnings forecasts, we further remove the revenue estimates. As in Jame et al. (2016) and Li et al. (2019), we also drop those estimates that are issued 90 days before the actual earnings announcement and those estimates that are issued after the actual announcement date. If a contributor makes multiple earnings forecasts for a firm on the same date, we replace the

[1]See Jame et al. (2016) for detailed institutional description of Estimize and factors that motivate individuals to contribute estimates on this platform.

observation with the average value of all such estimates. Lastly, when a user issues multiple forecasts for a firm in a given reporting quarter, we keep the user's most recent estimate in our analysis (Jame et al., 2016).

Subsequently, we merge the Estimize data with the Center for Research on Security Prices (CRSP) and Thomson Reuters' Institutional (13F) holdings data to obtain information about the return, size, and institutional ownership of firms that Estimize users cover. From the merged sample, we exclude firms with fewer than three distinct users (Zhu, 2002) or firms whose stock price is less than five dollars (Ertan et al., 2016). Our final sample comprises $45,627$ unique analyst-firm-quarter forecasts, issued by $1,754$ users, covering $1,364$ firms over the reporting period of Q4-2010 to Q1-2017.

2.1.2 Gallup Analytics

By interviewing at least 500 adults each day, Gallup provides a representative, ongoing assessment of Americans' health. To assess depressed mood, respondents are asked "Have you ever been told by a physician or nurse that you have depression," with three predetermined categories of "Yes," "No," and "Don't Know." Gallup then aggregates the responses in each category to reflect the proportion of individuals who have (or have not) depression on a given day.[2]

In addition to depressive mood, we further collect data on individuals' transient emotions, including their sadness, happiness, and enjoyment. For these affects, individuals are asked "Did you experience sadness/happiness/enjoyment during a lot of the day yesterday," with similar predetermined response categories as for depressed mood. To align the data with the Estimize information, we aggregate the daily measures to a quarterly frequency.

[2]In aggregating these responses, Gallup accounts for various characteristics of the survey, to generate a representative assessment of individual emotion.

2.2 Dependent Variable

Our main dependent variable is absolute forecast error of Estimize users. We follow Hong et al.'s (2000) method and define this variable as:

$$\text{Absolute Forecast Error}_{i,f,t} = |\text{User Forecast}_{i,f,t} - \text{Actual Earnings}_{f,t}|, \tag{1}$$

where User Forecast$_{i,f,t}$ shows the most recent earnings forecast issued by analyst i for firm f for reporting quarter t. Actual Earnings$_{f,t}$ shows the actual earnings of the firm. A larger deviation from the actual earnings indicates a larger inaccuracy in the analyst's earnings forecast.

Prior studies (e.g., Clement, 1999; Hong and Kubik, 2003; Malmendier and Shanthikumar, 2014; Jannati et al., 2020) have also used scaled versions of the above variable to assess analysts' forecast accuracy. Although widely used, this method of standardizing suffers from the impact of using price. In particular, Qian (2009) documents that because price changes over time, it impacts inferences by introducing a new source of variation. To avoid this issue, in our analysis we use Equation (1) as our baseline measure of analysts' inaccuracy. However, to ensure that our estimates are not sensitive to this choice, we further define an alternative measure of forecast inaccuracy as:

$$\text{Standardized Absolute Forecast Error}_{i,f,t} = \frac{|\text{User Forecast}_{i,f,t} - \text{Actual Earnings}_{f,t}|}{\text{Price}_{f,t}} \tag{2}$$

where $Price_{f,t}$ is the stock price two days prior to firm announcement date (Malmendier and Shanthikumar, 2014; Jannati et al., 2020). As before, a larger value of the above variable indicates a larger inaccuracy in the analyst's earnings forecast.

2.3 Explanatory Variables

Our main independent variable is *Have Depression: Yes*, which identifies the proportion of individuals in the Gallup survey with depressive mood. As previously discussed, we also use alternative measures of negative mood in our analysis including the proportion of individuals in the survey who declare experiencing sadness (*Sadness: Yes*), lack of happiness (*Happiness: No*), and lack of enjoyment (*Enjoyment: No*).

To control for attributes that impact analysts' performance, we follow prior studies (e.g., Holmstrom, 1999; Clement and Tse, 2005; Jame et al., 2016) and include various characteristics of analysts and firms in the analysis. For analysts' attributes, we include *Number of Covered Industries*, *Number of Covered Firms*, *Forecast Horizon*, *Firm-specific Experience*, *Estimize Experience*, and *Professional Status*. In particular, *Number of Covered Industries* and *Number of Covered Firms* are equal to the total number of industries and firms users cover in a given quarter. We measure *Forecast Horizon* by subtracting the forecast date from the earnings announcement date. *Firm-specific Experience* shows the total number of quarters an analyst has covered a firm. Similarly, *Estimize Experience* shows the total number of quarters an analyst has appeared in the Estimize database since she opened her account. Lastly, *Professional Status* is a dummy variable equal to 1 if an analyst identifies herself as financial professional, and 0 otherwise.

For firm attributes we add *Institutional Ownership*, *Size*, and *Market-to-Book Ratio* as explanatory variables. *Institutional Ownership* shows the percentage of a firm's outstanding shares held by institutions. *Size* is the natural logarithm of the market capitalization. *Market-to-Book Ratio* shows a firm market value divided by its total assets. Lastly, we include quarterly average of *Income per Capita* to control for the impact of income on well-being and individuals' financial decision making (Campbell, 2006; Kahneman and Deaton, 2010).

2.4 Summary Statistics

Table 1 reports the summary statistics of the main variables. Panel A describes the dependent variable. *Absolute Forecast Error* (*Standardized Absolute Forecast Error*) has an average value of 0.0858 (0.0021) with a standard deviation equal to 0.1447 (0.0058). These values are close to the corresponding values obtained by prior studies (e.g., Li et al., 2019).

Panel B shows that, on average, 17.3% of individuals declared having depression. This number remains similar when we consider alternative measures of negative affect. Specifically, the average value for other negative mood variables ranges from 11.7% (*Happiness: No*) to 17.6% (*Sadness:Yes*). For perspective, these averages are in line with the 12.7% of the US population who were prescribed anti-depressant medication during the 2011 - 2014 period (Pratt et al., 2017).

Panel C shows the descriptive statistics for our control variables. Estimize users cover about 42 firms and 4 sectors per quarter, on average. They also make forecasts about 8 days before the actual announcement date.[3] The average *Firm-specific Experience* is 2.64, suggesting that users follow a firm for about 3 quarters. An average firm on Estimize has a 30% *Institutional Holdings* with a *Firm Size* of $5.4 billion (i.e., natural logarithm of 8.6), and and *Market-to-Book Ratio* of 2.54.

Finally, Panel D of Table 1 reports the Pearson within correlation coefficients and statistical significance between the two forecast accuracy measures and the negative mood measures. The depression measure has a negative and significant correlation with both accuracy measures. The alternative negative mood measures (i.e. sadness, enjoyment, and happiness) exhibit similar correlation.

3 Depressive Realism and Forecast Accuracy

In this section, we examine whether depressive mood affects the accuracy of Estimize analysts. We also examine the causal influence of depressive mood on analysts' earnings forecast through an IV analysis.

[3] The mean number of firms covered and forecast horizon in Jame et al. (2016)'s two-year sample are 8.41 and 5.03, respectively. When we restrict our sample to only reporting years 2012 and 2013, the values come close to Jame et al. (2016)'s values (9.56 and 6.76 for number of firms covered and forecast horizon, respectively).

3.1 Baseline Results

To empirically investigate the depressive realism hypothesis, we test if an increase in the proportion of households with depression affects the forecasts accuracy of Estimize users. Specifically, we run the following pooled ordinary least squares (OLS) regression:

$$\begin{aligned} \text{Absolute Forecast Error}_{i,f,t} = \beta_1 \text{ Have Depression}_{t-1} + \beta_2 \text{ Analyst Char}_{i,t-1} + \\ \beta_3 \text{ Firm Char}_{f,t-1} + \delta_q + \delta_y + \lambda_f + \gamma_i + \epsilon_{i,f,t}. \end{aligned} \quad (3)$$

Above, *Absolute Forecast Error*$_{i,f,t}$ shows the absolute deviation of analyst i's earnings forecasts for firm f at time t from the actual earnings value (Equation 1). Our main independent variable is *Have Depression*$_{t-1}$ that shows the proportion of the U.S. population (from Gallup survey) who declared having depression at time $t-1$.

In our analysis, we control for various characteristics of analysts that may affect their earnings forecasts, including *Number of Firms Covered*, *Number of Industries Covered*, *Forecast Horizon*, *Firm-specific Experience*, *Estimize Experience*, and *Professional Dummy*. We also add firm-level regressors to our test, including firms' *Institutional Holdings*, *Size*, and *Market-to-Book Ratio*. To control for the economic condition of households we also include *Income per Capita* as a regressor. Moreover, we include a battery of FEs in our model to control for unobserved characteristics, over time or for a specific firm or analyst, that may simultaneously affect negative mood and the forecast accuracy of Estimize users. These include quarter (δ_q), year (δ_y), firm (λ_f), and analyst (γ_i) FEs. Lastly, we account for possible correlation of analysts' earnings forecast errors by clustering the standard errors at the analyst level.

Table 2 shows the results. As shown in Column (1), the estimated β_1 from the above regression is negative and statistically significant. This result suggests that a higher level of depressive mood is related with a lower level of forecast error in the next period, confirming the depressive realism hypothesis. In economic terms, a 1-standard-deviation increase in the segment of the U.S. population with depression leads to a 0.25% (i.e., 3% of the sample mean) increase in the forecast accuracy.

The above results hold when we gradually add FEs to our model. Specifically, we find economically and statistically similar results in Columns (2) to (5) when we gradually add year, quarter, firm, and analyst FEs to our model. As shown in Column (4) the economic significance of our main independent variable is larger than other known determinants of analysts' accuracy, such as professional status or experience. Together, these results suggest that over and above various analyst- and firm-level characteristics, an analyst's forecast accuracy for a given firm improves when the national-level depressive mood is higher.

3.2 Establishing Causality: IV Analysis

To further establish the causality argument of Table 2, we investigate the depressive realism hypothesis, using an IV analysis. Although in our baseline regression (Equation 3) we control for various characteristics of analysts and firms they cover, one could be still concerned about the omitted variable bias. Moreover, some households may (for unobserved reasons) feel more comfortable declaring their depression status in a given period, a choice that makes our main independent variable non-random.

We use IV analysis to ensure that our results are not affected by the above endogeneity concern. Specifically, we obtain U.S. precipitation data from the National Centers for Environmental Information (NCEI) and use quarterly change in the average precipitation as an IV to estimate the proportion of the population with depression.

The psychology literature has long linked weather with individuals' mood. For instance, Mirzakhani and Poursafa (2014) and Baylis et al. (2018) note that higher precipitation is related with negative sentiment and depressive mood. Motivated by this argument, we test the economic relevance of our IV, running the following pooled OLS regression:

$$\begin{aligned}\text{Have Depression}_t = \beta_1 \text{ Change in Precipitation}_t + \beta_2 \text{ Analyst Char}_{i,t} + \\ \beta_3 \text{ Firm Char}_{f,t} + \delta_q + \delta_y + \lambda_f + \gamma_i + \epsilon_t.\end{aligned} \tag{4}$$

In the above analysis, we use the same set of control variables and FEs as in our baseline regression. Panel A of Table 3 support the economic relevance of our IV: a larger increase in the average national precipitation has a positive and statistically significant correlation with the proportion of individuals with depressive mood. Moreover, the estimated F-statistic (19.52 in the most conservative regression) suggests that our analysis does not suffer from a weak instrumental variable (Stock et al., 2002).

For our IV to be valid, it needs to also satisfy the economic restriction requirement. Although there is a not a direct way to test this criteria, it is unlikely that change in precipitation directly affect forecast accuracy of Estimize users.

In the next step, we use the estimates from the above Equation (i.e., $Have\ \widehat{Depression}$) to test the second-stage of our 2-SLS regression as follows:

$$\begin{aligned}\text{Absolute Forecast Error}_{i,f,t} = \beta_1 \text{ Have } \widehat{\text{Depression}}_{t-1} + \beta_2 \text{ Analyst Char}_{i,t-1} + \\ \beta_3 \text{ Firm Char}_{f,t-1} + \delta_q + \delta_y + \lambda_f + \gamma_i + \epsilon_{i,f,t}.\end{aligned} \tag{5}$$

Panel B of Table 3 shows the same pattern as before: an increase in the proportion of the population with depression is associated with a lower level of forecast error among Estimize users. Again, this result is economically significant: a 1-standard-deviation increase in the proportion of the U.S. population with depression predicts a 0.47% (i.e., 5% of the sample mean) increase in the standard deviation of forecast accuracy (Column (5)). Together, this result provides evidence for the casual impact of depressive mood on forecast accuracy of analysts, confirming the depressive realism hypothesis.

4 Economic Channel: Pessimistic Behavior

In this section, we examine the economic channel through which depressive mood may spur analysts' forecast accuracy. In doing so, we focus on a dominant explanation for the depressive realism: relative pessimism of depressive individuals compared with non-depressive individuals (Allan et al., 2007). Specifically, it is shown that, for an identical set of information, forecasts of depressed individuals of future outcome are more pessimistic than those of non-depressed people (Alloy and Ahrens, 1987). Such pessimistic behavior leads depressed individuals to assume occurrence of an event only when they are very confident about it (Allan et al., 2007). Motivated by this evidence, we conjecture that through higher pessimistic behavior, depressive mood increases the forecast accuracy of Estimize users. To examine this hypothesis, we run the following pooled OLS regression:

$$\begin{aligned}\text{Absolute Forecast Error}_{i,f,t} = {} & \beta_1 \text{ Have Depression}_{t-1} \times \text{Pessimism Dummy}_{i,f,t-1} + \\ & \beta_2 \text{ Have Depression}_{t-1} + \beta_3 \text{ Pessimism Dummy}_{i,f,t-1} + \beta_4 \text{ Analyst Char}_{i,t-1} + \\ & \beta_5 \text{ Firm Char}_{f,t-1} + \delta_q + \delta_y + \lambda_f + \gamma_i + \epsilon_{i,f,t},\end{aligned} \tag{6}$$

where, Pessimism Dummy$_{i,f,t-1}$ is an indicator variable equal to 1 if at time $t-1$ analyst i's earnings forecast for firm f is below the management guidance. We use the same set of control variables and FEs as in the baseline regression.

If higher relative pessimism of depressed individuals is the mechanism through which depressed mood affects analysts' earnings accuracy, β_1 from the above regression should be negative and statistically significant. This is indeed what we find in Table 4. As shown, the interaction between the pessimism dummy and the proportion of depressed individuals loads negative and statistically significant in the majority of the specifications. Although in two specifications (i.e., Columns 1 and 3) the statistical power of our estimates drops, these results still econometrically confirm the above conjecture.

5 Robustness Tests and Alternative Explanations

For the last section of our study, we provide additional tests that support our main findings. Specifically, we show that our results are not sensitive to how we measure analysts' forecast accuracy or individuals' negative affect. We further confirm that our result remains robust when we account for the impact of other known sentiment measures. Lastly, we examine the influence of severe depressive mood on our results and show that some skewness features of our sample do not affect our previous results.

5.1 Alternative Measure of Forecast Accuracy

In our baseline analysis, we measured analysts' forecast inaccuracy using the deviation of their earnings forecasts from the actual earnings of a firm (see Equation 1). Although this measure has been widely used in the previous papers (e.g., Hong and Kubik, 2003), to ensure that our findings are not sensitive to how we calculate our main independent variable, we re-estimate Equation 3, using an alternative measure of forecast accuracy.

In particular, we follow Dolvin et al. (2009) and Jame et al. (2016) and standardize absolute forecast error by stock price (Equation 2). Subsequently, we repeat our baseline regression, but replace the main independent variable with the above measure. Table 5 reports the estimation results. As shown, our point estimates remain very consistent as in Table 2: an increase in the proportion of individuals with depression is related to a lower level of errors in analysts' forecast (i.e., a higher level of accuracy). This result holds when we control for various characteristics of analysts and firms they cover (Column (1)) or when we include various FEs in our model (Columns (2) to (5)).

5.2 Alternative Measure of Negative Affect

Next, we examine whether our previous results remain if we use other measures of negative affect to proxy for individuals' depressive mood. In doing so, we use alternative, but related, dimensions of depressed mood such as sadness, lack of enjoyment, and lack of happiness (Waterman, 1993). In particular and for robustness, we construct three alternative measures, *Sadness*, *Lack of Enjoyment*, and *Lack of Happiness* analogously to *Have Depression* using responses to the question "Did you experience sadness/happiness/enjoyment during a lot of the day yesterday?" and re-perform the analysis. We report the results in Table 6.

Consistent with the primary analysis, we find that all three alternative measures predict higher forecast accuracy among Estimize users. Moreover, the economic magnitudes of the effects of these measures and *Have Depression* are similar. For instance, the estimate on *Sadness* in Column (1) suggests that a 1-standard-deviation increase in sadness corresponds to a 0.58% decline in the standard deviation of absolute forecast error.

5.3 Depressive Realism beyond Known Sentiment Indices

A potential concern could be that our measures of depression may capture the same element of individuals' emotions as in previously documented indices. Therefore, one may argue that once we control for other known sentiment measures, our measure of depression may become redundant. To address this concern, we first explore the correlation between our various affect measures with other indices, related to investors' sentiment, including Baker and Wurgler's (2006) Investor Sentiment Index, Consumer Confidence Index, and Gallup Economic Confidence index. As shown in Figure 1, there is not a clear correlation pattern between our affect variables and other indices, indicating that these measures capture distinct dimensions of individuals' affects.[4]

In Table 7, we further re-estimate our baseline regression (Equation 3), but additionally control for the above indices. As shown in Columns (1) and (2), our previous results remain consistent beyond Baker and Wurgler's (2006) investor sentiment index. We find the same result in Columns (3) and (4) (Columns 5 and 6) when we control for Consumer Confidence (Gallup Economic Confidence) index. Lastly, in Columns (7) and (8) we control for all these indices jointly and again find the same outcome. Together, these results suggest that the impact of individuals' depressive mood on the accuracy of their earnings forecast accuracy is beyond the potential impacts of other known sentiment measures.

[4] The Pearson correlation between our depression measure and the above indices are -0.4577 (p-value: 0.0143), 0.6773 (p-value: 0.0001), 0.0015 (p-value: 0.0015), respectively

5.4 Aggregate-level Analysis

As explained before, our analysis uses pooled-panel OLS regression. However, constructing the panel in this way may raise the concern of a within-unit error correlation related to the panel's repeated values (i.e., the proportion of individuals with depressive mood). To ensure that the results are not affected by this issue, we repeat the baseline regression by aggregating the analysis at the analyst-level. That is, we run the following OLS regression:

$$\begin{aligned} \text{Absolute Forecast Error}_{i,t} = \beta_1 \text{ Have Depression}_{t-1} + \beta_2 \text{ Analyst Char}_{i,t-1} + \\ \beta_3 \text{ Average Firm Char}_{t-1} + \delta_q + \delta_y + \gamma_i + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where Absolute Forecast $\text{Error}_{i,t}$ shows the average of analyst i's absolute forecast accuracy for all the firms he/she covers in quarter q in year y. We use the same set of analyst-level control variables as in the previous analysis. For the firm-level controls, we account for the same characteristics as before, but aggregate them at the analyst level (for instance, we consider the average institutional holdings of all firms that an analyst covers at a given time).

The results in Table 8 show similar results as before: an increase in the proportion of depressed individuals is related to smaller earnings forecast errors among Estimize analysts. Compared with the baseline results the economic significance of the aggregate estimates is even higher. As before, this result is robust to various FEs in the model.

5.5 Effects of Severe Depression

In the previous analysis, we documented that individuals' depressed mood is associated with higher accuracy in crowd-based earnings forecasts. We further showed that such an increase in accuracy is related to the lower optimistic behavior of analysts. Although previous studies have also shown a similar connection between individuals' depressed mood and higher accuracy, one might be concerned about the impact of severe depression cases on our results. Specifically, one could argue that individuals who are severely depressed are more likely to suffer from negative perceptual and memory biases, and hence are less likely to have accurate judgment (Beck, 1967, 1976).

Using the available data on Gallup, we are not able to directly identify the severeness of individuals' depression. Therefore, we indirectly estimate the proportion of severely depressed individuals as those who use drugs for relaxation on a daily base. In doing so, we repeat our baseline regression but replace our main independent variable (i.e., Have Depression) with the proportion of individuals who declared using drugs for relaxation almost every day on the Gallup surveys.

We report the results in Table 9. As shown, unlike the results in Table 2 an increase in the proportion of individuals who regularly use drugs does not have a consistent impact on the accuracy of analysts' earnings forecasts. This result suggests that our previous results are less likely to be affected by individuals who may suffer from severe depressions.

5.6 Analysts with Large Number of Covered Firms

A final potential concern relates to the distribution skewness of the number of firms covered by Estimize users. An average user covers around 42 firms, while the median user covers 8 firms. The reason for this skewed distribution can be explained by the Estimize contribution criteria. The website itself states that a user should generate at least ten estimates per quarter. However, in order to be considered a "highly ranked analyst" a user is urged to cover fifty or more firms within or across sectors.[5] To ensure that our results are not driven by this feature of the Estimize dataset, we re-preform the analysis on a winsorized sample, as well as a trimmed sample.

Table 10 provides the results. Columns (1) and (2) (Columns 3 and 4) provide that the results remain when the sample of analysts is winsorized at the 1% (2%) level. We also winsorize and redo the analysis for the right-tail of the sample alone. Columns (5) and (6)

[5] A direct quotation from Estimize's FAQ on the website states, "In order to generate meaningful metrics, at least 10 estimates per quarter are suggested. Highly ranked analysts on average cover between 50-60 stocks within a sector, and may cover multiple sectors. For Economic Indicators, some analysts focus on one area, but many cover the full set on Estimize. There is a healthy range of contribution amongst analysts on the platform." Source: https://www.estimize.com/faqdata

(Column 7) show that the results hold when the right-tail is winsorized at the 1% level (when we trim the sample at the 1% level). These robustness checks provide confidence that the skewness of the analyst coverage is not material in driving the results.

6 Summary and Conclusion

This paper tests the depressive realism hypothesis using quarterly earnings forecasts provided by Estimize users. The hypothesis states that a person feeling mildly depressed is better able to solve problems due to an increase in focus, a slower pace of and smaller increments of information ingestion. This hypothesis contrasts outstanding evidence in the psychology literature showing the creative and critical thinking is enhanced in good moods.

We measure national mood using responses from the Gallup Survey and find that earnings forecasts are more accurate following periods where higher levels of the US population report feeling depressed. We attempt to establish the causality of the findings by performing a 2-SLS IV analysis using the change in precipitation levels to instrument for mood. We also document that it is pessimistic forecasts made during high depression periods, that drive the results.

Additionally, we re-preform the analysis using alternative measurements of negative moods, as well as earnings forecast accuracy. Finally, we attempt to rule out alternative explanations by including other well-known sentiment measures in our analyses, aggregating the analysis at the analyst-level, and isolating the analysis to highly depressed individuals. We find that our results remain robust to all alternative measurements and explanations.

We contribute to the psychology literature by providing a natural experiment incorporating a task with a standard and objective benchmark to shed light on cognitive performance during periods of good or bad mood. We also contribute to the behavioral finance and accounting literature by documenting further evidence of how mood plays a significant role in the processing of market information. We also contribute by showing that the impact of depression on decision making is different from that of fear and anxiety.

References

Adebambo, B., Bliss, B. A., and Kumar, A. (2019). Geography, Diversity, and Accuracy of Crowdsourced Earnings Forecasts by.

Allan, L. G., Siegel, S., and Hannah, S. (2007). The sad truth about depressive realism. *Quarterly Journal of Experimental Psychology*, 60(3):482–495.

Alloy, L. B. and Ahrens, A. H. (1987). Depression And Pessimism For The Future: Biased Use of Statistically Relevant Information In Predictions For Self Versus Others. *J Pers Soc Psychol*, 52(2):366–78.

Andrews, P. W. and Thomson, J. A. (2009). The Bright Side of Being Blue: Depression as an Adaptation for Analyzing Complex Problems. *Psychological Review*, 116(3):620–654.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61(4):1645–1680.

Baker, M. and Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of economic perspectives*, 21(2):129–152.

Baylis, P., Obradovich, N., Kryvasheyeu, Y., Chen, H., Coviello, L., Moro, E., Cebrian, M., and Fowler, J. (2018). Weather Impacts Expressed Sentiment. *PLoS Oned*, 13(4).

Beck, A. T. (1967). Depression: Clinical, experimental, and theoretical aspects. *New York: Harper Row.*

Beck, A. T. (1976). Cognitive therapy and emotional disorders. *New York: International Universities.*

Campbell, J. Y. (2006). Household finance. *Journal of Finance*, 61:1553–1604.

Chang, J. W. and Choi, H. M. (2017). Analyst Optimism and Incentives under Market Uncertainty. *Financial Review*, 52(3):307–345.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 27(3):285–303.

Clement, M. B. and Tse, S. Y. (2005). Financial Analyst Characteristics and Herding Behavior in Forecasting. *Journal of Finance*, 60:307–341.

Cuculiza, C., Antoniou, C., Kumar, A., and Maligkris, A. (2019). Terrorist Attacks, Analyst Sentiment, and Earnings Forecasts. *Working Paper.*

Da, Z., Engelberg, J., and Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies*, 28(1):1–32.

Da, Z. and Huang, X. (2019). Harnessing the Wisdom of Crowds. *Management Science*.

Deaton, A. (2018). What do self-reports of wellbeing say about life-cycle theory and policy? *Journal of Public Economics*, 162(March):18–25.

Deaton, A. and Stone, A. A. (2013). Two happiness puzzles. *American Economic Review*, 103(3):591–97.

Dolvin, S. D., Pyles, M. K., and Wu, Q. (2009). Analysts Get SAD Too: The Effect of Seasonal Affective Disorder on Stock Analysts' Earnings Estimates. *Journal of Behavioral Finance*, pages 214–225.

Engelberg, J. and Parsons, C. A. (2016). Worrying about the Stock Market: Evidence from Hospital Admissions. *Journal of Finance*, 71(3):1227–1250.

Ertan, A., Karolyi, S. A., Kelly, P., and Stoumbos, R. C. (2016). Pre-Earnings Announcement Over-Extrapolation. *Working paper*.

Forgas, J. P. (1995). Mood and judgment: The affect infusion model (AIM). *Psychological Bulletin*, 117(1):39–66.

Forgas, J. P. and Bower, G. H. (1987). Mood Effects on Person-Perception Judgments. *Journal of Personality and Social Psychology*, 53(1):53–60.

Grinblatt, M., Jostova, G., and Philipov, A. (2018). Analyst Bias and Mispricing. *Working paper*.

Hilary, G. and Hsu, C. (2013). Analyst Forecast Consistency. *Journal of Finance*, 57(No.1):271–297.

Hirshleifer, D. and Shumway, T. (2003). Good Day Sunshine: Stock Returns and the Weather. *Journal of Finance*, 58:1009–1032.

Holmstrom, B. (1999). Managerail Incentive Problem: A Dynamic Perspective. *The Review of Economic Studies*, 66(1):169–182.

Hong, H., Kubik, J., and Solomon, A. (2000). Security Analysts' Career Concerns and Herding of Earnings Forecasts. *The RAND Journal of Economics*, 31(1):121.

Hong, H. and Kubik, J. D. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *The Journal of Finance*, 58(1):313–351.

Isen, A. (2008). Some Ways in Which Positive Affect Influences Decision Making and Problem Solving. In Lewis, M., Haviland-Jones, J. M., and Barrett, L. F., editors, *Handbook of Emotions*, chapter 34, pages 548 – 573. The Guilford Press, New York, third edition.

Jame, R., Johnston, R., Markov, S., and Wolfe, M. C. (2016). The Value of Crowdsourced Earnings Forecasts. *Journal of Accounting Research*, 54(4):1077–1110.

Jannati, S., Kumar, A., Niessen-Ruenzi, A., and Wolfers, J. (2020). In-Group Bias in Financial Markets. *Working paper*.

Kahneman, D. and Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences of the United States of America*, 107(38):16489–16493.

Kamstra, M. J., Kramer, L. A., and Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review*, 93(1):324–343.

Kaplanski, G. and Levy, H. (2010). Sentiment and stock prices: The case of aviation disasters. *Journal of Financial Economics*, 95(2):174–201.

Kemeny, M. E. and Shestyuk, A. (2008). Emotions, the Neuroendocrine and Immune Systems, and Health. In Lewis, M., Haviland-Jones, J. M., and Barrett, L. F., editors, *Handbook of Emotions*, chapter 34, pages 661 – 675. The Guilford Press, New York, third edition.

Li, Q., Lourie, B., and Teoh, S. H. (2019). How Salience of Management Guidance Affects Forecasting Behavior: Evidence from a Quasi-Natural Experiment on Estimize. Technical report, Rochester, NY.

Lin, H. W. and McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics*, 25(1):101–127.

Malmendier, U. and Shanthikumar, D. (2014). Do security analysts speak in two tongues? *Review of Financial Studies*, 27(5):1287–1322.

Mirzakhani, L. and Poursafa, P. (2014). The association between depression and climatic conditions in the iran way to preventive of depression. *Int J Prev Med*, 5(8):947–951.

Moore, M. T. and Fresco, D. M. (2012). Depressive realism: A meta-analytic review. *Clinical Psychology Review*, 32(6):496–509.

Nikolic, B., Bliss, B. A., and Kumar, A. (2016). Geography, Diversity, and Accuracy of Crowdsourced Earnings Forecasts. *Working Paper.*

Pratt, L. A., Brody, D. J., and Gu, Q. (2017). Antidepressant Use Among Persons Aged 12 and Over:United States,2011-2014. *NCHS data brief*, (283):1–8.

Qian, H. (2009). Time Variation in Analyst Optimism: An Investor Sentiment Explanation. *Journal of Behavioral Finance*, 10(3):182–193.

Sinclair, R. C. and Mark, M. M. (1995). The Effects of Mood State on Judgemental Accuracy: Processing Strategy as a Mechanism. *Cognition and Emotion*, 9(5):417–438.

Stock, J., Yogo, M., and Wright, J. (2002). A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments. *Journal of Business and Economic Statistics*, 20:518 – 529.

Wang, Y. A. and Young, M. (2019). Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics (JFE), Forthcoming.*

Waterman, A. S. (1993). Two conceptions of happiness: Contrasts of personal expressiveness (eudaimonia) and hedonic enjoyment. *Journal of Personality and Social Psychology*, 64(4):678.

Womack, K. L. and Michaely, R. (1999). Conflict of Interest and the Credibility of Underwriter Analyst Recommendations. *Review of Financial Studies*, 12(4):653–686.

Yang, S. Y., Yin, S., Mo, K., and Liu, A. (2015). Twitter financial community sentiment and its predictive relationship to stock market movement. *Working Paper.*

Zhu, N. (2002). The local bias of individual investors. *Working Paper.*

Figure 1. Summary Statistics

This figure plots quarterly time series of negative affect measures from Gallup and other sentiment proxies, including the Consumer Confidence Index, the Baker-Wurgler Investor Sentiment Index, and the Gallup Economic Confidence Index for the period from 2011Q1 to 2017Q4. The red solid line in each plot represents the time series of the negative emotion measure. All measures are quarterly average values and normalized by subtracting their values from its minimum, then dividing by the difference between their maximum and minimum values.

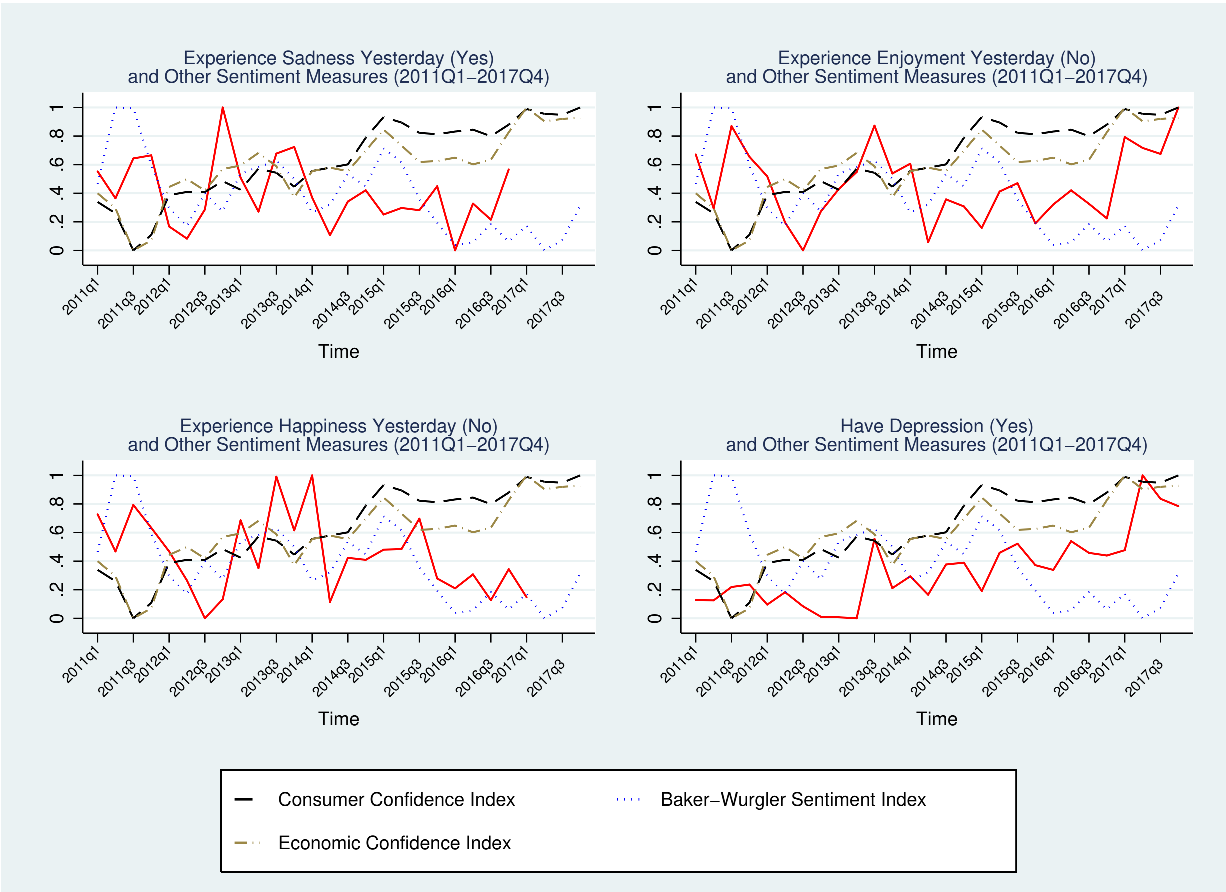

Table 1. Summary Statistics

This table presents the summary statistics of the main variables used in the analysis. Panel A reports statistics for two dependent variables. Panel B reports statistics for main independent variables. Panel C reports statistics for control variables. Panel D reports the Pearson correlation between the main variables of interest. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mean	Std.	25 pctl	Median	75 pctl	# of Obs.
	Panel A: Dependent Variables					
Absolute Forecast Errors	0.0858	0.1447	0.0200	0.0400	0.0900	45,627
Standardized Absolute Forecast Errors	0.0021	0.0058	0.0003	0.0008	0.0019	27,971
	Panel B: Main Independent Variables					
Have Depression: Yes	0.1733	0.0051	0.1687	0.1742	0.1769	39
Sadness: Yes	0.1762	0.0037	0.1746	0.1759	0.1797	39
Enjoyment: No	0.1531	0.0055	0.1509	0.1535	0.1563	39
Happiness: No	0.1172	0.0048	0.1129	0.1165	0.1206	39
	Panel C: Control Variables					
Number of Firms Covered	42.0882	130.1049	3.0000	8.0000	27.0000	4,195
Number of Sectors Covered	3.7676	2.7483	1.0000	3.0000	6.0000	4,195
Forecast Horizon (days)	7.7140	15.1204	0.0000	2.0000	7.0000	45,627
Firm-specific Experience (quarters)	2.6400	2.2422	1.0000	2.0000	3.0000	45,627
Estimize Experience (quarters)	5.0133	3.7534	2.0000	4.0000	7.0000	45,627
Institutional Holdings	0.3177	0.1049	0.2532	0.3210	0.3825	7,634
Firm Size	8.6560	1.5504	7.4877	8.5062	9.6635	7,634
Market-to-Book Ratio	2.5393	1.7969	1.3915	1.9780	3.0367	7,634
Income Per Capita (in 2012 $)	40,373.21	1,174.67	39,299.00	40,179.50	41,610.00	110

	Panel D: Pearson Within Correlation	
	Abs. Forecast Error	Standardized Abs. Forecast Error
Have Depression: Yes	-0.0145**	-0.0351***
Sadness: Yes	-0.0168***	-0.0076
Enjoyment: No	-0.0129**	-0.0269***
Happiness: No	-0.0097*	-0.0233***

Table 2. Depressive Realism and Forecast Accuracy: Baseline Results

This table tests the depressive realism hypothesis, by examining the impact of national-level depression on the earnings forecast accuracy of Estimize users. Specifically, the table reports estimation results from Regression (3), where Have Depression: Yes is the main independent variable. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Dependent Variable: Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes (t-1)	-0.2485***	-0.1890**	-0.1412*	-0.2141***	-0.1999***
	(0.081)	(0.075)	(0.076)	(0.069)	(0.068)
Number of Firms Covered (t-1)	-0.1422	-0.2428**	-0.2384**	-0.0001	-0.2158
	(0.109)	(0.109)	(0.110)	(0.085)	(0.152)
Number of Sectors Covered (t-1)	-0.9520***	-0.9501***	-0.9561***	-0.2744***	0.0821
	(0.129)	(0.129)	(0.128)	(0.075)	(0.151)
Firm-specific Experience (t-1)	-0.1822	-0.1353	-0.1143	-0.1904**	-0.0888
	(0.156)	(0.163)	(0.163)	(0.081)	(0.065)
Estimize Experience (t-1)	-0.1732	-0.2891**	-0.2449*	-0.0041	4.2914
	(0.139)	(0.140)	(0.143)	(0.106)	(4.053)
Forecast Horizon (t-1)	-0.0055	-0.0528	-0.0346	0.1410**	0.0076
	(0.107)	(0.108)	(0.106)	(0.056)	(0.059)
Professional Dummy	-0.4967**	-0.3713	-0.4102*	0.0680	
	(0.226)	(0.238)	(0.229)	(0.126)	
Institutional Holdings (t-1)	-0.1899***	-0.1903***	-0.2019***	0.3566**	0.2465
	(0.071)	(0.071)	(0.071)	(0.164)	(0.161)
Firm Size (t-1)	0.4612***	0.4641***	0.4272***	6.4201***	5.8089***
	(0.109)	(0.110)	(0.109)	(0.981)	(1.001)
Market-to-Book Ratio (t-1)	-0.1462	-0.1271	-0.1343	-2.2238***	-1.9689***
	(0.099)	(0.101)	(0.100)	(0.246)	(0.233)
Income Per Capita (t-1)	1.5233***	-0.5269**	-0.0586	0.4959**	0.5106*
	(0.106)	(0.219)	(0.254)	(0.248)	(0.262)
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓
Adj. R^2	0.02	0.02	0.02	0.52	0.54
# of Obs.	45,627	45,627	45,627	45,584	44,934

Table 3. Depressive Realism and Forecast Accuracy: IV Analysis

The table uses an instrumental variable (IV) analysis to test the depressive realism hypothesis. Specifically, we use quarterly change in average precipitation as an IV to estimate the proportion of individuals with depression. Panel A reports the estimation results for the first-stage regression (Equation 4). Panel B shows the estimation results for the second-stage regression (Equation 5). Additional control variables in each column are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Panel A: First-stage Regression				
	Dependent Variable: Have Depression: Yes (t)				
	(1)	(2)	(3)	(4)	(5)
Change in Average Precipitation (t)	0.1901***	0.2317***	0.3309***	0.3176***	0.2936***
	(0.020)	(0.026)	(0.058)	(0.058)	(0.066)
	Panel B: Second-stage Regression				
	Dependent Variable: Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes (t-1)	1.1892***	-0.0008	-0.7379***	-0.5192**	-0.4677**
	(0.403)	(0.310)	(0.285)	(0.235)	(0.238)
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓
First-stage F-stat	87.06	76.52	32.75	29.87	19.52
# of Obs.	45,627	45,627	45,627	45,584	44,934

Table 4. Economic Channel: Pessimism Behavior

The table examines the role of pessimism behavior as an economic channel through which depression mode leads to forecast accuracy. Specifically, we repeat the same analysis of Table 2, but further include *Pessimism* and its interaction with *Have Depression* to our model, where *Pessimism* is an indicator variable equal to 1 if an analyst's estimate for a firm is below its management guidance, and 0 otherwise. Additional control variables in each column are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Dependent Variable: Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes ×	-0.0547	-0.3145**	-0.2014	-0.4268***	-0.4241***
Pessimism Dummy (t-1)	(0.141)	(0.134)	(0.137)	(0.107)	(0.106)
Have Depression: Yes (t-1)	-0.1187	0.1349	0.0950	0.1586*	0.1664*
	(0.105)	(0.113)	(0.121)	(0.093)	(0.097)
Pessimism Dummy (t-1)	3.7850***	3.8993***	3.8817***	0.5951***	0.5290***
	(0.236)	(0.246)	(0.244)	(0.134)	(0.131)
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓
Adj. R^2	0.02	0.03	0.03	0.52	0.54
# of Obs.	45,627	45,627	45,627	45,584	44,934

Table 5. Alternative Measure of Forecast Accuracy
This table repeats the same analysis of Table 2, but uses the standardized absolute forecast errors (Equation 2) as the main independent variable. Additional control variables in each column are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.. Standardized absolute forecast errors are also standardized to have mean 0 and variance 1.

	Dependent Variable: Standardized Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes (t-1)	-0.0167***	-0.0164***	-0.0112***	-0.0173***	-0.0176***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓
Adj. R^2	0.10	0.10	0.10	0.65	0.66
# of Obs.	27,971	27,971	27,971	27,914	27,384

Table 6. Alternative Measures of Depressed Mood

This table repeats the same analysis of Table 2, but uses proportion of individuals' with sadness, lack of enjoyment, or lack of happiness as the main dependent variables. Additional control variables in each column are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Dependent Variable: Absolute Forecast Error (t)					
	(1)	(2)	(3)	(4)	(5)	(6)
Sadness: Yes (t-1)	-0.5805***	-0.5150***				
	(0.083)	(0.079)				
Enjoyment: No (t-1)			-0.1939***	-0.1674***		
			(0.052)	(0.054)		
Happiness: No (t-1)					-0.1763***	-0.1788***
					(0.056)	(0.057)
Analyst Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Analyst FEs		✓		✓		✓
Adj. R^2	0.53	0.54	0.52	0.54	0.52	0.54
N	45,584	44,934	45,584	44,934	45,584	44,934

Table 7. Depressive Realism beyond Known Sentiment Indices

This table repeats the same analysis of Table 2, but additionally controls for other known indices related to individuals' sentiment, including Baker and Wurgler's (2006) investor sentiment index, Consumer Confidence Index, and Gallup Economic Confidence Index. Additional control variables in each column are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Dependent Variable: Absolute Forecast Error (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Have Depression: Yes (t-1)	-0.2075***	-0.1933***	-0.1979***	-0.1942***	-0.1536**	-0.1422**	-0.1597**	-0.1643**
	(0.073)	(0.069)	(0.068)	(0.069)	(0.072)	(0.070)	(0.071)	(0.068)
Investor Sentiment Index (t-1)	0.0307	0.0299					-0.1189	-0.1790
	(0.134)	(0.132)					(0.168)	(0.150)
Consumer Confidence Index (t-1)			0.1379**	0.0470			0.1012	0.0040
			(0.067)	(0.073)			(0.072)	(0.076)
Gallup Economic Confidence Index (t-1)					0.2586**	0.2355**	0.2895**	0.3050**
					(0.111)	(0.119)	(0.134)	(0.139)
Analyst Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Analyst FEs		✓		✓		✓		✓
Adj. R^2	0.52	0.54	0.52	0.54	0.52	0.54	0.52	0.54
# of Obs.	45,584	44,934	45,584	44,934	45,584	44,934	45,584	44,934

Table 8. Analyst-level Analysis

This table repeats the same analysis of Table 2, but aggregate the analysis at the analyst level (Equation 7). Additional control variables in are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Dependent Variable: Absolute Forecast Error (t)			
	(1)	(2)	(3)	(4)
Have Depression: Yes (t-1)	-0.5499***	-0.3962**	-1.0577***	-0.8855***
	(0.159)	(0.161)	(0.197)	(0.202)
Analyst Controls	✓	✓	✓	✓
Average Firm Controls	✓	✓	✓	✓
Income Control	✓	✓	✓	✓
Year FEs		✓	✓	✓
Quarter FEs			✓	✓
Analyst FEs				✓
Adj. R^2	0.03	0.03	0.04	0.22
# of Obs.	7,461	7,461	7,461	5,546

Table 9. Effects of Severe Depression

This table repeats the same analysis of Table 2, but replaces the main independent variable with the proportion of individuals who declare using drug on the Gallup Analytics. Additional control variables in each column are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Dependent Variable: Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Use Drug for Relaxation:	0.0070	0.9269***	0.2786	0.1578	0.2856*
	(0.093)	(0.228)	(0.192)	(0.141)	(0.148)
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓
Adj. R^2	0.01	0.02	0.02	0.55	0.56
# of Obs.	41,689	41,689	41,689	41,648	41,069

Table 10. Analysts with Large Number of Covered Firms

This table repeats the same analysis of Table 2, but winsorize the number of firms covered at the 1% level in Columns 1 and 2; at the 2% level in columns 3 and 4; at the 1% of right-tail in Columns 5 and 6; and trimmed at the 1% level in Columns 7 and 8. Additional control variables in each column are the same as those used in Table 2. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Information on individuals' emotions is from Gallup Analytics. Income data are from FRED. The sample period is from 2010 to 2017. All control variables, except for *Professional Dummy* are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage points. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered at the analyst level and are shown in parentheses.

	Dependent Variable: Absolute Forecast Error (t)							
	1% winsorized		2% winsorized		1% right-tail winsorized		1% trimmed	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Have Depression: Yes (t-1)	-0.2146***	-0.2048***	-0.2117***	-0.1992***	-0.2146***	-0.2048***	-0.2355**	-0.1763
	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.068)	(0.106)	(0.127)
Analyst Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Analyst FEs		✓		✓		✓		✓
Adj. R^2	0.52	0.54	0.52	0.54	0.52	0.54	0.46	0.49
# of Obs.	45,584	44,934	45,584	44,934	45,584	44,934	18,765	18,101

Table A1

This table defines the main variables used in the empirical analyses.

Variable	Definition
Absolute forecast error	The absolute value of the difference between Estimize user's forecast and actual earnings per share
Standardized absolute forecast error	The absolute forecast error divided by price two days before announcement date
Have Depression: Yes	The quarterly average proportion of people who declared having depression
Experience Sadness/Enjoyment/Happiness	The quarterly average proportion of people who declared experiencing the emotion yesterday
Number of firms covered	The total number of firms each unique Estimize contributor made forecasts on in each quarter
Number of sectors covered	The total number of sectors each unique Estimize contributor made forecasts on in each quarter
Forecast horizon	The number of days from forecast date to announcement date
Firm-specific experience	The cumulative number of forecasts an Estimize contributor has made on a firm
Estimize experience	The cumulative number of quarters an Estimize contributor has been on Estimize
Institutional holdings	The quarterly average proportion of firm shares held by institutions
Firm size	The monthly average of log market capitalization each quarter
Market-to-book ratio	The monthly average of market-to-book ration each quarter
Income per capita	Income per capita with 2012 as the base year