The Up Side of Being Down: Depressive Realism and Analyst Forecast Accuracy

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Abstract

This paper tests the depressive realism hypothesis using earnings forecasts from Estimize. The hypothesis states that mild depression improves judgment tasks by tempering overoptimism or increasing rumination. We find that a 1-standard-deviation increase in the segment of the U.S. population with depression leads to, on average, a 0.25% increase in future forecast accuracy, supporting the hypothesis. This impact is comparable to other determinants of Estimize users' accuracy and is robust to alternative measures and explanations. We find that reduced optimism is primarily how depression improves accuracy. We contribute to the literature by linking negative integral emotions to financial decision making.

Keywords: depressive realism; Estimize; earnings forecast accuracy; cognition

JEL Classification: G00, G24

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1 Introduction

Depression, one of the most common mental disorders in the U.S., affects 5.9% of the population as of 2015, according to the World Health Organization (WHO, 2017). The American Psychiatry Association characterizes depression by psychomotor patterns, caused by extreme problems or stressors (Andrews and Thomson, 2009). Depression is part of an affective continuum that starts at transient sadness on one end, and moves to severe chronic depression on the other (Barbic et al., 2014). Although it is established that depression affects judgment through the cognitive functioning of a person (Forgas, 1995), whether it helps or hinders decision making is less clear (Von Helversen et al., 2011; Moore and Fresco, 2012).

On the one hand, the psychology literature has documented a mood congruency effect, whereby negative information is made more salient when an agent is in a depressed mood, leading to poorer cognition (Forgas and Bower, 1987; Isen, 2008). On the other hand, several studies have documented a bright side of depression. Specifically, they show evidence for the *depressive realism* hypothesis, contending that depressive people have better problem-solving abilities (Smoski et al., 2008; Moore and Fresco, 2012). The proposed mechanism is that individuals with mild depression tend to spend more time ruminating. Hence, they pay greater attention to detail, process information in smaller increments and at a slower pace, rendering a realistic reasoning style (Andrews and Thomson, 2009; Von Helversen et al., 2011; Szu-Ting Fu et al., 2012).

In this paper, we investigate this debate using a financial judgment task and ask, in what way does mild depression affect financial judgments? This question is important for three reasons. First, it is known that market participants' mood affects their expectations of future cash flows and levels of risk aversion, which in turn, may affect financial information and outcomes (e.g., Kamstra et al., 2003; Hirshleifer and Shumway, 2003; Dolvin et al., 2009; Hirshleifer et al., 2020). Given the prevalence of depression among the population, it is important to understand its impact on financial outcomes. Second, while the behavioral finance and economics literature are concerned with the influence of mood; depression, further along the affective continuum, may present different effects on cognition and decision making. In particular, previous studies generally use "positive" and "negative" emotions as umbrella terms for various underlying types of affect, whereas the psychology literature distinguishes between integral (from one's thoughts) and incidental (from one's surroundings) types of emotions (Rick and Loewenstein, 2008). Our question, in contrast to others, focuses on the impact of negative integral emotions on financial decisions.[1] Lastly, financial outcomes present real-world judgment tasks that can shed light on the psychological findings due to depression.

To answer our question, we rely on a setup that utilizes a time series of crowd-sourced quarterly earnings forecasts, as well as a representative measure of aggregate depression. Our test then entails comparing the accuracy of forecasts made in a depressive environment with those made in less depressive environments. If the depressive realism hypothesis applies to our setting, we expect that the accuracy of quarterly earnings forecasts (i.e., our judgment task) improves as the proportion of individuals experiencing depression is higher, because depression should either temper optimism or induce more focused thinking.

We test this hypothesis using 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 error as our measure of judgment because it allows us to compare users' output to a standard and objective benchmark; that is, 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 user 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. 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

[1] See Hirshleifer and Shumway (2003); Kaplanski and Levy (2010); Cuculiza et al. (2020); Agarwal et al. (2019); Wang and Young (2020) for studies examining the impact of incidental emotions on financial decision-making.

incentives (Lin and McNichols, 1998; Womack and Michaely, 1999; Hong and Kubik, 2003). Second, a recent feature of the Estimize platform is that the consensus forecasts, either made by Wall Street analysts or other users, are hidden when a user is inputting her own estimates. Therefore, it is less likely that known biases, such as anchoring or herding, drive our results (Da and Huang, 2019). Despite these advantages, we also use I/B/E/S and examine the impact of depression on the forecast accuracy of sell-side equity analysts.

To measure the level of depression, 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 been told by a physician or nurse that they have depression.[2] Due to the nature of the question, we expect responses to include all diagnoses ranging from mild to chronic depression. Given that our hypothesis focuses on the impact of mild depression, in the later part of the analysis, we perform a number of tests to ensure that our results are not driven by severe or chronic depression.

The data from Gallup provides a nationally representative sample of individuals across the U.S., which has been used in several studies, including those examining subjective well-being (e.g., Kahneman and Deaton, 2010; Deaton and Stone, 2013; Deaton, 2018). The Gallup survey renders several advantages in measuring affective states. 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. Additionally, recent financial studies try to generate other measures of sentiment using alternative sources of information

[2]In terms of diagnosing depression, studies argue that there are differences between clinical and subclinical depression. Some show that impairment and the prospect of being diagnosed with major depression increases as the number of symptoms do (Andrews and Thomson, 2009), while others argue only 25% to 50% of patients with depression are accurately diagnosed by primary care physicians, and that both clinical and subclinical episodes should be treated with medication (Barbic et al., 2014). We recognize that these issues lead to measurement error in our variable of interest. However, we aim to examine the impact of mild depression and as such this type of measurement error biases against finding support for our conjectures.

such as Twitter (Yang et al., 2015) and Google Trends (Da et al., 2015), to provide a more exogenous proxy of emotion. Although these alternative measures cover a broader part of the population, they are taken from user-generated tweets or inquiries; thus, they do not reflect a representative sample of emotions. Lastly, the Gallup survey allows us to disentangle and distinguish between diagnoses of depression and various types of mood from the variety of questions it provides.

We begin our analysis by testing whether the depressive realism hypothesis holds in the Estimize sample. To this end, we examine if an analyst's absolute forecast error in a given quarter is affected by the national level of depression in the prior quarter. Over and above the effects of various firm and analyst time-varying characteristics and 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, such as the geographic proximity of users to firms (Adebambo et al., 2016), users' experience, and their professional status.

Recent studies show that seasonal affective disorder (SAD), a medical condition that causes temporary depression in winter months, affects stock market returns (Kamstra et al., 2003) and analyst forecasts (Dolvin et al., 2009). Therefore, we need to establish that seasons do not moderate the impact of depression. We find that the positive effects of depression on forecast accuracy are still present when our variable is both de-trended or when we restrict our sample to low-SAD months. We also examine if our findings are affected by the professional experience of analysts. We find that the impact of depression on forecast accuracy remains among Estimize users who identify themselves as professionals, as well as sell-side equity analysts in the I/B/E/S database.

We then attempt to narrow our depression variable by measuring depression at the metropolitan statistical area (MSA) level. We then aggregate these data to each state and retest our conjecture. We find support for the depressive realism hypothesis on earnings forecasts using this geographically narrower measure of depression. We also rely on Google Trends to create a broader measurement of our variable. Although user-generated inquiries may not be representative, they capture more details from a broader segment of the population. For this test, we first generate a depression-related word list and use it to construct a Google Trend Search Volume Index to proxy for depression. Using our broad depression measure, we retest the depressive realism conjecture on forecast accuracy. Again, we confirm that earnings forecasts are more accurate following periods of high depression.

In our baseline analysis, we include a battery of FEs to ensure that unobserved time-invariant or cross-sectional firm or analyst characteristics do not drive our results. Despite this, the omitted variable bias may remain a concern. Therefore, we perform an instrumental variable (IV) analysis to establish a causal link between depression and improved forecast accuracy. In this test, we instrument the *Have Depression* variable with the national quarterly change in precipitation.

In addition to the weather being truly exogenous to earnings forecasts, we 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 expect depression to be positively related to days with higher precipitation levels. Precipitation is our preferred proxy as it is more random and less predictable than the number of daylight hours (Shumway, 2010). We conjecture that these weather changes are related to episodes of mild depression, similar to the mechanism of SAD. To test our conjecture, 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, firm, and analyst FEs. Our IV analysis confirms our finding that higher levels of depression positively affect the forecast accuracy of Estimize users.

According to our hypothesis, a reduction in optimism is one mechanism through which depressive realism leads to an increase in accuracy (Dolvin et al., 2009; Von Helversen et al., 2011). Previous studies have shown that equity analysts are overly optimistic (see Bradshaw, 2011). Therefore, a condition, such as a mild form of depression that dampens the user's overoptimism can, in turn, generate greater accuracy. Another mechanism proposed by the literature is through increased ruminating, whereby depressed individuals pay greater attention to detail, and process information in smaller increments (Andrews and Thomson, 2009; Von Helversen et al., 2011; Szu-Ting Fu et al., 2012). We examine and test both channels to establish the importance of each.

We perform three tests to examine the first economic channel. First, 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 this variable with *Have Depression* and re-estimate our previous analysis. Second, we use signed forecast errors and re-examine our result on negative and non-negative errors separately. Finally, we sort analysts according to their optimism levels and re-test our conjecture on the least and most optimistic analysts.

We find that pessimistic forecasts during higher national levels of depression are more accurate relative to the optimistic forecasts, lending support to the idea that the effect of increased accuracy is driven through a reduction of optimism. Further support for the depressive realism hypothesis is that the pessimism channel itself does not provide a higher level of accuracy (as the coefficient on the pessimism term alone is in the opposite direction). Reduced optimism only enhances forecasts when national levels of depression are higher. We also find that our results hold for non-negative forecast errors, as well as the most optimistic analysts, supporting our previous results.

To test the second mechanism, we perform a test on analyst forecasting days. Following a method similar to Cooper et al. (2001), we calculate the number of days between the date of an analyst's forecast and that of other analysts who cover the same firm in the same period but issue their forecasts earlier. We use this variable as our proxy for analysts' speed of processing information. If depression induces more focused thinking, then analysts with larger forecasting days should be more accurate because higher values of this variable suggest a slower speed of processing information. We include forecasting days and their interaction with the *Have Depression* variable in our baseline model and find that forecasting days have no impact on forecast accuracy, ruling out information processing speed as a mechanism for depressive realism.

Lastly, we perform several additional tests to ensure that our results are robust. We find that our results are robust to alternate measures of forecast accuracy used in the literature, as well as, alternate measures of negative affect, such as sadness and lack of enjoyment. We also examine whether severe depression drives our findings, and rule out that explanation. Specifically, we use other questions in the survey related to treatment of depression or using drug for relaxation to proxy for severe depression and find that, unlike our baseline results, these variables do not predict improved accuracy. Given that sentiment is closely related to affect, we also include several economic indicators in the analysis, to see if we capture effects beyond those of known indicators. We find that our results are different from Baker and Wurgler's (2007) sentiment index, the consumer confidence index (CCI), the VIX index, Jurado et al.'s (2015) macroeconomic uncertainty index, and Baker et al.'s (2016) economic policy uncertainty index. Moreover, we control for firms' information environment by following Kothari et al. (2005) and measuring management's discretionary accruals. Our results remain despite the information environment of a firm. Finally, we ensure that the structure of our sample or specifications does not affect our results. We aggregate the analysis at the analyst level and find a consistent outcome. We also winsorize and trim the sample to remove the impact of analysts who cover a large number of firms, and find that our results also hold in this case.

Our findings contribute to the behavioral finance and economics literature. We show that mild depression may indeed facilitate financial problem solving by counterbalancing overly optimistic expectations. The effect is economically significant and compares to that of analyst geography, experience, and professional status. Moreover, related to studies examining emotions on the negative affect continuum, fear and anxiety have been previously linked to pessimistic financial outcomes (Kaplanski and Levy, 2010; Cuculiza et al., 2020; Agarwal et al., 2019; Wang and Young, 2020). However, these findings have mostly focused on the impact of disastrous events (e.g., aviation disasters, terrorist attacks, etc.) that influence the incidental affective environment. We distinguish depression from previous studies and establish an instance where integral emotions impact cognition and financial decision-making. Moreover, we disentangle the impact of depression from the temporary SAD by showing that the effect holds even in low-SAD seasons. Finally, our study contributes to the psychology literature on depressive realism. While the hypothesis has been tested in the lab, according to Moore and Fresco (2012), studies lack a "gold standard of reality with which to compare a participants' perceptions of events." In this regard, our paper provides a real-world setup with a judgment task that has a clear and objective benchmark, facilitating comparisons across individuals and over time.

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 robustness tests. We conclude the paper in Section 6.

2 Data and Variables

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' depression levels 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. 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 been shown to positively affect the overall forecast accuracy of Estimize users compared with Wall Street consensus (Jame et al., 2016; Adebambo et al., 2016).

Following previous studies (e.g., Jame et al., 2016; Li et al., 2019), we apply several filters to our data. First, we exclude all duplicate observations which may come from erroneous data input. Given that our focus is on users' earnings forecasts, we also remove the revenue estimates. 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 observation with the average value of 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.

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 stock price, 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 at the beginning of each quarter (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 2010-Q4 to 2017-Q1.

2.1.2 Gallup Analytics

By interviewing at least 500 adults each day, Gallup provides a representative, ongoing assessment of Americans' health. To assess depression levels, 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/Refuse." Accounting for various characteristics of the respondents, Gallup aggregates the responses in each category to reflect the proportion of individuals who report having (or not having) depression on a given day.

In addition to depressive diagnoses, we further collect data on individuals' 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 depression. To align the data with the Estimize information, we aggregate the daily measures to a quarterly frequency. In particular, we first merge Gallup's daily values with the Estimize data using the date users create an estimate. We then take the daily average in each quarter to construct the quarterly measure. In untabulated results, we confirm that our findings remain consistent if we first measure the quarterly values of emotions in Gallup, and then merge those values with the Estimize database.[3]

2.2 Dependent Variable

Our main dependent variable is the 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 $\text{Forecast}_{i,f,t}$ shows the most recent earnings forecast issued by analyst i for firm f for reporting quarter t. Actual $\text{Earnings}_{f,t}$ 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) have also used scaled versions of the above variable to assess analysts' forecast accuracy. Although widely used, this method of standardizing suffers from the effect of using price. In particular, Qian (2009) documents that because price changes over time, it affects inferences by introducing a new source of variation. To avoid this issue, in our analysis we mainly use Equation (1) as our measure of analysts' inaccuracy. However, to ensure that our estimates

[3] Unreported results are available upon request.

are not sensitive to this choice, we further define an alternative measure of forecast inaccuracy as:

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

where $Price_{f,t}$ is the stock price two days prior to firm announcement date (Malmendier and Shanthikumar, 2014). 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 depression. As previously discussed, we also use measures of negative emotion in our analysis, including the proportion of individuals in the survey who declares experiencing sadness (*Sadness: Yes*), lack of happiness (*Happiness: No*), or lack of enjoyment (*Enjoyment: No*).

To control for attributes that affect analysts' performance, we follow prior studies 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* (Mikhail et al., 1997; Holmstrom, 1999; Clement and Tse, 2005; Jame et al., 2016; Da and Huang, 2019).

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 (Jame et al., 2016; Adebambo et al., 2016).

Lastly, we control for economic conditions that may correlate with both self-reported mood and judgment. For instance, Deaton (2008) show a strong connection between income distribution and emotional well-being. Walther and Willis (2013) show that analyst forecast accuracy is correlated with a measure of underlying economic factors that includes income. Motivated by this evidence, we obtain the quarterly average of national-level *Income per Capita* from the Federal Reserve Bank of St. Louis (FRED) and include this variable as a regressor to our analysis.

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 of 0.1447 (0.0058). These values are close to the corresponding values obtained by prior studies (e.g., Li et al., 2019).

Panel B of Table 1 shows that, on average, 17.3% of individuals declared having depression. This number is similar to other 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 to 2014 period (Pratt et al., 2017). In unreported results, we find a positive and statistically significant correlation between depression and other affective measures. Specifically, the Pearson correlation coefficient of daily depression with sadness, lack of enjoyment, and lack of happiness is equal to 32%, 15%, and 18%, respectively.

To gain a fuller picture of the above variables, we plot the quarterly time-series distribution of these measures in Figure 1. As shown, the quarterly values for individual depressive states suggest an upward trend over time. For instance, the proportion of individuals with depression has increased from 15.5% in 2008 to over 17% in 2017.

We show the descriptive statistics for our control variables in Panel C of Table 1. An average Estimize user covers 42 firms and 4 sectors per quarter. She also makes forecasts about 8 days prior to the actual announcement date. 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 *Market-to-Book* ratio of 2.54.

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

3 Depressive Realism and Forecast Accuracy

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

3.1 Baseline Results

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

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

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 population who declared having depression at time $t-1$.

In our analysis, we control for various characteristics of analysts (*Analyst Char*) and firms they cover (*Firm Char*), as explained in Section 2.3. We also include a battery of fixed effects (FEs) in our model. As shown in Figure 1, our main independent variable depicts an upward trend over the sample period. Therefore, to account for unobserved time-variant variables that may affect our results, we include year and quarter FEs (δ_y and δ_q) in our regressions. Moreover, it is possible that unobserved firm characteristics, such as the amount of information they provide, affect the forecast accuracy of Estimize users. Users also choose firms they cover in their portfolios. Therefore, those who cover "easier-to-value" firms may have higher forecast accuracy. To mitigate these issues, we include firm FEs (λ_f) in our model. We also acknowledge that unobserved characteristics of users, such as their gender, education, or talent, may affect their accuracy. To account for these attributes, we add analyst FEs (γ_i) to our estimates. Lastly, we account for the possible correlation of analysts' earnings forecast errors by clustering the standard errors at the analyst level. Table 2 shows the estimation results.

In Column (1), we report the results, excluding all FEs from the regression. As shown, the estimated β_1 is negative and statistically significant. This result suggests that a higher level of depression is related to a lower level of forecast error in the following period, supporting the depressive realism hypothesis. In economic terms, a 1-standard-deviation increase in the segment of the U.S. population with depression, on average, leads to a 0.25% (i.e., 3% of the sample mean) increase in the forecast accuracy. This result holds when we gradually add FEs to our model. Specifically, our results show economically and statistically similar outcomes as before when we add time (Columns (2) and (3)), firm (Column (4)), or analyst FEs to our model (Column (5)).

The results also indicate that the economic significance of our main independent variable is comparable to those of other known determinants of analysts' accuracy, such as professional status or experience.[4] 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 aggregate depressive mood is higher.[5]

3.2 Distinguishing Depressive Realism from SAD

Several studies have examined the impact of affective states on financial outcomes, such as stock prices, returns, and analyst forecasts (e.g., Kamstra et al., 2003; Hirshleifer and Teoh, 2003; Dolvin et al., 2009; Dehaan et al., 2016). These studies proxy for mood using the weather and examine the impact of good versus bad moods on financial outcomes. The proposed channels through which mood impacts judgment and decision making are changes to pessimism or optimism, in addition to changes in risk aversion.

Kamstra et al. (2003) examine the impact of SAD, which they classify as a form of depressive disorder, on security returns and find that returns are significantly lower during

[4] All coefficients are standardized; hence, are comparable across determinants of forecast accuracy. For economic significance in the baseline regression without any fixed effects (Column (1)), a series of Wald tests show that the effect of depression on forecast accuracy is equivalent to that of analyst's experience and professional dummy, and larger than the effect of forecast horizon. Adebambo et al. (2016) finds that the geographic proximity improves forecast accuracy by roughly 0.01 percentage point, whereas the effect of depression is about 0.25 percentage points.

[5] To identify the region and country of its users Estimize employs the "reverse IP lookup" method. This method sometimes leads to conflicting information as to whether users are located within the U.S. or not. Although, Estimize confirms that over 90% of the users are within the U.S., in untabulated results, we exclude observations with conflicting geographic information and find a consistent outcome.

the months with fewer sunlight hours. In contrast, Hirshleifer and Teoh (2003) examine the impact of sunshine, which influences a person's mood, on stock prices, and find that sunshine relates positively to returns. More recently, Dolvin et al. (2009), closely related to this study, examine analyst forecasts under the impact of SAD. The authors find that during the winter months and in geographic areas most prone to SAD, analyst forecasts are more accurate due to a reduction in analyst optimism. Although the mechanism through which depressive realism impacts financial judgments might be similar to that of mood and SAD, we develop a test that allows us to differentiate our findings. We hypothesize that since we are not examining a strictly seasonal effect, the impact of depressive realism on forecast accuracy should hold throughout the year, irrespective of the season. In this regard, we perform two tests.

The first test re-estimates Equation (3), however with the variable of interest replaced by a demeaned and de-trended daily time series of *Have Depression*. This test allows us to examine whether our results are affected by the potential non-stationary feature in the Gallup survey responses. Our second test involves restricting the sample to only those months in the low-SAD seasons, which correspond to the second and third quarters of the year. If our baseline results are merely driven by the influence of SAD on analysts, depression should no longer have a significant effect on forecast accuracy during the low-SAD seasons.

Table 3 shows the results of the first and second tests in Panels A and B, respectively. In both Panels, the strictest specification in Column (5) shows that the coefficient on the *Have Depression* variable is negative and statistically significant, indicating that higher levels of the U.S. population reporting having depression predict lower forecast errors in the subsequent quarter. Although our previous specifications included quarter and year fixed effects, which may have controlled for variation arising from seasonality, Table 3 further allows us to see that the size of the effect remains economically significant despite the season. These results distinguish our findings from the impact of SAD and indicate a more pervasive cognitive phenomenon impacting judgment.

3.3 Depressive Realism Among Professional Analysts

We recognize that managers and market participants focus most heavily on the forecasts provided by professional or Wall Street analysts. Therefore, the professional analyst status may moderate the influence of depression on decision making. Such a possibility makes it important to understand whether analysts' job status affects the previous results. To investigate this idea, we perform two tests. First, we divide the Estimize sample into two subsamples based on users' self-identified professional status: non-professional and professional. We then re-run the baseline regression separately on each sample. Second, we re-run the regression on the I/B/E/S sample of analysts, using the same sample period and data filters as in our baseline analysis. Table 4 shows the results.

Panels A and B report the estimation results for the sample of Estimize users who identify themselves as non-professional and professional analysts, respectively. As shown, the sign and the magnitude of the depression effect are similar across the two groups. Although depression manifests a stronger magnitude among the professional group, its impact among the two groups is statistically identical.

We find similar results in Panel C, where we focus on the sell-side equity analysts on I/B/E/S. This evidence highlights that the impact of depressive realism is not restricted to non-professionals only and that depressive realism impacts both groups of professional and non-professional analysts similarly by raising the average forecast accuracy.

3.4 A Narrower Measure of Depression

The previous results establish our baseline relationship between the national proportion of people with depression and forecast accuracy. One concern with the baseline results pertains to the level of aggregation. Specifically, there could be some additional variation in depression at the state level that our national-level analysis does not capture. This concern is valid because one may argue that individuals are more likely to be influenced by the aggregate moods in their immediate geography rather than those at the national level. Therefore, with the increase of the proximity and variation in our depression variable, we expect to see a larger impact of the depressive realism phenomenon on forecast accuracy.

Data availability drives our choice in measuring the depressive mood at the national level. In particular, our variable of interest *Have Depression: Yes* is only available at the annual frequency for more defined geographic areas. Despite such limitations, we gather annual depression data at the MSA level, and create a state-level depression variable, using the average value of depression in all MSAs within a state. Similar to the national-level analysis, this variable identifies the average proportion of individuals in each state who declared having depression.

Using the above variable, we run two sets of tests. First, we re-run Equation (3) but replace the quarterly national depression with the above annual state-level variable. In addition to previous control variables, we account for state-level characteristics, such as the percentages of the population who are male, whose age is between 18 to 54, who have college, bachelor, master, or professional degrees. We also control for the population income and unemployment rate. We calculate each characteristic's mean value across all the MSAs within a state for each year.

Column (1) of Table 5 shows a similar effect as before: a higher level of depression is associated with lower forecast errors. We find the same outcome in Column (2), where we add state FEs to the model to account for unobserved characteristics of analysts' geographic location that may affect their accuracy. Moreover, and in line with our expectations, we can see that the magnitudes of the coefficients on the state-level *Have Depression* are greater than those in Table 2.

The above analysis may raise the concern of within-unit error correlation related to the repeated values of annual state-level depression in the pooled panel. To mitigate this concern, in our second test, we mirror our baseline specification at the state level, using the annual measure of our dependent variable (i.e., *Absolute Forecast Error*) as well as other control variables. In our sample, Estimize users, on average, follow a given firm only for three quarters. Therefore, this specification considerably reduces our sample size, as indicated in

Panel B of Table 5. Despite this disadvantage, we continue to find a similar pattern as before in Columns (3) and (4), suggesting that the depressive realism hypothesis holds at the state level.

3.5 A Broader Measure of Depression

This paper relies on a nationally representative measure of affect. We argue that alternative sources of information on affect or mood, such as Twitter and Google Trends, may not be sufficiently representative as they are user-generated. However, these alternate sources incorporate a broader part of the population, and they may also provide more detailed data than a single survey question. As such, we aim to capture these alternative dimensions of affect using Google Trends to establish the depressive realism hypothesis.

To this end, we use the Google Trend Search Volume Index (SVI) to construct an alternative proxy for national-level depression. First, we create a depression-related word list by filtering the General Inquirer's Harvard IV-4 Psychological Dictionary for the Psychological Well Being and the Negative categories.[6] The filtered list results in 164 words. We then follow Da et al.'s (2015) methodology by adjusting the SVI for each word in the list and choosing component words for the depression index. The specification entails running a rolling regression with a 180-day window, over our sample period, of the adjusted SVI on the Gallup depression series and obtaining the t-statistic for each word in each regression period.

Next, we construct the daily depression index using words that are positively correlated with the Gallup depression variable at least at the 10% confidence level. That is, words with a positive t-statistic greater than 1.3.[7] This analysis leaves us with a short word list that contains 7 words, which include *melancholy, neurosis, confident, relaxation, figure, afraid, unhappily*. Using this list, we aggregate the index to the quarterly level following our aggregation of the Gallup depression measure.

[6]The dictionary can be found here: http://www.wjh.harvard.edu/ inquirer/homecat.htm.

[7]The one-sided critical t value at the 10% confidence level equals to 1.282.

Given that the resulting list above is restrictive, we expand it by constructing another index using words that have an absolute t-statistic greater than 1.3, accounting for words that either have a positive or negative correlation with Gallup depression (Da et al., 2015). Under this criterion, the resulting long word list contains 25 words, including *lone, desperate, lonely, carry, loser, hatred, horrible, blue, collect, irritation, hideous, glad, guilty, gloomy, resort, grave, melancholy, neurosis, confident, relaxation, figure, afraid, instable, irk, unhappily.* Using the two variations of the Google Trends SVI indices, we repeat our baseline analysis in Equation (3) but replace our main variable of interest with one of the two SVI indices.

Table 6 reports the results of both the short and long word lists in Panel A and B, respectively. As displayed in both panels, our coefficient of interest remains negative and statistically significant throughout all specifications, indicating that when we expand our measure of national depression, we find that forecasts are more accurate following periods of higher levels of depression. These findings supplement the results obtained using our Gallup measure as they apply to a broader, but not necessarily representative portion of the population.

3.6 Establishing Causality: IV Analysis

Although in our baseline regression we control for various characteristics of analysts and firms they cover, the omitted variable bias remains a valid concern. Additionally, some individuals (for unobserved reasons) may feel more comfortable declaring their depression status in a given period; a choice that makes our main independent variable non-random.

Therefore, we use an IV analysis to further establish the causality argument of Table 2. 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. Although the psychology literature has long linked weather with individuals' mood (Howarth and Hoffman, 1984; Mirzakhani and Poursafa, 2014; Baylis et al., 2018), recent evidence suggests that at the variable *level* and for self-reported mood change, meteorological variables either show no or weak relationships with mood (Huibers et al., 2010; Kööts et al., 2011). However, Bullock et al. (2017) find that for self-reported mood change, *relative* measures of meteorological variables have more consistent explanatory power. Moreover, compared with other variables, like daylight hours, precipitation is more random and less predictable (Shumway, 2010).

Motivated by the above evidence, we use the same set of control variables and FEs as in our baseline regression and test the economic relevance of our IV by running the following regression:

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

Panel A of Table 7 supports 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 reporting depression. Moreover, the estimated F-statistic (i.e., 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 also needs to satisfy the exclusion restriction. While there is no direct way to test this criterion, it is unlikely that changes in aggregate precipitation have any influence on the forecast accuracy of Estimize. As also proposed by Dehaan et al. (2016), we argue that the impact of weather (here, the change in aggregate precipitation) on analysts' behavior should happen through changes of their mood.

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

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

Panel B of Table 7 shows the same pattern as before. Specifically, we find that 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 forecast accuracy. Together, this result provides evidence for the casual impact of depression on forecast accuracy of analysts, confirming the depressive realism hypothesis.

4 Economic Channel: Reduced Optimism or Speed of Processing Information?

The psychology literature highlights two main channels through which the impact of the depressive realism hypothesis can manifest. The dominant mechanism entails a higher relative pessimism of depressive individuals, arguing that, for an identical set of information, forecasts of depressed individuals of future outcomes are more pessimistic than those of non-depressed people (Alloy and Ahrens, 1987). Such pessimism leads depressed individuals to assume the occurrence of an event only when they are very confident about it (Allan et al., 2007).

The second channel through which a depressive mood may enhance cognition is through the relatively increased rumination of depressive individuals. According to this mechanism, depressive mood allows individuals to process information more slowly and in smaller increments, which in turn, may lead to a more accurate judgment (Andrews and Thomson, 2009). In what follows, we empirically investigate the role of these mechanisms on our findings.

4.1 Reduced Optimism

To begin, we focus on the dominant explanation, that is, relative pessimism of depressive individuals compared with non-depressive individuals. Previous studies have shown that equity analysts are overly optimistic (see Bradshaw, 2011 for a review). Although some of the incentives of sell-side analysts, such as promotion incentives (Hong and Kubik, 2003), to issue optimistic forecasts may not apply to Estimize, users' *choice* to cover a firm may potentially generate an overly optimistic view about its future performance (Malmendier and Shanthikumar, 2014). Such a favorable view can upwardly bias a user's decision, leading to an inaccurate forecast. Therefore, a condition like a mild form of depression that dampens the user's overoptimism can, in turn, generate greater accuracy.

To examine the above hypothesis, we measure Estimize users' pessimistic behavior by comparing their earnings forecasts with the guidance issued by the firm's management. Management guidance is a strict benchmark for pessimism. Since management is more likely to issue guidance to "walk-down" analysts' optimistic forecasts to beatable targets (Matsumoto, 2002; Richardson et al., 2004; Cotter et al., 2006), forecasts that are lower than management guidance are plausibly pessimistic. We create a dummy variable, $\text{Pessimism}_{i,f,t-1}$, that is equal to 1 if at time $t-1$ analyst i's earnings forecast for firm f is below the management guidance, and 0 otherwise. Next, we use the interaction of this variable with *Have Depression* as the main independent variable in the following regression:

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

Above, we use the same set of control variables and FEs as in the baseline regression (Equation (3)). If higher relative pessimism of depressed individuals is a valid mechanism, β_1 from the above regression should be negative. This is what we find in Table 8. As shown, the interaction between the pessimism dummy and the proportion of depressed individuals loads negatively in all specifications. Although in two specifications (i.e., Columns (1) and (3)) the statistical power of our estimates drops, the results still economically support the above conjecture.[8] According to our hypothesis, a depressive mood may lead to more ac-

[8]As shown in Table 8, the Pessimism dummy loads positively in our model. Although some studies argue that pessimistic *analysts*, on average, are more accurate (Butler and Lang, 1991; Ke and Yu, 2006), ex-ante, it is not clear whether pessimistic *forecasts*, should be associated with a greater (or smaller) level of accuracy.

curate forecasts by reducing analysts' overoptimism. However, the evidence in Table 8 may arise from depression lowering optimistic forecasts or depression intensifying pessimism. To further investigate our findings, we perform two additional tests.

First, we use the signed forecast errors and divide our sample into the non-negative and negative forecast error groups. If depression reduces analysts' optimism, our baseline results should be most salient for the non-negative forecast errors (i.e., when analysts issue favorable forecasts). The estimation results in Table A2 support this conjecture. Specifically, Panel A reports the results with the sample of non-negative forecast error as the dependent variable. Similar to our baseline results, the coefficients on *Have Depression* load negative and statistically significant. The same pattern holds when we further include the pessimism dummy and its interaction with depression in our model (Columns (6) and (7)). On the contrary, the results in Panel B of Table A2 show that depression (or its interaction with the pessimism dummy) does not have a significant impact on negative earnings forecasts, that is, when analysts issue less favorable earnings forecasts. Together, these results confirm that the main driver of our previous findings stems from depression lowering optimistic forecasts.

Second, we examine the role of the pessimism channel among analysts with different levels of optimism. In particular, at the start of each quarter, we calculate the average signed forecast errors across all firms that each analyst cover in the previous quarter. Based on the values, we sort analysts into quartiles where the lowest (highest) quartile contains the least (the most) optimistic analysts. Our results remain unchanged if we sort analysts into terciles or quintiles groups. Finally, we repeat the baseline regression on the two sub-samples of least and most optimistic analysts and report the results in Table A3.

Similar to the previous results, the coefficients on *Have Depression* load negatively and are statistically significant in the strictest specification only for those analysts who are in the most optimistic quartile (Panel B). Although the coefficient of interest is negative for the *Have Depression* for the least optimistic analysts, it is not statistically significant through all specifications (Panel A). We also find that the difference between the estimated coefficients in Panels A and B are statistically significant at least at the 10% confidence level. For instance, the statistical test for the difference between coefficients in the strictest specification (Column (5) of Panels A and B) has a p-value of 0.065, and an F-statistic of 4.12.

Together, these findings provide supporting evidence for the dominant explanation of the depressive realism hypothesis, showing that by reducing analysts' optimism, a depressive mood can spur forecast accuracy.

4.2 Speed of Information Processing

As explained earlier, the psychology literature also hypothesizes that slower information processing of depressed individuals may drive the improvement in cognition resulting from a depressive affect (Andrews and Thomson, 2009). To empirically test this channel, we perform a test on the forecasting days of Estimize analyst forecasts. Specifically, we hypothesize that those analysts who take a longer time issuing a forecast relative to other analysts are more likely to process information slowly. Therefore, if the above channel is valid, an analyst in a depressed mood who require more time to process the same information should be, on average, more accurate.

To test the above idea, we follow a method similar to Cooper et al. (2001). For each firm an analyst covers, we measure her forecast's lead time as the number of days between the date of her forecast and that of all other analysts who cover the same firm in the same period, but issue their forecasts before the analyst.[9] Next, we calculate the cumulative lead time among all firms the analyst covers as:

$$D_0 = \sum_{k=1}^{K} \sum_{i=1}^{N} d_{ik}^0, \tag{7}$$

where d_{ik}^0 shows the number of days that forecast i of other analysts, covering the same firms as an analyst, precedes the kth forecast made by the analyst. We use D_0 as our proxy for the analyst's speed of information processing, where a larger number of D_0 implies that the analyst takes a longer time to follow other analysts. Subsequently, we repeat our baseline

[9] Our results remain consistent if we only consider the past five earnings forecasts of other analysts.

regression but additionally include D_0 and its interaction with $Have\ Depression$ to the estimation model.

To provide support for the information processing channel, we expect the coefficient on the above interaction term to be negative. Our tests, however, find no support for this hypothesis. Specifically, in untabulated results, we find that there is no statistically significant difference between the forecast accuracy of analysts, who issue forecasts in high depression periods with a higher D_0 and those with a lower D_0. For instance, accounting for the control variables and FEs, we find a point estimate of 0.0257 (t-statistic = 0.75) for the interaction term between D_0 and $Have\ Depression$. This null result allows us to rule out a mechanism through which the depressive realism hypothesis impacts judgments. Coupled with the findings from Section 4.1, we provide the support that the impact of depressive realism is mainly driven through an decrease in individual optimism.

5 Robustness Tests

In this section, 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 also rule out severe or chronic depression as a driver of our findings. Moreover, we ensure that our results remain robust when we account for the impact of known sentiment measures and economic uncertainty indicators. We also account for differences in firm information environments that may influence analyst forecast accuracy and show that our results remain. Lastly, we show that some features of our sample do not affect our previous results. Appendix A tabulates the results for this section.

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. Panel A of Table A4 reports the estimation results. As shown, our point estimates remain consistent with those in Table 2. 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 hold if we use other measures of negative affect to proxy for individuals' mild depression. In doing so, we use alternative, but related, dimensions of depression such as sadness, lack of enjoyment, and lack of happiness (Waterman, 1993). In particular, 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 Panel B of Table A4.

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 absolute forecast error.

5.3 Effects of Severe Depression

Our results show that depressive realism improves forecast accuracy through a decline in overoptimism. As previously discussed, depression is a part of an affective continuum, and as such, one might be concerned about the impact of severe depression cases on our results. This issue also relates to the format of the Gallup question used in our measure of depression. Because the question does not specify a time-frame for which the individual has received a diagnosis of depression, as well as a severity for the diagnosis, we need to rule out the impact of chronic or severe depression. 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 daily. In doing so, we repeat our baseline regression but replace our main independent variable with the proportion of individuals who declared using drugs for relaxation almost every day on the Gallup survey.

We report the results in Table A5. As shown in Panel A, and unlike the estimates 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. In Panel B, we further interact the proxy for severe depression with the main independent variable and rerun the analysis. Again, we find that, while depression maintains a negative and significant impact on analysts' absolute forecast error, our proxy for severe depression (i.e., use drug for relaxation) or its interaction with depression do not have a similar effect.

Additionally, we repeat the analysis with a different proxy for severe depression: the proportion of individuals who have been treated for depression. Studies suggest that medication treatment is mainly effective for severe depression while the effect on mild depression is nonexistent (Arroll et al., 2009; Fournier et al., 2010; Barbui et al., 2011). Motivated by this evidence, we assume that those individuals who get treatment are more likely to have a severe form of depression. As shown in Panel C of Table A5, the coefficient on the interacted term is again either positive or statistically insignificant.[10] We draw the same conclusion that there is no significant improvement in forecast accuracy among severely depressed individuals.

5.4 Depressive Realism Beyond Known Economic Indicators

Previous studies have documented various indicators, both related to investor sentiment and market uncertainty, that affect financial decisions (e.g., Baker and Wurgler, 2006; Baker et al., 2016). For instance, Chang and Choi (2017) find that as market uncertainty (measured by the VIX index) increases, analysts increase their optimism in their earnings forecasts. Therefore, one could argue that the main measures of depression may capture these known indicators. If so, our variable may become redundant once one accounts for the effects of other indicators. In this section, we perform multiple tests to address these concerns.

5.4.1 Effects of Known Sentiment Indices

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 A1, there is no clear correlation pattern between our affect variables and other indices, indicating that these measures capture distinct dimensions of individuals' emotions. In particular, 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.

In Table A6, we re-estimate our baseline regression 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 the

[10] Gallup only collects data on this question in 2013 and 2014, reducing the number of observations in Panel C.

surrounding level of depression on the accuracy of an individual's earnings forecast accuracy captures different effects from the impact of other known sentiment measures.

5.4.2 Effects of Economic Uncertainty Measures

Similar to market sentiment, our measure of depression might be capturing an aspect of market uncertainty that affects analysts' judgments. To rule out this alternative explanation, we control for market uncertainty in our baseline estimations. Specifically, we rely on several measures of market uncertainty, including the VIX index, Jurado et al.'s (2015) macroeconomic uncertainty index, and Baker et al.'s (2016) economic policy index to test whether our depression measure captures elements beyond market uncertainty.

Table A7 displays the results. Panel A of Table A7 shows the regression estimates when controlling for the VIX index. The strictest specification in Column (5) shows a negative and statistically significant coefficient on the *Have Depression* variable, suggesting that the inclusion of the VIX does not account for the depressive realism impact on absolute forecast error. This pattern is repeated when controlling for the Jurado et al.'s (2015) macroeconomic uncertainty index, and Baker et al.'s (2016) economic policy index in Panels B and C, respectively. Together, these results suggest the influence of depressive mood on analysts' forecast accuracy is not affected by other known measures of market uncertainty.

5.5 Earnings Management

Firms covered by analysts on the Estimize platform have different information environments. These differences may contribute to the differences in earnings forecast accuracy of analysts. In particular, some firms tend to manage earnings to a greater extent, and such behavior may affect analysts' forecasts. To rule out this explanation, we follow Kothari et al. (2005) to measure discretionary accruals as a proxy for the information environment of firms. Next, we include this variable in our model and rerun Equation (3). Table A8 displays the results. While the coefficient on discretionary accruals is positive and significant, implying a relationship between absolute forecast error and the information environment, the coefficient on our variable of interest remains negative and statistically significant throughout all specifications.

5.6 Robustness to Sample and Specifications

For our final analyses, we show the robustness of our results to the sample specification.

5.6.1 Aggregate-Level Analysis

As explained before, our analysis uses pooled-panel OLS regression. 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:

$$\begin{aligned}\text{Absolute Forecast Error}_{i,t} = \beta_1 \text{ Have Depression}_{t-1} + \beta_2 \text{ Analyst Char}_{i,t-1} + \\ \beta_3 \text{ Average Firm Char}_{t-1} + \delta_q + \delta_y + \gamma_i + \epsilon_{i,t},\end{aligned} \tag{8}$$

where Absolute Forecast Error$_{i,t}$ shows the average of analyst i's absolute forecast accuracy across all the firms she covers in a given time. We use the same set of analyst- and firm-level control variables as in the previous analysis. As for the dependent variable, we aggregate the firm-level characteristics at the analyst level.

In untabulated findings we 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.

5.6.2 Analysts with Large Number of Covered Firms

Another potential concern regarding our setup 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 states that a user should generate at least ten estimates per quarter. In order to be considered a "highly ranked analyst" a user is even urged to cover fifty or more firms within or across sectors.[11]

To ensure that our results are not driven by the above feature, we re-preform the analysis on a winsorized sample, as well as a trimmed sample. In untabulated findings we find that the results remain consistent when the sample of analysts is winsorized at the 1% (or 2%) level, winsorize for the right-tail of the sample alone, and when the right-tail is winsorized at the 1% level. We also find the same outcome 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 mildly depressed person is better able to solve problems either due to an increase in focus and a slow pace of ingesting small increments of information, or through reducing heightened optimism applied to the problems. This hypothesis contrasts outstanding evidence in the psychology literature, which shows that the creative and critical thinking is enhanced in positive affective environments.

We measure levels of national depression using responses from the Gallup survey and find that earnings forecasts are more accurate following periods where higher levels of the U.S. population report feeling depressed. We show that this effect remains during low-SAD months and is not moderated by the professional experience of an analyst. We also find that the same result holds when we tighten the definition of depression down to the state-level,

[11] 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/faqqualifications

or broaden it using information from Google Trends. 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 mild depression. We document that it is the reduction in the optimism of forecasts made during high depression periods, that drives the results.

Additionally, our results are robust to using alternative measurements to proxy for negative moods, as well as earnings forecast accuracy. We rule out chronic depression as a driver, and control for well-known sentiment measures, economic uncertainty measures, and firm information environments in our analyses. We also aggregate the analysis at the analyst-level, and trim the sample to remove the influence of analysts who cover a large number of firms. We find that our results remain robust to all alternative measurements and explanations.

We contribute to the behavioral finance and economics literature by showing that depressive realism holds in financial settings and works through the reduction of optimism. We provide evidence for the impact of an integral emotion on financial decision making, as opposed to previously established findings using incidental emotional environments (e.g., terrorist events or aviation disasters). Finally, we contribute to the psychology literature by providing a non-laboratory setup incorporating a task with a standard and objective benchmark to shed light on cognitive performance during periods of mild depression.

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Figure 1. Time Series Distribution of Affective Measures

This figure plots the quarterly time series of four measures: Depression, Sadness, Lack of Happiness, and Lack of Enjoyment from 2008-Q1 to 2017-Q4. *Have Depression: Yes* (*Sadness: Yes*) is the quarterly average of respondents who declared having depression (experiencing sadness). *Enjoyment: No* (*Happiness: No*) is the quarterly average of respondents who declared not experiencing enjoyment (happiness). Information on individuals' emotions is from Gallup Analytics. Table A1 describes the variables in detail.

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 within 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 Industries 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 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 Equation (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 *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 point. $***$, $**$, 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 Industries 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)
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
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 3. Distinguishing Depressive Realism from SAD

This table examines the effect of seasonality on the depressive realism hypothesis. Specifically, Panel A reports estimation results from Equation (3), where we demean and de-trend *Have Depression: Yes* in the analysis. Panel B repeats the baseline regression but restricts the sample to the low-SAD seasons, that is, the second and the third calendar quarter in each year. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. Model specifications of each column, including control variables and fixed effects, are identical in all panels. ∗∗∗, ∗∗, 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)				
	Panel A: Detrended Depression				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes (t-1)	-0.2776***	-0.1382**	-0.1134*	-0.1762***	-0.1664***
	(0.068)	(0.063)	(0.065)	(0.059)	(0.058)
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
	Panel B: Low-SAD Seasons				
Have Depression: Yes (t-1)	-0.3651***	-0.3451***	-0.4908***	-0.6345***	-0.6203***
	(0.087)	(0.125)	(0.134)	(0.130)	(0.134)
Adj. R^2	0.01	0.01	0.01	0.48	0.52
# of Obs.	20,549	20,549	20,549	20,439	19,956
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 4. Depressive Realism among Professional Analysts

This table tests the impact of national-level depression on the earnings forecast accuracy of two Estimize sub-samples: non-professionals and professionals in Panels A and B, as well as earnings forecast accuracy of sell-side analysts on I/B/E/S in Panel C. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. Model specifications of each column, including control variables and fixed effects, are identical in all panels. $***$, $**$, 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)				
	Panel A: Estimize Non-Professionals				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes (t-1)	-0.2182*	-0.1760*	-0.0930	-0.1996**	-0.1962*
	(0.114)	(0.099)	(0.112)	(0.101)	(0.103)
Adj. R^2	0.02	0.02	0.02	0.54	0.55
# of Obs.	26,532	26,532	26,532	26,416	25,938
	Panel B: Estimize Professionals				
Have Depression: Yes (t-1)	-0.2936***	-0.2088*	-0.1820*	-0.2006**	-0.1907**
	(0.108)	(0.110)	(0.097)	(0.091)	(0.095)
Adj. R^2	0.01	0.02	0.02	0.50	0.52
# of Obs.	19,095	19,095	19,095	18,948	18,777
	Panel C: I/B/E/S				
Have Depression: Yes (t-1)	0.0924	-0.1017	-0.2930***	-0.2268***	-0.2316***
	(0.072)	(0.074)	(0.084)	(0.069)	(0.071)
Adj. R^2	0.02	0.02	0.02	0.41	0.41
# of Obs.	113,665	113,665	113,665	113,655	113,247
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 5. Depression Realism and Forecast Accuracy at State Level

This table tests the depressive realism hypothesis, by examining the impact of state-level depression on the earnings forecast accuracy of Estimize users. Panels A and B report regression results at the quarter and annual level, respectively. State controls include the population gender, age, income, and unemployment rate. Analyst, firm, and income control variables are the same as those in Table 2. Continuous control variables 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)			
	Panel A: Quarterly Regression		Panel B: Annual Regression	
	(1)	(2)	(3)	(4)
Have Depression: Yes (t-1)	-0.6904***	-0.6904***	-2.3424***	-2.3424***
	(0.256)	(0.257)	(0.868)	(0.869)
Adj. R^2	0.54	0.54	0.62	0.61
# of Obs.	44,934	44,934	8,796	8,796
Analyst Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
State Controls	✓	✓	✓	✓
Income Control	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Quarter FEs	✓	✓		
Firm FEs	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓
State FEs		✓		✓

Table 6. Google Trend-Based Depression Index and Forecast Accuracy
This table tests the depressive realism hypothesis by using the Google Trend Search Volume for depression-related words as an alternative measure of national-level depression. Specifically, Panel A repeats our baseline regression using the depression index with a word list that have positive and statistically significant correlation with the depression variable from Gallup. Panel B repeats the same analysis as in Panel A, but extends the word list to those with statistically significant correlation (positive or negative) with the depression variable from Gallup. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. Table A1 describes all control variables in detail. Control variables are the same as those used in Table 2. The sample period is from 2010 to 2017. To facilitate readability, coefficients are expressed in percentage points. Model specifications used in each column are identical in all panels. $***$, $**$, 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 Errors (t)				
	Panel A: Short Word List				
	(1)	(2)	(3)	(4)	(5)
Depression Index (t-1)	-0.2198***	-0.5231***	-0.4115***	-0.2742**	-0.2438*
	(0.074)	(0.098)	(0.150)	(0.134)	(0.131)
Adj. R^2	0.02	0.02	0.02	0.53	0.55
# of Obs.	43,339	43,339	43,339	43,291	42,659
	Panel B: Long Word List				
Depression Index (t-1)	0.2562***	0.1358*	-0.4667***	-0.3600***	-0.2780***
	(0.082)	(0.082)	(0.154)	(0.098)	(0.099)
Adj. R^2	0.02	0.02	0.02	0.53	0.55
# of Obs.	43,339	43,339	43,339	43,291	42,659
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 7. Depressive Realism and Forecast Accuracy: IV Analysis

The table uses an 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)).Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. Model specifications of each column, including control variables and fixed effects, are identical in all panels. $***$, $**$, 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)
First-stage F-statistic	87.06	76.52	32.75	29.87	19.52
Adj. R^2	0.29	0.36	0.50	0.51	0.55
# of Obs.	45,627	45,627	45,627	45,584	44,934
	Panel B: Second-stage Regression				
	Dependent Variable: Absolute Forecast Error (t)				
$Have\widehat{Depression}: Yes(t-1)$	1.1892***	-0.0008	-0.7379***	-0.5192**	-0.4677**
	(0.403)	(0.310)	(0.285)	(0.235)	(0.238)
# of Obs.	45,627	45,627	45,627	45,584	44,934
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 8. Economic Channel: Reduced Optimism

The table examines the role of reduced optimism 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. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. $***$, $**$, 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)
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
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Appendix

Figure A1. Time-Series Distribution of Affective Measures And Sentiment Indices The 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 2011-Q1 to 2017-Q4. The red solid line in each plot represents the time series of the negative emotion measure. All measures are quarterly average values and are normalized by subtracting their values from its minimum, then dividing by the difference between their maximum and minimum values.

Table A1. Variable Definition

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

Variable	Definition	Source
Absolute forecast error	The absolute value of the difference between Estimize user's forecast and actual earnings per share	Estimize
Standardized absolute forecast error	The absolute forecast error divided by price two days before announcement date	Estimize and CRSP
Have Depression: Yes	The daily average proportion of respondents who declared having depression in each quarter	Gallup Analytics
Sadness/Enjoyment/Happiness	The daily average proportion of respondents who declared experiencing the asked emotion yesterday in each quarter	Gallup Analytics
Number of firms covered	The total number of firms each unique Estimize user covers in each quarter	Estimize
Number of industries covered	The total number of industries each unique Estimize user covers in each quarter	Estimize
Forecast horizon	The number of days from forecast date to actual earnings announcement date	Estimize
Firm-specific experience	The cumulative number of forecasts an Estimize user has made on a firm up to the current forecast	Estimize
Estimize experience	The cumulative number of quarters an Estimize user has been on Estimize up to the current forecast	Estimize
Institutional holdings	The proportion of firm shares held by institutional investors in each quarter	Thomson Reuters' Institutional Holdings (13F)
Firm size	The monthly average of log market capitalization in each quarter	CRSP
Market-to-book ratio	The monthly average of market-to-book ratio in each quarter	CRSP
Income per capita	Income per capita with 2012 as the base year	Federal Reserve (FRED)

Table A2. Reduced Optimism or Increased Pessimism?
The table further examines the role of reduced optimism as an economic channel through which depression improves forecast accuracy. Specifically, we divide our sample into two groups: non-negative (Panel A) and negative forecast errors (Panel B), and repeat the baseline regression on each group separately. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. Model specifications of each column, including control variables and fixed effects, are identical in all panels. $***$, $**$, 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: Forecast Error (t)						
	Panel A: Non-Negative Forecast Error						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Have Depression: Yes (t-1)	-0.4690***	-0.2720**	0.4164***	-0.3106***	-0.3378***	0.0833	0.0526
	(0.143)	(0.123)	(0.113)	(0.110)	(0.105)	(0.130)	(0.134)
Pessimism Dummy (t-1)						-0.2373	-0.1939
						(0.276)	(0.284)
Have Depression: Yes ×						-0.4618***	-0.4589***
Pessimism Dummy (t-1)						(0.129)	(0.126)
Adj. R^2	0.02	0.03	0.04	0.55	0.56	0.55	0.56
# of Obs.	19,716	19,716	19,716	19,618	19,087	19,618	19,087
	Panel B: Negative Forecast Error						
Have Depression: Yes (t-1)	0.1431	0.1963**	0.5670***	0.0988	0.0620	-0.0334	-0.0892
	(0.090)	(0.080)	(0.098)	(0.079)	(0.084)	(0.140)	(0.148)
Pessimism Dummy (t-1)						-0.4452**	-0.3003*
						(0.183)	(0.181)
Have Depression: Yes ×						0.1496	0.1760
Pessimism Dummy (t-1)						(0.139)	(0.140)
Adj. R^2	0.01	0.01	0.02	0.59	0.61	0.59	0.61
# of Obs.	25,911	25,911	25,911	25,818	25,261	25,818	25,261
Analyst Controls	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓	✓	✓
Quarter FEs			✓	✓	✓	✓	✓
Firm FEs				✓	✓	✓	✓
Analyst FEs					✓		✓

Table A3. Depressive Realism among Optimistic and Pessimistic Analysts

The table further examines the role of reduced optimism as an economic channel through which depression improves forecast accuracy. Specifically, for each analyst in a given quarter, we first calculate the average of her forecast errors across all firms she covers. Next, we sort analysts into quartile groups based on the average forecast errors in the previous quarter, where the highest (lowest) quartile contains the most optimistic (least optimistic) analysts. Subsequently, we repeat the baseline regression on the least (Panel A) and most (Panel B) optimistic analysts separately. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. Model specifications of each column, including control variables and fixed effects, are identical in all panels. $***$, $**$, 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)				
	Panel A: The Least Optimistic Group				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes (t-1)	-0.2254	-0.2150*	-0.1785	-0.2856**	-0.2002
	(0.151)	(0.127)	(0.168)	(0.144)	(0.162)
Adj. R^2	0.02	0.03	0.03	0.53	0.57
# of Obs.	11,302	11,302	11,302	11,071	10,614
	Panel B: The Most Optimistic Group				
Have Depression: Yes (t-1)	-0.6202***	-0.4325**	-0.3829**	-0.3954**	-0.4711**
	(0.195)	(0.188)	(0.169)	(0.164)	(0.211)
Adj. R^2	0.01	0.02	0.02	0.52	0.54
# of Obs.	10,805	10,805	10,805	10,409	9,967
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table A4. Alternative Measure of Forecast Accuracy and Depressed Mood

Panel A repeats the same analysis of Table 2 but uses the standardized absolute forecast errors (Equation (2)) as the main independent variable. Panel B repeats the same analysis of Table 2 but uses the proportion of individuals with sadness, lack of enjoyment, or lack of happiness in the Gallup survey as the main independent variables. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. $***$, $**$, 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: Alternative Accuracy Measure				
	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)
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
Control Variables	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

	Panel B: Alternative Affect Measures					
	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)
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
Control Variables	✓	✓	✓	✓	✓	✓
Year, Quarter, Firm FEs	✓	✓	✓	✓	✓	✓
Analyst FEs		✓		✓		✓

Table A5. Effects of Severe Depression

The table examines the effects of severe depression on forecast accuracy. Panel A repeats the same analysis of Table 2, but replaces the main independent variable with the proportion of individuals who declare using drug for relaxation in the Gallup survey. Panel B shows the results when we interact the variable *Have Depression: Yes* with *Use Drug for Relaxation*. Panel C repeats the same analysis as in Panel B, but uses *Treated for Depression* to proxy for the proportion of individuals with severe depression. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017 in Panels A and B. The sample period is from 2013 to 2014 in Panel C. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. Model specifications of each column, including control variables and fixed effects, are identical in all panels. $***$, $**$, 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)				
	Panel A: Use Drug for Relaxation				
	(1)	(2)	(3)	(4)	(5)
Use Drug for Relaxation (t-1)	0.0070	0.9269***	0.2786	0.1578	0.2856*
	(0.093)	(0.228)	(0.192)	(0.141)	(0.148)
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
	Panel B: Use Drug for Relaxation				
Use Drug for Relaxation ×	-0.0581	0.2999**	0.1352	0.1313	0.1553
Have Depression: Yes (t-1)	(0.080)	(0.137)	(0.149)	(0.110)	(0.116)
Use Drug for Relaxation (t-1)	-0.0625	1.6686***	1.0506***	0.8199***	0.9283***
	(0.169)	(0.303)	(0.320)	(0.214)	(0.248)
Have Depression: Yes (t-1)	-0.3004***	-0.6034***	-0.5232***	-0.4429***	-0.4142***
	(0.108)	(0.126)	(0.128)	(0.096)	(0.103)
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
	Panel C: Treated for Depression				
Treated for Depression ×	0.7232***	0.0883	0.1649	0.3488	0.3280
Have Depression: Yes (t-1)	(0.257)	(0.433)	(0.469)	(0.360)	(0.354)
Treated for Depression (t-1)	0.5154**	-0.3343	-0.6269	-0.7378*	-1.0476**
	(0.250)	(0.464)	(0.503)	(0.402)	(0.406)
Have Depression: Yes (t-1)	0.5982***	0.1695	0.2288	0.2545	0.1971
	(0.216)	(0.345)	(0.450)	(0.366)	(0.350)
Adj. R^2	0.02	0.03	0.03	0.43	0.45
# of Obs.	10,513	10,513	10,513	10,445	10,238
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FE		✓	✓	✓	✓
Quarter FE			✓	✓	✓
Firm FE				✓	✓
Analyst FE					✓

Table A6. Depressive Realism beyond Known Sentiment Indices

The 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 (Columns (1) and (2)), Consumer Confidence Index (Columns (3) and (4)), Gallup Economic Confidence Index (Columns (5) and (6)). Columns (7) and (8) report the results controlling for all the above sentiment measures jointly. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. ∗∗∗, ∗∗, 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)
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
Control Variables	✓	✓	✓	✓	✓	✓	✓	✓
Year, Quarter, Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Analyst FEs		✓		✓		✓		✓

Table A7. Depressive Realism, Forecast Accuracy, and Economic Uncertainty

The table repeats the same analysis of Table 2, but additionally controls for various economic uncertainty indices, including the VIX (Panel A), Jurado et al.'s (2015) macroeconomic uncertainty index (Panel B), and Baker et al.'s (2016) economic policy uncertainty index (Panel C). Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. Model specifications of each column, including control variables and fixed effects, are identical in all panels. $***$, $**$, 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)				
	Panel A: VIX				
	(1)	(2)	(3)	(4)	(5)
Have Depression: Yes (t-1)	-0.2247***	-0.1902***	-0.1836*	-0.2989***	-0.2561***
	(0.077)	(0.070)	(0.094)	(0.080)	(0.073)
VIX (t-1)	0.0367	0.0361	0.0610	0.1587	0.0883
	(0.091)	(0.093)	(0.183)	(0.137)	(0.122)
Adj. R^2	0.01	0.01	0.01	0.52	0.54
# of Obs.	45,627	45,627	45,627	45,584	44,934
	Panel B: Macroeconomic Uncertainty Index				
Have Depression: Yes (t-1)	-0.2694***	-0.2137***	-0.1684**	-0.2714***	-0.2595***
	(0.085)	(0.079)	(0.080)	(0.072)	(0.067)
Macro Uncertainty Index (t-1)	-0.1482	-0.0916	-0.1070	-0.4685***	-0.4670***
	(0.093)	(0.112)	(0.164)	(0.149)	(0.132)
Adj. R^2	0.01	0.01	0.01	0.52	0.54
# of Obs.	45,627	45,627	45,627	45,584	44,934
	Panel C: Economic Uncertainty Index				
Have Depression (Yes) (t-1)	-0.2584***	-0.2071***	-0.1930**	-0.2583***	-0.2291***
	(0.074)	(0.073)	(0.081)	(0.073)	(0.069)
Economic Policy Uncertainty Index (t-1)	-0.0983	-0.0994	-0.1709	-0.0612	-0.0001
	(0.086)	(0.084)	(0.105)	(0.082)	(0.081)
Adj. R^2	0.01	0.01	0.01	0.52	0.54
# of Obs.	45,627	45,627	45,627	45,584	44,934
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table A8. Earnings Management

The table repeats the same analysis of Table 2, but additionally controls for firms' earnings management. Specifically, we follow Kothari et al. (2005) and calculate the discretionary accruals measure of firms, and include the variable as a regressor in the analysis. Table A1 describes all control variables in detail. Control variables and their sources are the same as those used in Table 2. The sample period is from 2010 to 2017. Continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. To facilitate readability, coefficients are expressed in percentage point. ∗∗∗, ∗∗, 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)	-0.2742***	-0.2154***	-0.1653**	-0.2368***	-0.2183***
	(0.080)	(0.072)	(0.077)	(0.069)	(0.068)
Discretionary Accruals (t-1)	0.2423***	0.3141***	0.3214***	0.1987***	0.1659***
	(0.054)	(0.056)	(0.057)	(0.064)	(0.061)
Adj. R^2	0.02	0.02	0.02	0.50	0.52
# of Obs.	40,656	40,656	40,656	40,618	39,991
Analyst Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Income Control	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓