The Up Side of Being Down: Depression and Crowdsourced Forecasts

Sima Jannati, Sarah Khalaf, and Du Nguyen

Abstract

Using earnings forecasts from Estimize, we test whether crowdsourced financial judgments are affected by persistent mild depression. We find that a 1-standard-deviation increase in the segment of the U.S. population with depression leads to a 0.25% increase in users' forecast accuracy. This effect is robust to alternative measures and is distinct from the influence of temporary seasonal depression or other sentiment measures on decision-making. Reduced optimism and slow processing of information are two mechanisms that explain our findings. Overall, we contribute to the literature by linking depression to crowdsourced financial evaluations.

Keywords: depression; crowdsourced earnings forecasts; forecast accuracy; cognition; Estimize

JEL Classification: G00, G24

Jannati is at the Finance Department, Robert J. Trulaske, Sr. College of Business, University of Missouri, email: jannatis@missouri.edu. Khalaf is at the Department of Finance and Financial Institutions, College of Business Administration, Kuwait University, email: sarah.khalaf@ku.edu.kw. Nguyen is at the Finance Department, Robert J. Trulaske, Sr. College of Business, University of Missouri, email: du.nguyen@mail.missouri.edu. Please address all correspondence to Sima Jannati. We thank Will Demeré, Sara Shirley, Jeffrey Stark, Kateryna Holland, Fred Bereskin, Inder Khurana, Srinidhi Kanuri (discussant), Tao Wang (discussant), and seminar participants at the Southwestern Finance Association Annual Meeting 2021, World Finance Conference 2021, and the University of Missouri for helpful comments and suggestions. Any errors or omissions are our own. Declarations of interest: none.

1 Introduction

Sources of online value-relevant information, such as crowdsourced websites, blogs, and social media have rapidly become instrumental in capital markets (Chen et al., 2014). Relative to traditional platforms, these online sources provide ease of access (Bartov et al., 2018), aggregation of opinions (Jame et al., 2016), and, in some cases, more accurate information to investors (Da and Huang, 2019). Not surprisingly, investors are substituting traditional sources in favor of their online counterparts (Grennan and Michaely, 2021). Such a growing prominence makes understanding the determinants of outputs on crowdsourced websites an important topic.[1]

Changes in crowd sentiment is among the behavioral determinants of financial decisions that have been robustly shown to affect asset prices (e.g., Camerer and Loewenstein, 2003; Hirshleifer et al., 2020). Despite evidence for the role of transitory affect on financial decisions; e.g., weather-induced moods (Dehaan et al., 2016) or seasonal depressive disorder (Dolvin et al., 2009; Lo and Wu, 2018), the likewise effects of persistent mood changes, such as depression, have remained unexamined.[2] In this paper, we ask whether persistent mild depression affects the financial decisions of online crowdsourced earnings forecasters, and if so, whether the mechanisms through which it operates are distinct from those of short-term negative affect (e.g., seasonal depression).

Examining these questions is important for several reasons. First, within the area of earnings forecasts, previous studies have focused on behavioral factors that affect the decisions of professional analysts. Whether these elements affect the opinions of crowds and professionals similarly requires investigation. Second, the prevalence of depression in society is increasing;

[1]The importance of crowdsourced opinions became clear to markets when Bloomberg licensed Estimize data to be on their news and research feeds, giving over 300,000 investment professional access to the crowsdsourced earnings and revenue consensus (Source: Business Wire).

[2]Depressive disorder is a diagnosable health condition that affects mood, cognition, sleep, eating, psychomotor abilities, among other things. These effects make depression distinct from feelings of sadness, stress or fear (WHO, 2017). Depression disorders include two main sub-categories; major depressive disorders (i.e., mild, moderate, or severe depressive episodes) and dysthymia (i.e., persistent mild depression) (Kocsis, 2000; WHO, 2017). Despite the sub-categories, evidence suggests that around one-fifth of those that experience a depressive episode may suffer from the condition over life (Hölzel et al., 2011).

with expectations for it to become the leading cause of the global burden of disease by 2030 (WHO, 2012; Hidaka, 2012). Third, the persistent nature of depression makes its cognitive effects inherently different than those of shorter-term moods.[3] This point is particularly important because, whether depression improves or deteriorates decision-making is, ex-ante, unclear (Beck, 1987; Andrews and Thomson, 2009).

Specifically, the psychology literature documents a mood congruency effect, whereby negative information is made more salient when an agent is depressed, leading to poorer cognition (Isen, 2008). On the other hand, there is evidence that depressive people do not suffer from overoptimism, have better problem-solving abilities as they tend to spend more time ruminating, pay greater attention to detail, and process information in smaller increments, rendering a realistic reasoning style (e.g., Au et al., 2003).[4] Given these mixed results, we focus on the impact of mild persistent depression on cognition and decision-making, rather than that of shorter-term major depressive disorder episodes.

To answer our question, we use a time-series of crowdsourced quarterly earnings forecasts from Estimize.com, a platform that allows users to submit their earnings and revenue forecasts for firms listed on the website. To measure the level of depression, we use over 2 million household responses to a well-being survey at the national level, collected by Gallup Analytics. We focus on the question "Have depression?," which measures the quarterly proportion of the population who declares a depression diagnosis by a physician or nurse.

Our baseline test compares the accuracy of forecasts made following depressive quarters with those made following less depressive quarters during 2011 to 2016. Specifically, we use absolute earnings forecast error as our measure of evaluation because it allows us to gauge users' output to an objective benchmark; that is, the actual earnings of a firm.[5] Beyond the effects of various firm and analyst time-varying characteristics and fixed effects (FEs),

[3]See Hirshleifer and Shumway (2003); Kamstra et al. (2003); Kaplanski and Levy (2010); Agarwal et al. (2019); Wang and Young (2020); Cuculiza et al. (2021) for examples of studies that examine the impact of emotions on financial decision-making.

[4]Other studies that support this argument include Au et al. (2003); Smoski et al. (2008); Andrews and Thomson (2009); Von Helversen et al. (2011); Szu-Ting Fu et al. (2012); Barbic et al. (2014).

[5]We also test the contemporaneous relationship of depression on forecast accuracy and find economically similar results.

we find that higher levels of depression reduce absolute forecast errors. This impact is economically meaningful: a 1-standard-deviation increase in the proportion of the population with depression increases the future accuracy of earnings forecasts by 0.25% (i.e., 3% of the sample's mean). To view the impact differently, the effect of an increase in depression on accuracy translates to over five quarters of firm-specific experience for the average analyst. Moreover, the influence of depression on forecast accuracy is comparable to previously documented determinants of Estimize users' performance, such as their geographic proximity to covered firms (Adebambo et al., 2016), their experience, and professional status.

Similar to most related studies, our data do not directly link the depressed state of an individual to her forecasts, raising the concern of omitted variable bias. Moreover, respondents' choice in answering the survey questions subjects our depression measure to selection bias. We also recognize that the persistent nature of our independent variable over 21 quarters of data in our sample leads to low variation in the depression value, posing a threat to our identification. To mitigate these concerns and to bolster our identification, we perform two instrumental variable (IV) analyses, utilize a non-survey measure of depression, and run several cross-sectional analyses.

Our first instrument aims to capture the persistent nature of depression. Employing data from the Medical Expenditure Panel Survey, we focus on medications that are related to treatments of mild depression and measure the cumulative average of the prescribed antidepressants to estimate the proportion of individuals with diagnosed depression. We find a positive and significant association between our depression value and prescribed antidepressants, confirming the economic relevance of the instrument. Regarding the exclusion restriction, we rely on previous studies that highlight the randomness in the propensities of physicians and hospitals to diagnose and treat an illness (Duggan, 2005; Dalsgaard et al., 2014; Buason et al., 2021). We replicate the results of our baseline test using the above IV in a two-stage least squares (2-SLS) regression.

Our second IV aims to capture the transient and short-term aspects of depression, using the quarterly changes in the national precipitation. Precipitation is our preferred proxy as it is more random and less predictable than the number of daylight hours (Shumway, 2010). Again, we find that our IV is positively and significantly associated with depression levels. As in recent studies, we argue that impact of a change in precipitation on the quality of earnings forecasts should be driven by changes in analysts' mood (e.g., Dehaan et al., 2016; Addoum et al., 2020).[6] Using a 2-SLS regression on absolute forecast error, we find support for our previous findings.

To address the selection bias concern, we employ a user-generated measure of depression by constructing a Google Trend Search Volume Index (SVI) and continue to find a consistent outcome. To address low variation in our depression variable, we repeat our baseline analysis using annual depression rates at the state level. We also use these cross-sectional data to compare the accuracy of analysts located in high-depression states relative to those in low-depression areas. We further repeat the analysis using Google Trends data as a proxy for local depression, as well as both IVs at the state level. All the cross sectional tests support our key finding that earnings forecasts are more accurate following periods of high depression.

Next, we explore economic channels that explain our findings. The first channel is a reduction in analyst optimism (Dolvin et al., 2009; Szu-Ting Fu et al., 2012; Moore and Fresco, 2012). Analysts have various incentives to issue optimistic forecasts (Ramnath et al., 2008). Therefore, a condition, like depression, that dampens this optimism may boost accuracy. We test this conjecture using signed forecast errors and find that higher levels of depression only reduce optimistic forecasts; i.e., non-negative errors. Additionally, we sort analysts according to their optimism levels and find that the results primarily hold for the most optimistic analysts, supporting the reduced optimism channel.

The second channel we examine is increased ruminating. According to this mechanism, depressed individuals pay greater attention to detail and process information more slowly, leading to better judgement (Alloy and Abramson, 1979; Sinclair and Mark, 1995; Au et al., 2003). To test whether a similar mechanism plays a role in generating our results, we fol-

[6]Specifically, Addoum et al. (2020) do not find a significant relationship between weather conditions and economic outcomes, such as production and profitability.

low Cooper et al.'s (2001) method and construct a follower-leader ratio that measures the cumulative follow- and lead-time for the number of days an analyst takes to issue forecasts relative to other analysts who cover the same firms. We use this ratio as our proxy for information-processing time of analysts. Supporting the above channel, we find that the absolute forecast errors of slower processing analysts during periods of high depression are indeed lower relative to others.

We recognize that competing explanations may account for our findings. For instance, seasonal affective disorder (SAD), a medical condition that causes temporary depression in winter months, affects analyst forecasts (Dolvin et al., 2009; Lo and Wu, 2018). Given that our variable captures both seasonal and non-seasonal forms of depression, whether the influence of the former is different from the latter remains unclear. We show that the influence of depression on forecast accuracy extends beyond seasons and holds when our variable is de-trended or when we restrict our sample to low-SAD months, as well as when we restrict the sample to southern states with more sunlight. We also examine what separates the effect of depression and SAD on forecast accuracy. Our results suggest that although reduced optimism is an overlapping channel between these effects, the slow information processing channel does not affect analyst forecasts during high-SAD months. This finding further distinguishes our findings from previous studies (e.g., Dolvin et al., 2009).

Another alternative explanation for our results could be that depression captures well-known sentiment indices or measures of economic uncertainty. We directly rule out this explanation by finding the same outcome when we control for Baker and Wurgler's (2006) investor Sentiment Index, Consumer Confidence Index, Gallup Economic Confidence Index, and the VIX index in our tests.

We conclude our analyses with several robustness tests. First, we find that our results are robust to an alternative measure of forecast accuracy and alternative estimation methods. Second, we rule out the impact of severe depression as a driver of our results by using responses to a survey question asking how often respondents experience little interest or pleasure in doing things, and we find insignificant outcomes. Additionally, we rule out the role of anxiety in driving our results, by finding the same outcome when we directly include proxies of anxiety in our model (i.e., feeling stressed or worried). Third, we control for differences in firm earnings quality using discretionary accruals and find a consistent result. Fourth, we examine whether the professional experience of analysts moderates our results and find that the same effect among professional and non-professional Estimize users as well as sell-side equity analysts in the I/B/E/S database. Finally, we rule out concerns related to the skewed distribution of some variables in Estimize.

Our findings contribute to the behavioral finance and economics literature. First, we build on the literature that examines the outcomes and determinants of crowdsourced earnings forecasts (Jame et al., 2016; Bartov et al., 2018; Da and Huang, 2019; Grennan and Michaely, 2021). We establish depression as a factor of forecast accuracy for both online and traditional forecasters. Second, we add to the literature that examines the influence of mental health conditions on market outcomes. We demonstrate that non-severe depression may indeed facilitate financial evaluations by counterbalancing optimistic expectations and slowing down the processing of information. The effect is economically significant, non-seasonal, and compares to other determinants of analysts' performance. Third, we add to prior studies that examine analysts' forecasts during SAD seasons. For instance, Dehaan et al. (2016) find that forecasts become more pessimistic following negative weather-induced moods, but they do not examine the impact on analyst forecast accuracy. Despite similarities with these studies, our results offer fundamentally distinct pieces of evidence. In particular, we offer a superior research design by utilizing a new instrumental variable to proxy for depression. Moreover, we distinguish depression from seasonal or temporary mood changes by showing the persistent and non-seasonal effects of depression. We also establish that a fundamental difference in our findings stems from the processing of information channel, through which seasonal depression does not impact forecast accuracy. Overall, we uncover some of the mechanisms through which persistent mild depression affects the forecasts of a popular crowdsourced platform. However, we recognize that our findings do not directly speak to the economic and social costs of depression, or reduce from the seriousness of this mental disorder.

2 Data and Variables

This section provides information about the data sets and main variables used in the empirical analyses. Specifically, 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 Estimize

Estimize is a private company that crowdsources quarterly earnings and revenue forecasts on its website. In addition to data on users' forecasts, we obtain data on their locations. Although this information is not available on the website, Estimize provides it upon request.[7] Compared with traditional databases of earnings forecasts (e.g., I/B/E/S), the contributors of Estimize are not limited to professional sell-side analysts. This diversity has been shown to positively affect the overall forecast accuracy of Estimize users compared with the Wall Street consensus (Jame et al., 2016).[8]

Although over 110,000 users are active on the Estimize platform, we acknowledge that the Estimize sample may not be representative of U.S. households relative to that of Gallup Analystics (discussed in Section 2.2 below). However, the sample constitutes a more representative sample than analysts contributing to the I/B/E/S database.[9] Despite this, in later sections, we also utilize data from I/B/E/S to examine whether the effect of depression on the sample professional analysts differs from that of the Estimize sample.

[7]Estimize extracts the IP address of each user for a given point in time, and uses the reverse IP lookup method to identify the region and county of a user. We acknowledge that this method may lead to conflicting information as to whether users are located within the U.S. or not. Although Estimize confirms that over 90% of its users are within the U.S., in untabulated results, we exclude observations with conflicting geographic information and find a consistent outcome. Untabulated results are available on request.

[8]See Estimize for more information about the platform and individuals' incentives to contribute to the website. These incentives include contributing to gain access to the website's consensus estimate– which is revealed only after a contribution is made–, comparing accuracy relative to peers as ranked by the Estimize scoreboards, and knowing that one's contribution is part of a consensus that is published and sold to institutional investors.

[9]Accounting for this limitation is important because the prevalence of depression is not uniform across different socioeconomic statuses. For instance, Ridley et al. (2020) document a negative relationship between depression and income, where the lowest income communities have up to 3 times higher depression frequencies. In addition, Bauldry (2015) finds a similar negative relationship between depression and education.

Following previous studies (e.g., Jame et al., 2016; Li et al., 2019), we apply several filters to our data. Specifically, we restrict the sample to earnings forecasts and exclude duplicate observations which may come from erroneous data input. We also limit the analysis to users' most recent estimate and drop those estimates that are issued 90 days before the actual earnings announcement or are issued after the actual announcement date.[10] Lastly, 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.

To obtain information about the firms covered, we merge the above information with data from the Center for Research on Security Prices (CRSP) and Thomson Reuters' Institutional (13F) holdings. From the merged sample, we exclude firms with fewer than three distinct users or firms whose stock price is less than five $US at the beginning of each quarter (Zhu, 2002; Ertan et al., 2016). Our final sample comprises $1,754$ users, covering $1,364$ firms over the reporting period of 2011-Q4 to 2016-Q4.

2.2 Gallup Analytics

By interviewing at least 500 adults daily, Gallup provides a representative and ongoing assessment of Americans' health. These data provide a nationally representative sample of individuals, which has been used in several studies. These include studies that compare well-being across time and U.S. states, as well as studies that utilize the data for economic policy related topics (e.g., Rentfrow et al., 2009; Kahneman and Deaton, 2010; Deaton and Stone, 2013; Deaton, 2018). To assess depression levels, respondents are asked "Have you ever been told by a physician or nurse that you have depression?" with three predetermined response categories of "Yes," "No," and "Don't Know/Refuse."[11] Accounting for various

[10] We utilize the 90-days window to remain consistent with methodology of prior studies. However, to ensure that our results are not affected by herding effects that are driven by a wide window length, we employ alternative window lengths (e.g., 10, 30, and 45 days before the earnings announcement dates) and find economically and statistically consistent results.

[11] In terms of diagnosing depression, some studies argue that impairment and the prospect of being diagnosed with major depression increases as the number of symptoms do, while others argue only 25% to 50% of patients with depression are accurately diagnosed by primary care physicians (Andrews and Thomson, 2009).

characteristics of the respondents, Gallup aggregates the responses in each category to reflect the daily proportion of individuals who report having (or not having) depression.

The information from Gallup offers several advantages over other measures. First, data from Gallup are unlike measures of general sentiment used in the financial literature that rely on market information (e.g., Baker and Wurgler's (2007) sentiment index and Qian's (2009) put-call ratios), and non-representative user-generated measures derived from Twitter and Google Trends (Yang et al., 2015; Da et al., 2015). More importantly, the variety of questions in the survey allows us to distinguish between diagnoses of depression, eliminating the need for an ex-post classification of whether subjects are indeed depressed (see Birinci and Dirik, 2010). In fact, a recent study by Buason et al. (2021) utilizes a similar question as an instrument for the number of depressed people, suggesting that the above question captures random variation in depression levels compared with other measures. This is because, ex-ante, the likelihood of a diagnosis by a physician is exogenous.

To align the above data with the Estimize information, we aggregate the daily measures to a quarterly frequency. In doing so, we first merge Gallup's daily values with the Estimize data using the date when users create an estimate. We then take the average of the daily measures in a quarter to construct the quarterly measure. In untabulated results, we confirm that our findings remain consistent if we first measure the quarterly values of depression in Gallup and then merge those values with the Estimize database.

2.3 Dependent and Explanatory Variables

Our main dependent variable is the absolute forecast error of Estimize users. We define this variable similar to Hong et al. (2000) and Da and Huang's (2019) as:

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

where $\text{User Forecast}_{i,f,t}$ shows the most recent earnings forecast issued by analyst i for firm f for reporting quarter t. $\text{Actual Earnings}_{f,t}$ shows the actual earnings of the firm. A larger deviation from the actual earnings indicates a larger inaccuracy in the analyst's earnings forecast. In later robustness tests, we account for the price difference of firms that may affect the above value, and show that our results remain economically and statistically consistent when we standardize Equation (1) by firms' price.

Our main independent variable is *Have Depression*, which identifies the proportion of individuals in the Gallup survey with diagnosed depression. To control for attributes that affect analysts' performance, we follow prior studies (e.g., Mikhail et al., 1997; Holmstrom, 1999; Clement and Tse, 2005; Jame et al., 2016; Da and Huang, 2019) and include various characteristics of analysts and firms in the analysis. Specifically, for analysts' attributes, we include *Number of Covered Industries*, *Number of Covered Firms*, *Forecast Horizon*, *Firm-specific Experience*, *Estimize Experience*, and *Professional Status*. For firm attributes, we add *Institutional Ownership*, *Size*, and *Market-to-Book Ratio* as explanatory variables. In addition to these variables, we control for the quarterly average of national-level *Income per Capita*, obtained from the Federal Reserve Bank of St. Louis (FRED).[12] We provide a detailed definition of these variables in Table A1 of the Appendix.

2.4 Summary Statistics

Table 1 reports the summary statistics of the main variables. As shown in Panel A, *Absolute Forecast Error* has an average value of 0.0858 with a standard deviation of 0.1447. These values are close to the corresponding values obtained by prior studies (e.g., Da and Huang, 2019). The data suggest that, on average, 17.3% of individuals declared having depression. For perspective, these averages are in line with the 12.7% of the U.S. population who were prescribed anti-depressant medication during the 2011 to 2014 period (Pratt et al., 2017). To gain a fuller picture of this variable, we plot its quarterly time-series distribution in Figure 1. This figure suggests that, the quarterly values for individual depressive states has an upward

[12] Deaton (2008) shows a strong connection between income distribution and well-being. Walther and Willis (2013) show that analyst forecast accuracy is correlated with underlying economic factors that include income.

trend over time. For instance, the proportion of individuals with depression has increased from 17.4% in late 2011 to nearly 18% in late 2016.

We further observe that the depression variable has a standard deviation of 0.0045. Such low variation in our measure is expected. First, the Gallup Survey elicits responses from a nationally representative sample and doesn't provide a time-frame to respondents. These features cause our measure to capture both life-time and short-term prevalence, making reports of depression relatively stable over time. Although a similar characteristic for depression has been shown in other studies, we recognize that the small variation in our variable may pose a threat to the validity of our identification.[13] In later sections, we address this issue by performing a series of cross-sectional tests, using a state-level measure of depression.

Proceeding with the descriptive statistics for other regressors, we note that 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.

Panel B reports the Pearson within correlation between our main variables. As shown, the depression measure has a negative and statistically significant correlation with the forecast accuracy measure. As in prior studies, we find a positive correlation between analysts' forecast inaccuracy and their forecast horizon (Burgstahler and Eames, 2003; Boone and White, 2015). Consistent with Clement and Tse (2003), we also find that attributes that may proxy for analysts' ability (such as experience and professional status) reduce forecast inaccuracy.[14]

[13]For instance, Kessler et al. (2003) find that the lifetime prevalence of depressive disorders is 16.2% across individuals in the U.S., in line with the documented responses from the Gallup Survey. The authors also note that about 49% of short-term (i.e., 12 months) cases are mild to moderate.

[14]The correlation matrix also suggests a different relationship between some of the attributes of Estimize users and their forecast inaccuracy compared with those of the I/B/E/S sample. For instance, prior studies have used the number of covered firms as a proxy for analysts' portfolio complexity and find a negative association between this proxy and performance (e.g., Clement and Tse, 2003). On the contrary, our finding suggests a positive association between the forecast accuracy of Estimize users and the number of firms and industries they cover. This difference could stem from users' access to a wider pool of information as they cover more firms.

We also note that our main independent variable has a low correlation with other control variables, suggesting that multicollinearity is less likely to be an issue in our setup.

3 Depression and Forecast Accuracy

This section explains our baseline analysis, followed by multiple tests that establish the causality of our findings.

3.1 Baseline Results

We begin our analysis by testing whether an increase in the proportion of individuals with a depression diagnosis affects future forecast accuracy of Estimize users. Specifically, we run the following pooled ordinary least squares (OLS) regression:

$$\begin{aligned} \text{Absolute Forecast Error}_{i,f,t} = \beta_1 \text{ Have Depression}_{t-1} + \beta_2 \text{ Analyst Char}_{i,t-1} + \\ \beta_3 \text{ Firm Char}_{f,t-1} + \delta_q + \delta_y + \lambda_f + \gamma_i + \epsilon_{i,f,t}. \end{aligned} \tag{2}$$

Above, *Absolute Forecast Error*$_{i,f,t}$ shows the absolute deviation of analyst i's earnings forecasts from the actual earnings of firm f in quarter t (Equation (1)). Our main independent variable is *Have Depression*$_{t-1}$ that shows the proportion of the population who declared a depression diagnosis in quarter $t-1$. In our analysis, we use the time-lagged value of depression to accurately estimate the predictive power of depression on Estimize users' forecast inaccuracy. According to Kessler et al. (2003), depression is a tenacious disorder, the treatment of which takes time.[15] Depressive episodes of at least two weeks, and chronic depression symptoms lasting a minimum of two months are the criteria for a patient to receive a diagnosis.[16] Using a time-lagged variable allows us to capture variability in *Have Depression* that includes new diagnoses. Despite this argument, in untabulated results, we examine the

[15]This view also implies that the depression effect we document in the baseline result is potentially persistent. To directly test this implication, we include additional lags of our depression variable to the baseline regression and find a consistent result for lags up to 2 quarters.

[16]The criteria is provided by the Diagnostic and Statistical Manual of Mental Disorder (DSM-IV). See National Library of Medicine.

role of depression at time t on analysts' forecast inaccuracy at time t and find a consistent outcome.[17]

We account for various characteristics of analysts ($Analyst\ Char$) and firms they cover ($Firm\ Char$), as explained in the previous sections. Our regression includes a battery of fixed effects. To account for unobserved time-variant factors, we include year and quarter fixed effects (δ_y and δ_q) in our regressions. These factors include an upward trend of the depression variable as depicted in Figure 1. Moreover, Estimize users have been growing over time as the website gains popularity. Changes to the economic business cycle may further affect users' forecasts (Loh and Stulz, 2018). It is also 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 wish to cover and this choice may lead to a higher forecast accuracy among users who cover "easier-to-value" firms. 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 the accuracy of their forecasts, and hence, add analyst FEs (γ_i) to our estimates. We account for the possible correlation of analysts' earnings forecast errors by clustering the standard errors at the analyst level. We confirm that our results remain consistent to alternative clustering methods (e.g., at the analyst and year or at the analyst and firm levels).

Table 2 shows the estimation results. In Column (1), we report the results by excluding all fixed effects from the regression and find a negative and statistically significant coefficient for β_1. This result suggests that a higher level of depression is related to a lower level of absolute forecast error in the following period. The same pattern remains when we gradually add time, firm, or analyst fixed effects to our model in Columns (2) to (5).

Economically, a 1-standard-deviation increase in the segment of the U.S. population with depression, on average, leads to a 0.25% increase in the forecast accuracy (i.e., 3% of the sam-

[17] In particular, the estimated coefficient for the contemporaneous measure of depression is equal to -0.1181 (p-value = 0.072), beyond the impact of all control variables and year FEs. Our test yields economically consistent, but statistically weaker, results once we add additional FEs to our estimates.

ple mean). This economic impact is meaningful as it compares to that of other determinants of analysts' accuracy, such as professional status or experience. For instance, the effect of an increase in depression on accuracy translates to 5 quarters of firm-specific experience for the average analyst.[18] Moreover, Adebambo et al. (2016) find that the geographic proximity of Estimize users to covered firms improves their forecast accuracy by roughly 0.01 percentage point, whereas the effect of depression is 25 times larger. 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 aggregate depression is higher.

Before proceeding to the remaining analyses, we address a few major concerns related to our baseline analysis. First, the low variation of our main independent variable over time may raise concerns about inclusion of time FEs. For this reason, we exclude time FEs from the analysis and find the same results (coefficient= -0.3166; t-statistic = -5.45). We also account for the heterogeneity in analysts' selection of covered firm by adding analyst-by-firm FEs to the model and find the same evidence (coefficient= -0.2026; t-statistic = -3.32).

Second, the voluntary contribution of users to the Estimize platform may raise the selection bias issue. Specifically, one could argue that individuals may hold off issuing forecasts when they are (mildly) depressed. In this case, our results might be primarily driven by the non- (or less-) depressed population. According to this argument, the number of forecasts issued on Estimize should be considerably smaller following high depressive times. On the contrary, we find that the average number of forecasts in the low-depression quarters (i.e., 1,139) is not significantly greater than that of high-depression quarters (i.e., 3,423) (one-sided p-value = 0.02).

Third, one may argue that those who are depressed and seek treatment would be the individuals who are diagnosed. In this case, we are capturing the decisions of individuals

[18] All coefficients are standardized; hence, are comparable across determinants of forecast accuracy. Therefore, we calculate the above effect by comparing the relative effect of *Have Depression* to *Firm-Specific Experience* in the strictest specification (i.e., 0.1999 / 0.0888 = 2.25), which translates into $2.25 \times 2.24 = 5$ quarters, relative to the *Firm-Specific Experience* standard deviation. Further, for economic significance in the baseline regression without any fixed effects (i.e., Column (1)), a series of Wald tests show that the effect of depression on forecast accuracy is equivalent to that of analyst's professional dummy and larger than the effect of forecast horizon.

who are treated for depression and may no longer realize any impact from their previous depressive disorder. We argue that this concern does not have a major effect on our findings. As explained above, evidence shows that treatment for depression takes time, suggesting that respondents who report having been diagnosed with depression most likely still deal with the condition (Kocsis, 2000; Kessler et al., 2003). In addition to this argument, in later sections, we show that our results continue to hold when we use the prescription of antidepressants (i.e., a proxy for treatment) as an instrument for our main variable of interest.

3.2 Establishing Causality

As in most of the related studies, our analysis does not directly link the depressed state of an individual to her forecasts. The lack of a direct link raises concerns about the causality of our results. Threats to our identification method include omitted variable bias, selection bias, and low variation in our main independent variable. This section aims at addressing these concerns by utilizing an IV analysis, an alternative source of information on depression, and performing several cross-sectional tests.

3.2.1 Instrumental Variable Analysis

Endogeneity represents a major concern for the majority of studies examining the impact and consequences of mental health conditions, such as depression, driven by the simultaneous determination of mental health and the studied outcomes (Chatterji et al., 2011). Although Buason et al. (2021) argue that the independent variable we use in Regression (2) is exogenous, we recognize that 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.[19]

[19]Specifically, Buason et al. (2021) calculate the propensity to diagnose depression across different regions in Australia using survey-responses to the Household, Income and Labour Dynamics in Australia survey. Similarly to our depression variable, their estimate relies on a yes or no survey question asking if the respondent has been previously diagnosed with depression.

Relying on instrumental variables analysis has been a common method to overcome the above limitation. These instruments have been one of two types: personal characteristics and social support variables.[20] These variables, however, are not suitable for our analysis. First, recent studies argue that both types suffer from the reverse causality and omitted variables bias issues (e.g., Peng et al., 2016). Second, variables that are related to social support, such as weekly religious service attendance, may simultaneously proxy for depression and a person's informativeness through her network.

Therefore, we rely on two different instruments. For the first one, we follow a similar method as in Peng et al. (2016) and use the dosage of prescribed antidepressant, while for the second instrument we rely on changes in rainfall. We utilize both instruments in our analysis since the former captures dimensions of depression that are more likely to persist over time, whereas the latter instrument allows us to estimate variations in mild depression that are more short-term in nature.

3.2.2 First IV: Prescribed Antidepressant

As mentioned above, our first instrument for the proportion of individuals with depression diagnosis is the dosage of prescribed antidepressants. Our choice in using this variable is motivated by several studies that posit that the propensity for being diagnosed can be used to estimate the number of depressed patients. For instance, Buason et al. (2021) use the propensity of receiving a diagnosis from a hospital as an instrument for measuring those diagnosed and currently suffering from depression and anxiety. Their approach relies on previous studies that use the propensity for psychiatrists and physicians to prescribe drugs as an instrument for treatment (e.g., Duggan, 2005; Dalsgaard et al., 2014).

Motivated by this evidence, we collect data on prescribed antidepressants from the Prescribed Medicines files of the Medical Expenditure Panel Survey (MEPS) and employ the

[20] For example, Chatterji et al. (2007) use the number of early onset psychiatric disorders, weekly religious service attendance, and use of religious means to handle problems, as instruments for mental health conditions. Other instruments include parental alcohol dependency (Mullahy and Sindelar, 1989), number of childhood psychiatric disorders (Ettner et al., 1997), long-term non-acute illnesses (McCulloch, 2001), religiosity (Alexandre and French, 2001), and state-level alcohol and illicit drug policies (Barrett, 2002).

time-series of these prescriptions to construct our IV from 2002 to 2017, while accounting for the classification of antidepressants.[21] The detailed information on the type of antidepressants is particularly beneficial in our setup, as it enables us to use the information on those antidepressants that are commonly associated with the treatment of mild depression; e.g., selective serotonin reuptake inhibitors (SSRIs).[22]

When constructing our instrument, we restrict the MEPS sample to antidepressants in the form of capsules or tablets, since the number of observations in other forms of treatment, such as liquid or concentration, is less than 2.5% of the sample, and hence, negligible. Next, we calculate the cumulative average of the antidepressant quantity, weighted by the survey's sample weight. We rely on the cumulative average to capture the persistent and long-term nature of depression and its treatment. In measuring the IV, we use data from the beginning of the sample up to the previous year to ensure timing consistency and to mitigate the look-ahead bias. Our final sample comprises 159,072 observations, with an annual average of 9,942. Consistent with the upward trend in our depression variable (Figure 1), we find that the average number of prescribed medicines for mild depression per survey respondent increases steadily in our sample from 37.52 in 2012 to 42.71 in 2016, with a mean of 40.92.

Using the above instrument, *Mild Drugs*, along with the same control variables and FEs as in our baseline regression, we test the economic relevance of our IV by running the following regression:

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

Panel A of Table 3 supports the economic relevance of this IV: a larger increase in the cumulative average doses of SSRIs has a positive and statistically significant correlation with

[21]MEPS is a nationally representative survey of the U.S. civilian non-institutionalized population that reports a wide range of medical information, including conditions, care use, and expenditures.

[22]Common classes of antidepressants include selective serotonin reuptake inhibitors (SSRIs), serotonin and norepinephrine reuptake inhibitors (SNRIs), tricyclics (TCAs), and monoamine oxidase inhibitors (MAOIs). In the MEPS sample, we use $TC1S1$ variable (code 249) to identify antidepressants and further use $TC1S1_1$ variable to identify antidepressants classes (i.e., 208 for SSRIs, 308 for SNRIs, and 209 and 307 for TCAs). For details of each class, see Appendix 2 of Rhee et al. (2017).

the proportion of individuals diagnosed with depression. Moreover, the estimated F-statistics (i.e., 16.24 in the most conservative specification) suggests that our analysis does not suffer from a weak instrumental variable (Stock et al., 2002).

For our IV to be valid, it needs to also satisfy the exclusion restriction requirement. Although we cannot directly test this criteria, as in other studies, we argue that different physicians and hospitals have varying probabilities of diagnosing and providing treatment to patients. Therefore, the measure of diagnosis and treatments should be exogenous to the patients themselves. Motivated by this reasoning, 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:

$$\begin{aligned} \text{Absolute Forecast Error}_{i,f,t} = \beta_1 \text{ Have } \widehat{\text{Depression}}_{t-1} + \beta_2 \text{ Analyst Char}_{i,t-1} + \\ \beta_3 \text{ Firm Char}_{f,t-1} + \delta_q + \delta_y + \lambda_f + \gamma_i + \epsilon_{i,f,t}. \end{aligned} \tag{4}$$

Panel B of Table 3 confirms our baseline results. Specifically, we find that an increase in the proportion of the population with depression is associated with a lower level of absolute 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 1.34% (i.e., 16% of the sample mean) increase in forecast accuracy for the cumulative average of doses of mild drugs.[23]

Despite our argument above, familiarity bias may pose a violation to the exclusion restriction of our IV. In particular, depressive individuals who receive antidepressant prescriptions, may become more familiar with the companies from which they receive their medications, and hence, these users may issue more accurate forecasts for such firms. We rule out this explanation by excluding pharmaceutical companies from our sample (i.e., firms with SIC codes of 2831 and 5122) and find economically and statistically consistent results (coefficient = -1.3458; t-statistic = -3.86).

[23] As shown, relative to the baseline test, the above economic effect is considerably larger. Such an increase in magnitude is expected. First, in the presence of the omitted variable bias, estimates are downward biased, and therefore, mitigating this bias may increase the estimated coefficients. Second, utilizing the instrument enables us to reduce the noise in Gallup responses by restricting the sample to those with a higher likelihood of having depression.

Moreover, to ensure that our analysis is not sensitive to our choice of using SSRIs antidepressants, we apply the above methodology and construct an alternative IV, utilizing both SSRIs and SNRIs to proxy for treatments of mild depression. Table A2 shows a replication of the above findings when using this alternative IV.

3.2.3 Second IV: Change in Precipitation

We construct our previous IV to reflect the persistent forms of depression. However, some depressive episodes may also be transient and short-lived. To capture this feature, we obtain U.S. precipitation data from the National Centers for Environmental Information (NCEI) and use quarterly changes in the average precipitation as a second 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). On the contrary, Bullock et al. (2017) find that for self-reported mood change, relative measures of meteorological variables have more consistent explanatory power. Compared with other variables, like daylight hours, precipitation also offers a higher randomness (Shumway, 2010).

Based on this evidence, we use change in precipitation as our instrument and run an identical 2-stage least squares regression to the one described in the previous section. Panel A of Table A3 supports the economic relevance of this IV as a larger increase in the average national precipitation has a positive and statistically significant correlation with the proportion of individuals reporting depression. We also find that this is not a weak instrument as the F-statistic in the most conservative regression is equal to 19.52.

In terms of satisfying the exclusion restriction, similar to the argument in Dehaan et al. (2016), we posit that the impact of weather on analysts' behavior should happen through changes in their mood. More recently, Addoum et al. (2020) find that weather-related phenomena (i.e., temperature changes) have no direct significant impact on sales, productivity, profitability, and ultimately economic growth. Despite this evidence, one can argue that Estimize's users may spend more time preparing their forecasts when the weather is gloomy, violating the exclusion restriction. We directly rule out this explanation by testing whether Estimize's users issue more forecasts when the weather condition increases their likelihood of being indoors. Our results indicate that the total number of forecasts made in high- and low-precipitation quarters are not statistically different (t-statistic of difference $= -0.099$).[24]

Panel B of Table A3 shows the second stage of the 2-SLS regression. Again, we find that an increase in the proportion of the population with depression is associated with a lower level of absolute forecast error among Estimize users. Similar to our first IV results, these findings are also 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.

3.3 A Non-Survey Measure of Depression: Google Trends

We also address issues related to selection bias in an attempt to strengthen our identification. In our setup, this bias stems from the choice of respondents to answer survey questions and seek treatment for depression, thereby rendering a diagnosis for their condition. To ensure that this issue is not the main driver of our results, we need a measure of depression that is based on non-survey data. To this end, we utilize information from Google Trends. Sources like Twitter and Google Trends may not be sufficiently representative, as they are user-generated. Despite this limitation, they incorporate a broader part of the population and provide more detailed data than a single survey question.

Accordingly, we use the Google Trend SVI and 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. 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

[24]We classify a quarter as a low (high) precipitation quarter if the instrument variable's value is less (greater) than the sample's median. Additionally, we repeat the IV analysis in Table A3 and explicitly control for the number of forecasts an analyst makes in the previous quarter and find the same outcome.

choosing component words for the depression index. This 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.[25] This analysis leaves us with a short word list that contains 7 words, including *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. Given that the resulting list above is restrictive, we further 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 (see 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 Regression (2), replacing our main variable of interest with one of the two SVI indices. Table 4 reports the results of both the short and long word lists in Panels A and B, respectively. As displayed, our coefficient of interest remains negative and statistically significant throughout all specifications, indicating that when we use a user-generated measure of national depression, we find that forecasts are more accurate following periods of higher levels of depression.

3.4 Cross-Sectional Tests

Lastly, we address the low variation in our variable of interest to improve our identification. Specifically, one concern with our baseline test is that we use a quarterly average of national depression over a time-series of 21 quarters, providing small changes in the depression

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

value. In addition to the short time-series, the drivers of the changes in the level of national depression are also naturally low in variation.[26] Another concern 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 is a valid concern 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.

To address these issues, we turn to cross-sectional tests at the state level. While state-level measures of depression provide advantages in testing our hypothesis, our choice in measuring depression at the national level is driven by data availability. In particular, our variable of interest 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 depression diagnosis. We confirm our prior that the state-level measure produces a higher level of variation in our depression variable since the state level measure of depression has an average value of 0.1670 with a standard deviation of 0.0173 (compared with the standard deviation of 0.0045 for the national-level measure).

Next, we re-run Regression (2) but replace the quarterly national depression with the above annual state-level variable. In addition to previous regressors, we account for state-level characteristics, such as the percentages of the population who are male, who have college or bachelor degrees, and whose age is between 18 to 24. We also control for the population's income and unemployment rate. We calculate each characteristic's mean value across all the MSAs within a state for each year. Given that our depression variable is constructed annually, we exclude year FEs from our regressions as we aim to compare the accuracy of

[26] Examining what drives the increasing prevalence of depression in a society, Hidaka (2012) cites several explanations like drug and alcohol abuse (Regier et al., 1990), declining mental health (Kaufman and Charney, 2000), modernization of society (Kessler et al., 2007), changes in living environment that include obesity (Must et al., 1999), diet (Christensen, 1996), micro-nutrient deficiencies (e.g., Freeman (2009)), reduced physical activity (Blumenthal et al., 2007), changes to sleep patterns (Baglioni et al., 2011), and sunlight exposure (Golden et al., 2005), as well as social environment changes like greater inequality, low social support, and intense individual competitiveness (Gilbert, 2006).

users across states. However, our results remain consistent when we also include year FEs in the model.

Table 5 reports the estimation results. Column (1) shows that, beyond various controls and FEs, a higher level of depression is associated with lower absolute forecast errors. In line with our expectations, we observe that the magnitudes of the coefficients on the state-level *Have Depression* are greater than those in Table 2.[27] Next, we account for differences between depression levels across states and examine whether forecast accuracy of analysts for a given firm differs depending on the depression levels of where they live. To this end, we create an indicator variable *Highly Depressed State* that takes the value of 1 if a state's depression level is above the median depression level across all states in the previous year, and 0 otherwise. If our previous results are driven by the depression at analysts' local areas, absolute forecast errors of analysts in highly depressed states should be lower. This is indeed what we find in Column (2).

We recognize that the annual state-level measure of depression from Gallup requires us to alter our specification setup. To ensure that the state-level results are directly comparable to our previous findings, for each state, we measure quarterly state-level depression using the short word list from the Google Trends data, following the same methodology explained in Section 3.3. We also redefine the indicator variable *Highly Depressed State* above, using the quarterly state-level depression and re-perform our baseline analysis. We find that our results continue to hold (see Column (3)). Finally, we perform a cross-sectional IV analysis, using the same instrument described in Section 3.2.2.[28] Column (4) of Table 5 confirms the same outcome as before. Lastly, in untabulated result, we use the change in precipitation at the state level as an instrument and, again, find the same outcome. For instance, in the most

[27] Using repeated values of annual state-level depression in the above analysis may raise the concern of within-unit error correlation. To address this concern, in untabulated results, we mirror our baseline specification at the state level, using the annual measure of our dependent variable and other control variables and find a similar pattern. For instance, in our most restricted test, the point estimate for the main independent variable is equal to statistically significant value of -2.342.

[28] To construct the state-level IV, we first merge the data from the Prescribed Medicines files with the Household Full Year Consolidated files, which contains information on respondents' location. Since MEPS only records location based on Census regions (i.e., Northeast, Midwest, South, and West), we rely on their classification and assign each Census region to the corresponding set of states in our analyst sample.

conservative specification, the first-stage (second-stage) estimated coefficient and t-statistic are equal to 0.0161 (-18.52) and 2.68 (-3.44), respectively.

4 Economic Channels

The psychology literature highlights two main channels through which the impact of depression on decision-making manifests. The dominant mechanism entails a lower relative optimism of depressive individuals; arguing that, for an identical set of information, forecasts of depressed individuals of future outcomes are less optimistic than those of non-depressed people (Alloy and Ahrens, 1987). Surveying the literature, Moore and Fresco (2012) find that non-depressed individuals register optimism bias relative to depressive individuals, which may alter their evaluation of information. As such, the lower optimism 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 depression may spur cognition is the increased rumination of depressive individuals relative to non-depressed ones. According to this mechanism, a 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 each mechanism in driving our findings.

4.1 Reduced Optimism

To begin, we focus on the lower optimism of depressive individuals compared with non-depressive ones. Why would a reduction in optimism boost forecast accuracy? Previous studies have shown that due to several reasons, equity analysts may be overly optimistic in their earnings and growth forecasts of firms (see Ramnath et al., 2008). Although Bradshaw (2011) argues that analysts' optimism is not systematic, it is shown that sell-side analyst have incentives to issue optimistic forecasts (e.g., promotion incentive documented by Hong and Kubik, 2003). Clearly, some of these incentives do not apply to Estimize users (Adebambo and Bliss, 2015). However, and as argued by Malmendier and Shanthikumar (2014), users' choice to cover a firm may potentially generate an overly optimistic view about its future performance. Such a favorable view can upwardly bias a user's decision, leading to an inaccurate forecast.

Therefore, we posit that a condition, such as a mild form of depression, that dampens the user's overoptimism can, in turn, generate greater accuracy. To evaluate this idea, we measure Estimize users' optimistic behavior using their signed earnings forecast errors. We then split the sample of forecasts into a sub-sample of forecasts with non-negative errors (i.e., optimistic forecasts), and a sub-sample of forecasts with negative errors. We then re-do our baseline analysis using each sub-sample. If depression reduces analysts' optimism, our baseline results should be most salient for the non-negative forecast errors.

Table 6 reports our findings. In Panel A, where we examine the non-negative forecast errors, we find that following periods of higher depression, non-negative forecast errors are reduced. Except for the estimates in Column (3), the coefficient on *Have Depression* is negative and statistically significant at the 1% level in all specifications. On the contrary, the effect of depression is absent when testing the sub-sample of negative forecast errors in Panel B of Table 6, as the coefficient on the *Have Depression* is not statistically different from zero across most specifications.

We also perform a different test of the reduced optimism channel. Specifically, we define an indicator variable, $Pessimism_{i,f,t-1}$, 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. We argue that the 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). Therefore, forecasts that are lower than this guidance are plausibly pessimistic. We include the interaction of this indicator variable with *Have Depression* as our main independent variable using the same two sub-samples of non-negative and negative analyst forecasts. If higher relative pessimism of depressed individuals is a valid mechanism, the interaction term should be negative within the non-negative forecast error sub-sample. This is indeed what we find in Column (6) of Panel A of Table 6.[29]

A concern with the above analysis is related with the distribution of the *Pessimism* variable in Panels A and B. In particular, one may argue that because a pessimistic analyst is more likely to remain pessimistic in the next period, the number of analysts for whom the above indicator is equal to 1 might be relatively limited in Panel A. In this case, the above results might be driven by a few observations only. We rule out this explanation by performing a difference-in-means t-test between the number of unique analysts for whom the *Pessimism* variable is equal to 1 in both panels and find that these numbers are not statistically different (p-value $= 0.4629$).

To provide additional evidence, we examine the reduced optimism channel among analysts with different levels of optimism. We calculate the average signed forecast errors across all firms that each analyst covers in the previous quarter. Next, we sort analysts into quartile groups, where the lowest (highest) quartile contains the least (the most) optimistic analysts. Our results remain unchanged if we sort analysts into tercile or quintile groups. Subsequently, we repeat the baseline regression on the two sub-samples of analysts and report the results in Table A4. Similar to the previous results, the coefficients on our variable of interest load negatively in the strictest specification only for those analysts who are in the most optimistic quartile (Panel A). Although the coefficient of interest is negative for the *Have Depression* for the least optimistic analysts, it is not statistically different from zero (Panel B).[30] Together, these findings provide supporting evidence for one channel through which depression may

[29] Using management guidance as a benchmark to distinguish pessimistic from optimistic forecasts may not be ideal because some firms do not issue management guidance for earnings. Therefore, we re-define the $Pessimism_{i,f,t-1}$ indicator variable using the consensus forecast as the benchmark. In this case, $Pessimism_{i,f,t-1}$ is equal to 1 if the forecast is below the consensus and 0 otherwise, where consensus is the median of earnings forecasts for all analysts who cover the same firm in a quarter. In unreported results, we find the same results when we use this measure.

[30] 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.

impact decisions. We show that by reducing analysts' optimism, a depressive mood can spur forecast accuracy.

4.2 Speed of Information Processing

A slower information processing of depressed individuals is another channel that may explain our results (Andrews and Thomson, 2009). People in depressed moods are less likely to use heuristics and succumb to the fundamental attribution error in judgements and decision-making (Forgas, 1998; Gasper, 2004). Because depressive individuals process information in a more systematic and detailed manner, they are more accurate in their judgements and more immune to a variety of biases (Alloy and Abramson, 1979; Taylor and Brown, 1988; Sinclair and Mark, 1995; Au et al., 2003). For instance, Barbic et al. (2014) and Von Helversen et al. (2011) show the improved cognition and out-performance of depressive individuals in complex tasks are driven by the extended bouts of persistent and distraction-resistant cognitive analysis relative to non-depressed individuals.

According to the speed of information channel, an analyst in a depressed mood who requires more time to process information should be, on average, more accurate. Clearly, we are not able to directly measure the time users take to process information or to issue their forecasts. Hence, to investigate the above channel, we employ and alter a metric used in prior studies to proxy for speed of information processing. Specifically, we measure the forecasting time of an analyst for a given firm relative to other analysts who cover the same firm. In doing so, we adopt a method similar to Cooper et al. (2001) and construct the follower-leader ratio (FLR) as:

$$FLR = \frac{T_1}{T_0}, \tag{5}$$

where, T_0 and T_1 show the cumulative lead- and follow-time for the K forecasts by a given analyst, respectively. Specifically,

$$T_0 = \sum_{k=1}^{K} \sum_{i=1}^{N} t_{ik}^{0}, \tag{6}$$

and,

$$T_1 = \sum_{k=1}^{K} \sum_{i=1}^{N} t_{ik}^1. \tag{7}$$

Above, t_{ik}^0 (t_{ik}^1) shows the number of days that forecast i of other analysts, covering the same firms as an analyst, precedes (follows) the kth forecast made by the analyst. Therefore, higher values of the FLR variable indicate taking a longer time in issuing forecasts, relative to other analysts covering the same firm. Next, we sort the FLR variable into quartiles and construct an indicator variable $Slow\ Processor$ that is equal to 1 if the analyst is in the top quartile, and 0 otherwise.[31] Subsequently, we repeat our baseline regression, including this indicator and its interaction with $Have\ Depression$ to the model. To provide support for the information processing channel, we expect the coefficient on the above interaction term to be negative.[32]

This is indeed what Table 7 suggests. Specifically, the absolute forecast errors of slower processing analysts during periods of high depression are lower relative to faster processors during other periods. This effect is marginally significant in all Columns except in the strictest specification in Column (5). In addition to this analysis, in untabulated results, we develop another test that captures users' time to process information around firms' earnings announcements. We argue that this test further enables us to rule out differences in information processing that are due to differences in the firm information environment. Specifically, we repeat the above analysis but restrict the sample to forecasts issued 10 days before the earnings announcement date. Our results show the same pattern. For instance, in the most restrictive specification, the estimated coefficient for the interaction of FLR and $Have\ Depression$ is equal to -0.3116 (t-statistic = -2.2).

[31] Our results remain economically and statistically consistent if we sort analysts into tertiles, or quintiles groups, or re-define the indicator to be 1 (0) for analysts in the top (bottom) quartile.

[32] Our findings also confirm that, as in I/B/E/S database, forecasts of Estimize users are clustered around the actual earnings announcement of firms they cover. For instance, about 70% of forecasts are issued in a 10-days window surrounding firms' earnings announcement date.

5 Alternative Explanations

In this section, we discuss and rule out alternative explanations for our results. In particular, we show that our results extend beyond the previously documented effect of seasonal disorders on analysts' forecasts and that they are not captured by the impact of other known sentiment measures.

5.1 Distinguishing Depression from SAD

Previous studies have shown the impact of affective states on financial outcomes, proposing changes to individuals' pessimism, optimism, or risk aversion as channels through which mood affects decision-making (e.g., Kamstra et al., 2003; Hirshleifer and Teoh, 2003; Dolvin et al., 2009; Dehaan et al., 2016).[33] A study that is closely related to this study is Dolvin et al. (2009) that examines analyst forecasts under the impact of SAD. The authors find that during the winter months and in geographic areas most prone to SAD (i.e., northern states), analyst forecasts are more accurate due to a reduction in their optimism. A similar effect has also been shown by Lo and Wu (2018). These results raise important questions about our findings. Is the impact of depression on forecast accuracy identical to that of SAD? If not, how are the two different?

We begin with the first question. Several studies have documented the long-term (and non-seasonal) aspect of depression. Such a long-term effect is characterized by high recurrence and persistence in patients. Specifically, between one-half and one-third of those individuals who experience clinical depression are likely to experience an annual episode during the remainder of their lives (Gotlib and Joormann, 2010). These studies further distinguish the cognitive effects of seasonal depression from those of non-seasonal depression.[34] Therefore, we

[33] For instance, 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 the months with fewer sunlight hours. In contrast, Hirshleifer and Teoh (2003) examine the impact of sunshine on stock prices and find that sunshine relates positively to returns.

[34] Michalak et al. (2002) find that the chance of cognitive impairment is higher among seasonally disordered individuals. Similarly, Bagby et al. (1996) show that individuals with SAD are more likely to entertain unconventional ideas compared with non-SAD patients.

conjecture that since we are not examining a strictly seasonal effect, the impact of depression on forecast accuracy should hold throughout the year, even during low-SAD months. To test this conjecture, we develop three tests.

First, we re-estimate Regression (2) but replace *Have Depression* with its demeaned and de-trended daily time-series value. This test allows us to examine whether our results are affected by the potential non-stationary feature in the Gallup survey responses. As shown in Panel A of Table 8, the coefficient on the *Have Depression* variable remains negative and statistically significant. Second, we restrict the sample to only those months in the low-SAD seasons, which correspond to the second and third quarters of the year. If our results are merely driven by the influence of SAD on analysts' forecasts, depression should no longer have a significant effect on forecast accuracy during these seasons. The results in Panel B contradicts this conjecture.

Third, we repeat our baseline analysis for the low-SAD seasons and additionally restrict the sample to the southern states, including Louisiana, Georgia, California, Arizona, Texas, Tennessee, New Mexico, Alabama, and Kansas, as in Dolvin et al. (2009). This is the restricted sample for which Dolvin et al. (2009) do not find a result for the SAD effect. Thus, finding a significant result in this sample provides a direct evidence that the impact of depression on forecast accuracy is distinct from that of SAD. The results in Panel C of Table 8 support this idea: depression affects the forecast accuracy of analysts, even when they are located in states in which the chance of seasonal depression is low.[35]

Although these results distinguish our findings from the impact of seasonal depression, it is not yet clear what channel drives such a difference. This question is particularly important to investigate since our findings share an overlapping mechanism (i.e., reduced optimism) with Dolvin et al. (2009). Based on our findings in Section 4, we examine whether the speed

[35] One may argue that the identification of southern states in Dolvin et al. (2009) is arbitrary. Given that southern states tend to have higher sunlight time, we construct an alternative set of southern states based on the estimated sunlight time following the methodology in Gibson and Shrader (2018). Specifically, we define southern states as states that have average sunlight time greater than the median across all states. In our most restrictive specification, we still find a significant result at the 5% level of significance (coefficient= -0.5171 ; t-statistic = 2.03). We thank Jeffrey Shrader for sharing his code to estimate the duration of sunlight for this analysis.

of processing information is also a mechanism driving the influence of SAD on accuracy. Testing this conjecture, we repeat the analysis performed in Section 4.2 but include a triple interaction between the *Slow Processor*, *Have Depression*, and *SAD* indicators, where the latter is an indicator variable that takes the value of 1 if an analyst's estimate for a firm is issued during the SAD season. If the impact of SAD on forecast accuracy functions through the same channel as depression, then we expect to see a negative coefficient on the triple interaction term in the regression.

Table 9 displays the results. First, we observe that the coefficient on the interaction of *Slow Processor* and *Have Depression* is negative and statistically significant throughout all specifications, confirming our previous results. Second, we find that the coefficient on the triple interaction is positive and statistically significant in the strictest specification. This finding strictly distinguishes the mechanism through which depression impacts judgements from that of the seasonal depressions.

5.2 Distinguishing Depression from Known Sentiment Measures

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).[36] 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.

To begin, in Figure A1, we explore the correlation between our depression measure with other indices related to investors' sentiment, including Baker and Wurgler's (2006) Investor Sentiment Index, Consumer Confidence Index, and Gallup Economic Confidence Index. We find no clear correlation pattern between depression and other indices, indicating that our

[36] 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. Loh and Stulz (2018) find that as uncertainty increases in bad times, analyst forecast errors increase.

measures capture distinct dimensions of individuals' emotions.[37] In Table 10, 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 surrounding level of depression on the accuracy of an individual's earnings forecast captures different effects from the impact of other known sentiment 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 explanation, we control for market uncertainty, relying on several measures, including the VIX index, Jurado et al.'s (2015) macroeconomic uncertainty index, and Baker et al.'s (2016) economic policy index. Panel A of Table A5 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 depression's 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.[38] Taken together, the evidence presented in this section distinguishes the impact of depression on financial decisions from that of sentiment and the temporary SAD phenomenon, indicating that the effect of depression is over and above the impact of both, and functions through a different channel that what has been previously documented in the literature.

[37] In particular, the Pearson correlations 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.

[38] Loh and Stulz (2018) use prominent market crashes, the NBER recessions, and Baker et al.'s (2016) economic policy index to measure uncertainty and find a positive association between sell-side analysts' forecast errors and economic uncertainty. However, and as shown in Table A5, using the sample of Estimize absolute forecast errors we find that the impact of economic uncertainty is not different from zero in the presence of our *Have Depression* variable.

6 Robustness Tests

In this section, we explain the results of multiple robustness tests that support our main argument. For brevity, we summarize these tests in the current section while providing a detailed description and tabulation of all tests in the Internet Appendix.

First, we use an alternative measure of forecast accuracy to ensure that our findings are not sensitive to how we calculate our dependent variable. Specifically, we following Dolvin et al. (2009) and Jame et al. (2016) and standardize analyst absolute forecast error using the stock price. Our findings remain consistent even when using this alternate measure. Second, we address potential correlation in the residuals in our baseline analysis due to the time-series nature of our panel by repeating the analysis while double-clustering the standard errors. The findings remain when we double-cluster at the analyst-quarter or analyst-firm levels. We also address the potential correlation between analyst absolute forecast errors in the Estimize sample. Such a correlation is driven by the skewness in forecasts generated by earnings surprises to stocks with a large number of contributors. In untabulated results, we repeat our baseline analysis while weighting each observation by the inverse of the number of forecasters for each firm-quarter and find that our results remain.

Third, we attempt to distinguish the impact of major depression versus that of mild depression. One could argue that individuals who are severely depressed may not have similar cognitive functioning and accurate judgements as those with mild depression (Beck, 1967, 1976). We proxy for the proportion of individuals with major depression by measuring those who report loss of interest in activities. A similar question has been widely used in various studies that screen for major depressive disorder (e.g., Manus et al., 2005; Macmillan et al., 2005). Our results also show that there is no significant improvement in the forecast accuracy among severely depressed individuals.

In addition, studies show a positive correlation between anxiety and severe depression (?Kessler et al., 2015). To rule out the possibility that either can account for our results, we explicitly control for anxiety in our baseline regression. To do so, we proxy for anxiety using the survey questions "*Experience Stress Yesterday: Yes*" and "*Experience Worry Yesterday: Yes*," following studies that highlight worry and related stress being a central feature of anxiety disorders (Olatunji et al., 2010). We find that our results remain in the presence of controls for anxiety.

Fourth, we control for the potential impact of differences in firm earnings quality, since the quality of earnings can impact analyst forecasts by creating information asymmetries (Eames and Glover, 2003; Francis et al., 2004). Following Kothari et al. (2005), we measure discretionary accruals as a proxy for the information environments and include this variable in our baseline analysis. Our findings remain robust to this inclusion. Fifth, we examine whether being a professional analyst moderates the impact of depression on forecast accuracy. In doing so, we perform two tests. In the first test we split the Estimize sample in two sub-samples based on contributors who identify themselves as professional and those that do not, and find that the impact of depression on accuracy remains in the two groups. In our second test, we re-perform our analysis on the sample of sell-side analysts on I/B/E/S, and again find similar results.

Finally, we address the concern relating to the skewness in the distribution of the number of firms covered by Estimize users. Estimize encourages their contributors to cover a large number of firms, as the ranking of a user increases when she covers fifty or more firms within or across sectors. Whether our sample is winsorized or trimmed, we find consistent results with our baseline findings, indicating that the skewed distribution is not driving our findings.

7 Summary and Conclusion

This paper tests whether financial judgements are improved by depression using quarterly earnings forecasts provided by Estimize users. 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. Through various IV analyses and cross-sectional tests we show support for the causality of this effect.

We document that it is the reduction in the optimism of forecasts made during high depression periods as well as the slow processing of information that drive the results. Additionally, we show that this effect remains during low-SAD months in low SAD locations, and is not explained by well-known sentiment or economic uncertainty measures.

Our findings contribute to the behavioral finance and economics literature by establishing depression as one driver of crowdsourced forecast accuracy. We also contribute by linking depression, a mental disorder, to financial outcomes. While these findings shed light on some of the mechanisms through which persistent mild depression affects the forecasts of a popular crowdsourced platform, they do not attest to the economic and social costs of depression, or reduce from the seriousness of this mental disorder. Finally, we establish fundamental differences between the outcomes and impact of depression from those of SAD, through the processing of information channel.

References

Addoum, J. M., Ng, D. T., and Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies*, 33(3):1331–1366.

Adebambo, B., Bliss, B. A., and Kumar, A. (2016). Geography, diversity, and accuracy of crowdsourced earnings forecasts. *Working Paper*.

Adebambo, B. N. and Bliss, B. A. (2015). The Value of Crowdsourcing: Evidence from Earnings Forecasts. *Working Paper*.

Agarwal, V., Ghosh, P., and Zhao, H. (2019). Extreme stress and investor behavior: Evidence from a natural experiment. *Working Paper*.

Alexandre, P. K. and French, M. T. (2001). Labor supply of poor residents in metropolitan miami, florida: The role of depression and the co-morbid effects of substance use. *Journal of Mental Health Policy and Economics*, 4(4):161–174.

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

Alloy, L. B. and Abramson, L. Y. (1979). Judgment of contingency in depressed and nondepressed students: Sadder but wiser? *Journal of Experimental Psychology: General*, 108(4):441–485.

Alloy, L. B. and Ahrens, A. H. (1987). Depression and pessimism for the future: Biased use of statistically relevant information in predictions for self versus others. *Journal of Personality and Social Psychology*, 52(2):366–78.

Andrews, P. W. and Thomson, J. A. (2009). The bright side of being blue: Depression as an adaptation for analyzing complex problems. *Psychological Review*, 116(3):620–654.

Au, K., Chan, F., Wang, D., and Vertinsky, I. (2003). Mood in foreign exchange trading: Cognitive processes and performance. *Organizational Behavior and Human Decision Processes*, 91(2):322–338.

Bagby, R., Schuller, D., Levitt, A., Joffe, R., and Harkness, K. (1996). Seasonal and nonseasonal depression and the five-factor model of personality. *Journal of Affective Disorders*, 38:89–95.

Baglioni, C., Battagliese, G., Feige, B., Spiegelhalder, K., Nissen, C., Voderholzer, U., Lombardo, C., and Riemann, D. (2011). Insomnia as a predictor of depression: a meta-analytic evaluation of longitudinal epidemiological studies. *Journal of Affective Disorders*, 135(1-3):10–19.

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

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

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Barbic, S. P., Durisko, Z., and Andrews, P. W. (2014). Measuring the bright side of being blue: A new tool for assessing analytical rumination in depression. *PLoS ONE*, 9(11).

Barrett, G. F. (2002). The effect of alcohol consumption on earnings. *Economic Record*, 78(240):79–96.

Bartov, E., Faurel, L., and Mohanram, P. S. (2018). Can twitter help predict firm-level earnings and stock returns? *The Accounting Review*, 93(3):25–57.

Bauldry, S. (2015). Variation in the protective effect of higher education against depression. *Society and Mental Health*, 5(2):145–161.

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

Beck, A. (1987). Cognitive models of depression. *Journal of Cognitive Psychotherapy: An International Quarterly*, 1:5–37.

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

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

Birinci, F. and Dirik, G. (2010). Depressive realism: happiness or objectivity. *Turk Psikiyatri Dergisi*, 21(1):1.

Blumenthal, J. A., Babyak, M. A., Doraiswamy, P. M., Watkins, L., Hoffman, B. M., Barbour, K. A., Herman, S., Craighead, W. E., Brosse, A. L., Waugh, R., et al. (2007). Exercise and pharmacotherapy in the treatment of major depressive disorder. *Psychosomatic Medicine*, 69(7):587.

Boone, A. L. and White, J. T. (2015). The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, 117(3):508–533.

Bradshaw, M. T. (2011). Analysts' forecasts: What do we know after decades of work? *Working Paper*.

Buason, A., Norton, E. C., McNamee, P., Thordardottir, E. B., and Asgeirsdóttir, T. L. (2021). The causal effect of depression and anxiety on life satisfaction: An instrumental variable approach. *Working Paper*.

Bullock, B., Murray, G., and Meyer, D. (2017). Highs and lows, ups and downs: Meteorology and mood in bipolar disorder. *PLoS ONE*, 12(3).

Burgstahler, D. C. and Eames, M. J. (2003). Earnings management to avoid losses and earnings decreases: Are analysts fooled? *Contemporary Accounting Research*, 20(2):253–294.

Camerer, C. F. and Loewenstein, G. (2003). Behavioral economics: past, present, future. In *Advances in Behavioral Economics, Princeton, Princeton University Press. Chang, H.(2000).'A Liberal Theory of Social Welfare: Fairness, Utility, and the Pareto Principle', Yale Law Review*. Citeseer.

Chang, J. W. and Choi, H. M. (2017). Analyst optimism and incentives under market uncertainty. *Financial Review*, 52(3):307–345.

Chatterji, P., Alegria, M., Lu, M., and Takeuchi, D. (2007). Psychiatric disorders and labor market outcomes: evidence from the national latino and asian american study. *Health Economics*, 16(10):1069–1090.

Chatterji, P., Alegria, M., and Takeuchi, D. (2011). Psychiatric disorders and labor market outcomes: Evidence from the national comorbidity survey-replication. *Journal of Health Economics*, 30(5):858–868.

Chen, H., De, P., Hu, Y. J., and Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, 27(5):1367–1403.

Christensen, L. (1996). *Diet–behavior relationships: Focus on depression.* American Psychological Association.

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

Clement, M. B. and Tse, S. Y. (2003). Do Investors Respond to Analysts' Forecast Revisions as If Forecast Accuracy Is All That Matters? *The Accounting Review*, 78(1):227–249.

Clement, M. B. and Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *Journal of Finance*, 60:307–341.

Cooper, R. A., Day, T. E., and Lewis, C. M. (2001). Following the leader: A study of individual analysts' earnings forecasts. *Journal of Financial Economics*, 61:383–416.

Cotter, J., Tuna, I., and Wysocki, P. D. (2006). Expectations management and beatable targets: How do analysts react to explicit earnings guidance? *Contemporary Accounting Research*, 23(3):593–624.

Cuculiza, C., Antoniou, C., Kumar, A., and Maligkris, A. (2021). Terrorist attacks, analyst sentiment, and earnings forecasts. *Management science*, 67(4):2579–2608.

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

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

Dalsgaard, S., Nielsen, H. S., and Simonsen, M. (2014). Consequences of adhd medication use for children's outcomes. *Journal of Health Economics*, 37:137–151.

Deaton, A. (2008). Income, health and wellbeing around the world: Evidence from the Gallup World Poll. *Journal of Economic Perspectives*, 22(2):53–72.

Deaton, A. (2018). What do self-reports of wellbeing say about life-cycle theory and policy? *Journal of Public Economics*, 162(4):18–25.

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

Dehaan, E., Madsen, J., and Piotroski, J. D. (2016). Do weather-induced moods affect the processing of earnings news? *Journal of Accounting Research*, 55(3):509–550.

Dolvin, S. D., Pyles, M. K., and Wu, Q. (2009). Analysts get SAD too: The effect of seasonal affective disorder on stock analysts' earnings estimates. *Journal of Behavioral Finance*, 10(4):214–225.

Duggan, M. (2005). Do new prescription drugs pay for themselves?: The case of second-generation antipsychotics. *Journal of Health Economics*, 24(1):1–31.

Eames, M. J. and Glover, S. M. (2003). Earnings predictability and the direction of analysts' earnings forecast errors. *The Accounting Review*, 78(3):707–724.

Ertan, A., Karolyi, S. A., Kelly, P., and Stoumbos, R. C. (2016). Pre-earnings announcement over-extrapolation. *Working Paper*.

Ettner, S. L., Frank, R. G., and Kessler, R. C. (1997). The impact of psychiatric disorders on labor market outcomes. *Industrial and Labor Relations Review*, 51(1):64–81.

Forgas, J. P. (1998). On Being Happy and Mistaken: Mood Effects on the Fundamental Attribution Error. *Journal of Personality and Social Psychology*, 75(2):318–331.

Francis, J., LaFond, R., Olsson, P. M., and Schipper, K. (2004). Costs of equity and earnings attributes. *The Accounting Review*, 79(4):967–1010.

Freeman, M. P. (2009). Omega-3 fatty acids in major depressive disorder. *The Journal of Clinical Psychiatry*, 70(suppl 5):7–11.

Gasper, K. (2004). Do you see what I see? Affect and visual information processing. *Cognition and Emotion*, 18(3):405–421.

Gibson, M. and Shrader, J. (2018). Time use and labor productivity: The returns to sleep. *The Review of Economics and Statistics*, 100(5):783–798.

Gilbert, P. (2006). Evolution and depression: Issues and implications. *Psychological Medicine*, 36(3):287–297.

Golden, R. N., Gaynes, B. N., Ekstrom, R. D., Hamer, R. M., Jacobsen, F. M., Suppes, T., Wisner, K. L., and Nemeroff, C. B. (2005). The efficacy of light therapy in the treatment of mood disorders: a review and meta-analysis of the evidence. *American Journal of Psychiatry*, 162(4):656–662.

Gotlib, I. H. and Joormann, J. (2010). Cognition and depression: current status and future directions. *Annual Review of Clinical Psychology*, 6:285–312.

Grennan, J. and Michaely, R. (2021). Fintechs and the market for financial analysis. *Journal of Financial and Quantitative Analysis*, 56(6):1877–1907.

Hidaka, B. H. (2012). Depression as a disease of modernity: explanations for increasing prevalence. *Journal of Affective Disorders*, 140(3):205–214.

Hirshleifer, D., Jiang, D., and DiGiovanni, Y. M. (2020). Mood beta and seasonalities in stock returns. *Journal of Financial Economics*, (137):272–295.

Hirshleifer, D. and Shumway, T. (2003). Good day sunshine: Stock returns and the weather. *Journal of Finance*, 58:1009–1032.

Hirshleifer, D. and Teoh, S. H. (2003). Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1):337–386.

Holmstrom, B. (1999). Managerial incentive problem: A dynamic perspective. *The Review of Economic Studies*, 66(1):169–182.

Hölzel, L., Härter, M., Reese, C., and Kriston, L. (2011). Risk factors for chronic depression—a systematic review. *Journal of Affective Disorders*, 129(1-3):1–13.

Hong, H., Kubik, J., and Solomon, A. (2000). Security analysts' career concerns and herding of earnings forecasts. *The RAND Journal of Economics*, 31(1):121.

Hong, H. and Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance*, 58(1):313–351.

Howarth, E. and Hoffman, M. S. (1984). A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology*, 75(1):15–23.

Huibers, M. J. H., de Graaf, L. E., Peeters, F. P. M. L., and Arntz, A. (2010). Does the weather make us sad? Meteorological determinants of mood and depression in the general population. *Psychiatry Research*, 180(2-3):143–146.

Isen, A. (2008). Some ways in which positive affect influences decision making and problem solving. In Lewis, M., Haviland-Jones, J. M., and Barrett, L. F., editors, *Handbook of Emotions*, chapter 34, pages 548 – 573. The Guilford Press, New York, third edition.

Jame, R., Johnston, R., Markov, S., and Wolfe, M. C. (2016). The value of crowdsourced earnings forecasts. *Journal of Accounting Research*, 54(4):1077–1110.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.

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

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

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

Kaufman, J. and Charney, D. (2000). Comorbidity of mood and anxiety disorders. *Depression and Anxiety*, 12(S1):69–76.

Kessler, R. C., Angermeyer, M., Anthony, J. C., De Graaf, R., Demyttenaere, K., Gasquet, I., De Girolamo, G., Gluzman, S., Gureje, O., Haro, J. M., et al. (2007). Lifetime prevalence and age-of-onset distributions of mental disorders in the world health organization's world mental health survey initiative. *World Psychiatry*, 6(3):168.

Kessler, R. C., Berglund, P., Demler, O., Jin, R., Koretz, D., Merikangas, K. R., Rush, A. J., Walters, E. E., and Wang, P. S. (2003). The epidemiology of major depressive disorder: results from the national comorbidity survey replication (ncs-r). *The Journal of the American Medical Association*, 289(23):3095–3105.

Kessler, R. C., Sampson, N. A., Berglund, P., Gruber, M., Al-Hamzawi, A., Andrade, L., Bunting, B., Demyttenaere, K., Florescu, S., De Girolamo, G., et al. (2015). Anxious and non-anxious major depressive disorder in the world health organization world mental health surveys. *Epidemiology and psychiatric sciences*, 24(3):210–226.

Kocsis, J. H. (2000). New strategies for treating chronic depression. *Journal of Clinical Psychiatry*, 61:42–45.

Kööts, L., Realo, A., and Allik, J. (2011). The influence of the weather on affective experience: An experience sampling study. *Journal of Individual Differences*, 32(2):74–84.

Kothari, S. P., Leone, A. J., and Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, 39(1):163–197.

Li, Q., Lourie, B., and Teoh, S. H. (2019). How salience of management guidance affects forecasting behavior: Evidence from a quasi-natural experiment on Estimize. *Working Paper*.

Lo, K. and Wu, S. S. (2018). The impact of seasonal affective disorder on financial analysts. *The Accounting Review*, 93(4):309–333.

Loh, R. K. and Stulz, R. M. (2018). Is sell-side research more valuable in bad times? *The journal of Finance*, 73(3):959–1013.

Macmillan, H. L., Patterson, C. J. S., and Wathen, C. N. (2005). Screening for depression in primary care: Task Force on Preventive Health Care. *Canadian Medical Association Journal*, 172(1).

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

Manus, D., Pipkin, S. S., and Whooley, M. A. (2005). Screening for depression in patients with coronary heart disease (data from the heart and soul study). *The American Journal of Cardiology*, 96(8):1076–1081.

Matsumoto, D. A. (2002). Management's incentives to avoid negative earnings surprises. *The Accounting Review*, 77(3):483–514.

McCulloch, A. (2001). Social environments and health: cross sectional national survey. *The British Medical Journal*, 323(7306):208–209.

Michalak, E., Wilkinson, C., Hood, K., and Dowrick, C. (2002). Seasonal and nonseasonal depression: how do they differ? Symptom profile, clinical and family history in a general population sample. *Journal of Affective Disorders*, 69:185–92.

Mikhail, M. B., Walther, B. R., and Willis, R. H. (1997). Do security analysts improve their performance with experience? *Journal of Accounting Research*, 35:131–157.

Mirzakhani, L. and Poursafa, P. (2014). The association between depression and climatic conditions in the iran way to preventive of depression. *International Journal of Preventive Medicine*, 5(8):947–951.

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

Mullahy, J. and Sindelar, J. (1989). Life-cycle effects of alcoholism on education, earnings, and occupation. *Inquiry*, pages 272–282.

Must, A., Spadano, J., Coakley, E. H., Field, A. E., Colditz, G., and Dietz, W. H. (1999). The disease burden associated with overweight and obesity. *The Journal of the American Medical Association*, 282(16):1523–1529.

Olatunji, B. O., Broman-Fulks, J. J., Bergman, S. M., Green, B. A., and Zlomke, K. R. (2010). A taxometric investigation of the latent structure of worry: Dimensionality and associations with depression, anxiety, and stress. *Behavior Therapy*, 41(2):212–228.

Peng, L., Meyerhoefer, C. D., and Zuvekas, S. H. (2016). The short-term effect of depressive symptoms on labor market outcomes. *Health Economics*, 25(10):1223–1238.

Pratt, L. A., Brody, D. J., and Gu, Q. (2017). Antidepressant use among persons aged 12 and over:United States,2011-2014. *NCHS Data Brief*, (283):1–8.

Qian, H. (2009). Time variation in analyst optimism: An investor sentiment explanation. *Journal of Behavioral Finance*, 10(3):182–193.

Ramnath, S., Rock, S., and Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, (24):37–75.

Regier, D. A., Farmer, M. E., Rae, D. S., Locke, B. Z., Keith, S. J., Judd, L. L., and Goodwin, F. K. (1990). Comorbidity of mental disorders with alcohol and other drug abuse: results from the epidemiologic catchment area (eca) study. *Jama*, 264(19):2511–2518.

Rentfrow, P. J., Mellander, C., and Florida, R. (2009). Happy states of america: A state-level analysis of psychological, economic, and social well-being. *Journal of Research in Personality*, 43(6):1073–1082.

Rhee, T. G., Capistrant, B. D., Schommer, J. C., Hadsall, R. S., and Uden, D. L. (2017). Effects of depression screening on diagnosing and treating mood disorders among older adults in office-based primary care outpatient settings: An instrumental variable analysis. *Preventive Medicine*, 100:101–111.

Richardson, S., Teoh, S. H., and Wysocki, P. D. (2004). The walk-down to beatable analyst forecasts: The role of equity Issuance and insider trading incentives. *Contemporary Accounting Research*, 21(4):885–924.

Ridley, M., Rao, G., Schilbach, F., and Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, 370(6522):eaay0214.

Salerno, D. (2014). The role of earnings quality in financial analyst forecast accuracy. *Journal of Applied Business Research*, 30(1):255–276.

Shumway, T. (2010). Mood. In Baker, H. and Nofsinger, J. R., editors, *Behavioral finance: Investors, corporations, and markets*, chapter 36, pages 671 – 679. JohnWiley Sons, Inc., New Jersey.

Sinclair, R. C. and Mark, M. M. (1995). The effects of mood state on judgemental accuracy: Processing strategy as a mechanism. *Cognition and Emotion*, 9(5):417–438.

Smoski, M. J., Lynch, T. R., Rosenthal, M. Z., Cheavens, J. S., Chapman, A. L., and Krishnan, R. R. (2008). Decision-making and risk aversion among depressive adults. *Journal of Behavior Therapy and Experimental Psychiatry*, 39(4):567–576.

Stock, J., Yogo, M., and Wright, J. (2002). A survey of weak instruments and weak identification in Generalized Method of Moments. *Journal of Business and Economic Statistics*, 20:518 – 529.

Szu-Ting Fu, T., Koutstaal, W., Poon, L., and Cleare, A. J. (2012). Confidence judgment in depression and dysphoria: The depressive realism vs. negativity hypotheses. *Journal of Behavior Therapy and Experimental Psychiatry*, 43(2):699–704.

Taylor, S. E. and Brown, J. D. (1988). Illusion and well-being: a social psychological perspective on mental health. *Psychological Bulletin*, 103(2):193.

Von Helversen, B., Wilke, A., Johnson, T., Schmid, G., and Klapp, B. (2011). Performance benefits of depression: Sequential decision making in a healthy sample and a clinically depressed sample. *Journal of Abnormal Psychology*, 120(4):962–968.

Walther, B. R. and Willis, R. H. (2013). Do investor expectations affect sell-side analysts' forecast bias and forecast accuracy? *Review of Accounting Studies*, 18(1):207–227.

Wang, Y. A. and Young, M. (2020). Terrorist attacks and investor risk preference: Evidence from mutual fund flows. *Journal of Financial Economics*, 137(2):491–514.

WHO (2012). Depression: A global crisis. World Health Organization, Geneva, Switzerland.

WHO (2017). Depression and other common mental disorders: Global health estimates. World Health Organization, Geneva, Switzerland.

Yang, S. Y., Yin, S., Mo, K., and Liu, A. (2015). Twitter financial community sentiment and its predictive relationship to stock market movement. *Quantitative Finance*, 15(10):1637–1656.

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

Figure 1. Time-Series Distribution of Depression
This figure plots the percentage of individuals with diagnosed depression per quarter over the sample period of 2011 to 2016. Depression data are from Gallup Analytics.

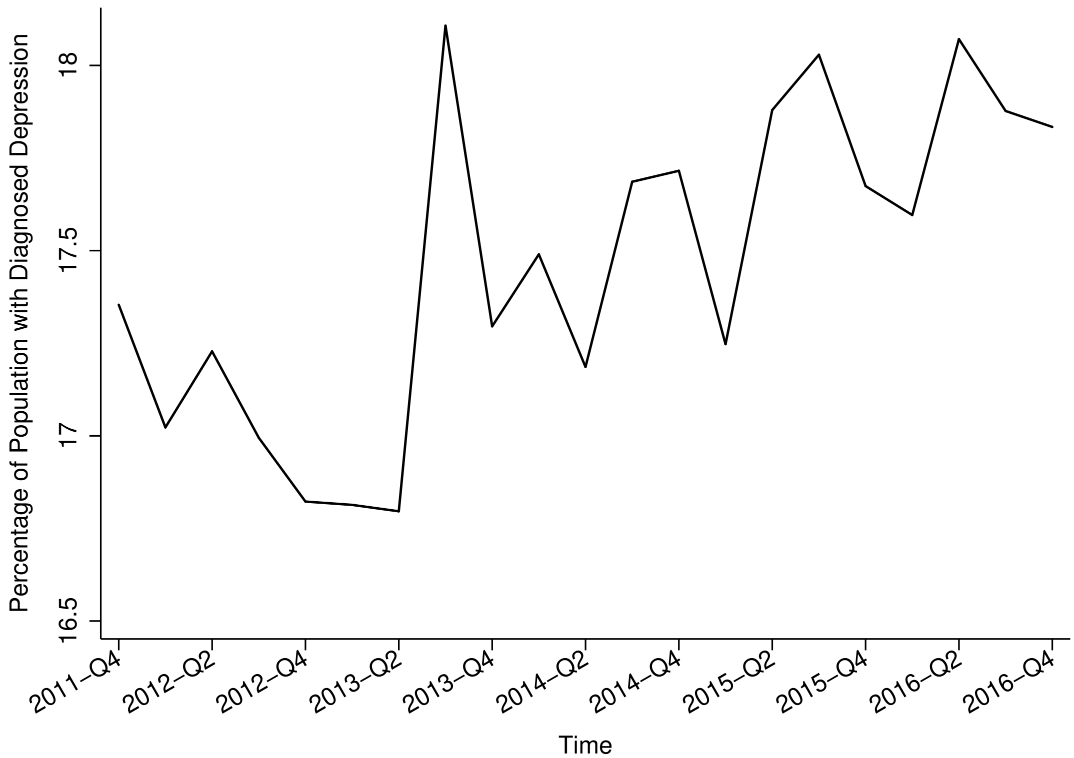

Table 1. Summary Statistics and Correlation

Panel A presents the summary statistics of the main variables used in the analysis. Panel B reports the Pearson within correlation between the main variables. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Depression data are from Gallup Analytics. Income data are from FRED. The sample period is from 2011 to 2016. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Descriptive Statistics					
	Mean	Std.	25 Pctl.	Median	75 Pctl.	# of Obs.
Dependent Variable						
Absolute Forecast Errors	0.0858	0.1447	0.0200	0.0400	0.0900	45,627
Main Independent Variable						
Have Depression	0.1731	0.0045	0.1690	0.1744	0.1763	21
Control Variables						
Number of Firms Covered	42.0882	130.1049	3	8	27	4,195
Number of Industries Covered	3.7676	2.7483	1	3	6	4,195
Forecast Horizon (Days)	7.7140	15.1204	0	2	7	45,627
Firm-Specific Experience (Quarters)	2.6400	2.2422	1	2	3	45,627
Estimize Experience (Quarters)	5.0133	3.7534	2	4	7	45,627
Professional Status	0.3300	0.4704	0	0	1	1,606
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 $US)	40,373	1,175	39,299	40,180	41,610	110

Table 1. Summary Statistics and Correlation-Continued

		Panel B: Pearson Correlation											
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
[1]	Absolute Forecast Errors	1											
[2]	Have Depression	-0.0145**	1										
[3]	Number of Firms Covered	-0.0332***	0.0896***	1									
[4]	Number of Industries Covered	-0.0664***	0.0530***	0.5559***	1								
[5]	Forecast Horizon	0.0201***	0.0859***	-0.1919***	-0.2712***	1							
[6]	Firm-specific Experience	-0.0208***	0.0850***	0.1135***	0.0872***	0.0263***	1						
[7]	Estimize Experience	-0.0105*	0.1386***	0.1183***	0.1526***	-0.0280***	0.4974***	1					
[8]	Professional Status	-0.0254***	0.0234***	0.0609***	-0.0084	0.0684***	0.2132***	0.0289***	1				
[9]	Institutional Holdings	-0.0297***	-0.0428***	0.0444***	0.0496***	-0.0059	0.0498***	0.0169***	0.0476***	1			
[10]	Firm Size	0.0437***	-0.0100*	-0.3140***	-0.2410***	0.0609***	0.0872***	-0.0466***	-0.0552***	-0.1563***	1		
[11]	Market-to-Book Ratio	-0.0155***	-0.0586***	-0.1668***	-0.1388***	0.0395***	0.0328***	-0.0077	-0.0017	0.2582***	0.0983***	1	
[12]	Income Per-Capita	0.0809***	0.4961***	0.2610***	0.1456***	0.0166***	0.0748***	0.2223***	-0.0247***	-0.0420***	-0.0828***	-0.1581***	1

Table 2. Depression and Forecast Accuracy

The table shows the estimation results from Regression (2), which tests the impact of national-level depression on the absolute earnings forecast errors of Estimize users. *Have Depression* is the main independent variable and shows the percentage of individuals with diagnosed depression. Table A1 describes all variables in detail. Analyst and earnings announcement data are from Estimize. Firm data are from CRSP and Thomson 13F databases. Depression data are from Gallup Analytics. Income data are from FRED. The sample period is from 2011 to 2016. 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)				
	(1)	(2)	(3)	(4)	(5)
Have Depression (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 Status	-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. IV Analysis: Prescribed Antidepressant

The table uses the cumulative average of mild antidepressants prescriptions (i.e., *Mild Drugs*) as an instrument to examine the impact of depression on forecast accuracy. Panel A reports the estimation results for the first-stage regression (i.e., Equation (3)), while Panel B shows the estimation results for the second-stage regression (i.e., Equation (4)). Information about antidepressants are obtained from the Prescribed Medicines files of the Medical Expenditure Panel Survey. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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.

	Panel A: First-Stage Regression				
	Dependent Variable: Have Depression (t)				
	(1)	(2)	(3)	(4)	(5)
Mild Drugs (t-1)	0.3489***	0.4877***	4.6445***	4.4768***	4.4364***
	(0.069)	(0.104)	(0.972)	(0.972)	(1.101)
First-stage F-statistic	25.82	22.21	22.84	21.21	16.24
Adj. R^2	0.28	0.35	0.48	0.48	0.54
# of Obs.	45,627	45,627	45,627	45,584	44,934
	Panel B: Second-Stage Regression				
	Dependent Variable: Absolute Forecast Error (t)				
$\widehat{\text{Have Depression}}$ (t-1)	-0.1519	-2.6396***	-1.1699***	-1.7671***	-1.3421***
	(0.578)	(0.673)	(0.394)	(0.441)	(0.340)
# of Obs.	45,627	45,627	45,627	45,584	44,934
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 4. A Non-Survey Measure of Depression: Google Trends

The table tests the impact of depression on forecast accuracy by using the Google Trend Search Volume for depression-related words as an alternative measure of national-level depression. Panel A repeats the baseline regression using the depression index with a word list that has positive and statistically significant correlation with the depression variable from Gallup. Panel B extends the word list to those with statistically significant correlation, positive or negative, with the depression variable from Gallup. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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 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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 5. Cross-Sectional Tests at the State Level

The table tests the impact of state-level depression on the earnings forecast accuracy of Estimize users. In Column (1), *Have Depression* shows the proportion of the population with depression in each state-year. In Column (2), *Highly Depressed State* is an indicator variable that equals 1 if a state has a depression value above-the-sample median, and 0 otherwise. Column (3) repeats the same analysis as in Column (2), but uses Google Trend data to identify highly depressed states. In Column (4), $Have\ \widehat{Depression}\ (t-1)$ is the estimated Gallup's continuous measure used in the second state of the IV test, where the IV is the state-level cumulative average of the most common antidepressants prescriptions. Control variables are identical to those in Table 2 and further include state-level regressors like the population gender, age, income, education, and unemployment rate. The sample period is from 2011 to 2016. 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)			
	(1)	(2)	(3)	(4)
Have Depression (t-1)	-0.9502***			
	(0.271)			
Highly Depressed State (t-1): Gallup		-1.0266*		
		(0.534)		
Highly Depressed State (t-1): Google Trends			-0.3456***	
			(0.123)	
Have $\widehat{\text{Depression}}$ (t-1)				-6.8529***
				(2.197)
Adj. R^2	0.54	0.54	0.54	0.96
# of Obs.	44,934	44,934	44,934	44,934
Controls	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓

Table 6. Economic Channel: Reduced Optimism

The table examines the role of reduced optimism as an economic channel through which depression leads to improved accuracy. Panel A (Panel B) repeats the baseline regression on the sub-sample of non-negative (negative) forecast errors. Column (6) in both panels further includes *Pessimism* and its interaction with *Have Depression* to the 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 identical to those used in Table 2. The sample period is from 2011 to 2016. 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: Signed Forecast Error (t)					
	Panel A: Non-Negative Forecast Error					
	(1)	(2)	(3)	(4)	(5)	(6)
Have Depression (t-1)	-0.4690***	-0.2720**	0.4164***	-0.3106***	-0.3378***	0.0526
	(0.143)	(0.123)	(0.113)	(0.110)	(0.105)	(0.134)
Pessimism Dummy (t-1)						-0.1939
						(0.284)
Have Depression ×						-0.4589***
Pessimism Dummy (t-1)						(0.126)
Adj. R^2	0.02	0.03	0.04	0.55	0.56	0.56
# of Obs.	19,716	19,716	19,716	19,618	19,087	19,087
	Panel B: Negative Forecast Error					
Have Depression (t-1)	0.1431	0.1963**	0.5670***	0.0988	0.0620	-0.0892
	(0.090)	(0.080)	(0.098)	(0.079)	(0.084)	(0.148)
Pessimism Dummy (t-1)						-0.3003*
						(0.181)
Have Depression ×						0.1760
Pessimism Dummy (t-1)						(0.140)
Adj. R^2	0.01	0.01	0.02	0.59	0.61	0.61
# of Obs.	25,911	25,911	25,911	25,818	25,261	25,261
Controls	✓	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓	✓
Quarter FEs			✓	✓	✓	✓
Firm FEs				✓	✓	✓
Analyst FEs					✓	✓

Table 7. Economic Channel: Speed of Information Processing

The table examines the information-processing hypothesis as an economic channel through which depression improves accuracy. Specifically, this table repeats the baseline regression but further includes *Slow Processor* and its interaction with *Have Depression* to the model, where *Slow Processor* is an indicator variable equal to 1 if a user belongs to the top-quartile of follower-leader ratio (FLR) sorted value (i.e., Equation (5)) in a quarter, and 0 otherwise. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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)				
	(1)	(2)	(3)	(4)	(5)
Have Depression ×	-0.3820**	-0.3400*	-0.3237*	-0.2054*	-0.1473
Slow Processor (t-1)	(0.141)	(0.148)	(0.139)	(0.102)	(0.105)
Have Depression (t-1)	-0.1477	-0.0999	-0.0561	-0.1597*	-0.1610*
	(0.078)	(0.078)	(0.085)	(0.072)	(0.073)
Slow Processor (t-1)	-0.5556***	-0.5787***	-0.5802***	-0.2465*	-0.2481*
	(0.154)	(0.157)	(0.149)	(0.096)	(0.104)
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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 8. Distinguishing Depression Effect from SAD

The table examines whether seasonality moderates the impact of depression on forecast accuracy. Panel A repeats the baseline analysis but demeans and de-trends the main independent variable. Panel B repeats the baseline regression but restricts the sample to the low-SAD seasons, i.e., the second and the third calendar quarters. Panel C repeats the baseline regression but restricts the sample to the southern states during the low-SAD seasons. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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: De-trended Depression				
	(1)	(2)	(3)	(4)	(5)
Have Depression (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 (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
	Panel C: Southern States During Low-SAD Seasons				
Have Depression (t-1)	-0.2510	-0.1812	-0.4995***	-0.5999***	-0.4776***
	(0.210)	(0.194)	(0.185)	(0.193)	(0.152)
Adj. R^2	0.02	0.02	0.03	0.47	0.48
# of Obs.	4,287	4,287	4,287	4,102	4,002
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 9. SAD and Speed of Information Processing

The table examines whether information-processing channel explains the influence of SAD on forecast accuracy. Specifically, this table repeats the same analysis of Table 7 but further adds the *SAD* variable and its interaction with the *Have Depression* and *Slow Processor* variables to the model, where *SAD* is an indicator variable that equals 1 for high-SAD months (i.e., the first and the fourth calendar quarters), and 0 otherwise. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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)				
Slow Processor × SAD ×	0.2465	-0.1413	0.0900	0.3819*	0.5116**
Have Depression (t-1)	(0.219)	(0.182)	(0.185)	(0.176)	(0.174)
Slow Processor ×	-0.5352***	-0.2521	-0.3797**	-0.4422***	-0.4620***
Have Depression (t-1)	(0.162)	(0.145)	(0.140)	(0.122)	(0.123)
Slow Processor ×	0.8981***	0.4297*	-0.3975	-0.3418	-0.2598
SAD (t-1)	(0.213)	(0.219)	(0.265)	(0.214)	(0.205)
Have Depression ×	0.7451***	0.3415	0.5565**	0.5187***	0.5342***
SAD (t-1)	(0.186)	(0.176)	(0.192)	(0.143)	(0.139)
Have Depression (t-1)	-0.1453	-0.1016	-0.0558	-0.1582*	-0.1585*
	(0.078)	(0.079)	(0.085)	(0.072)	(0.073)
Slow Processor (t-1)	-0.5202**	-0.5993***	-0.5670***	-0.1899*	-0.1722
	(0.159)	(0.159)	(0.153)	(0.096)	(0.107)
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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 10. Distinguishing Depression Effect from Known Sentiment Indices
The table repeats the baseline regression 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)), and 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 identical to those used in Table 2. The sample period is from 2011 to 2016. 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)			
	(1)	(2)	(3)	(4)
Have Depression (t-1)	-0.1933***	-0.1942***	-0.1422**	-0.1643**
	(0.069)	(0.069)	(0.070)	(0.068)
Investor Sentiment Index (t-1)	0.0299			-0.1790
	(0.132)			(0.150)
Consumer Confidence Index (t-1)		0.0470		0.0040
		(0.073)		(0.076)
Gallup Economic Confidence Index (t-1)			0.2355**	0.3050**
			(0.119)	(0.139)
Adj. R^2	0.54	0.54	0.54	0.54
# of Obs.	44,934	44,934	44,934	44,934
Controls	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓

Internet Appendix

Figure A1. Time-Series Distribution of Depression And Sentiment Indices
The figure plots quarterly values of depression from Gallup along with other sentiment indices, including the Consumer Confidence Index, the Baker-Wurgler Investor Sentiment Index, and the Gallup Economic Confidence Index over 2011 to 2016. All measures are quarterly average values and are normalized by subtracting their values from its minimum, divided by the difference between their maximum and minimum values.

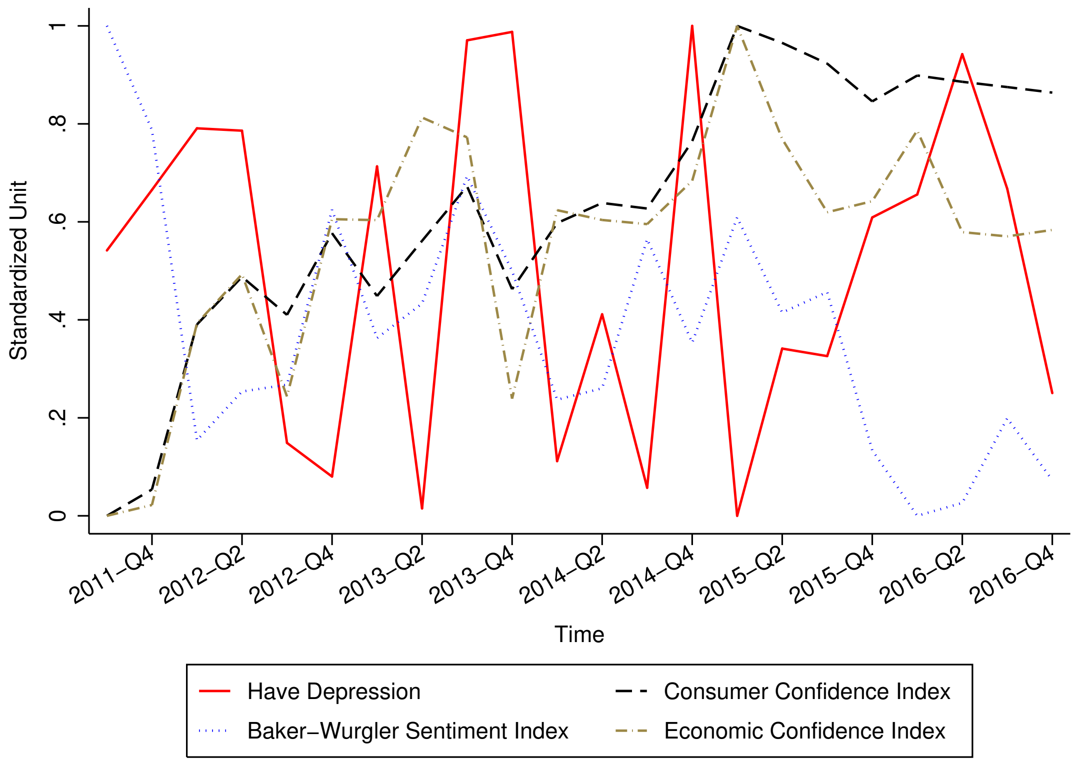

Table A1. Variable Definition

The table defines the main 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
Have Depression	The daily average proportion of respondents who declared having depression 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
Professional status	An indicator variable that is equal to 1 if the reported professional category is "financial professional", and 0 otherwise	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. Alternative Prescribed Antidepressants

The table repeats the same analysis of Table 3 but uses an alternative set of antidepressants (i.e., *Selected Drugs*) as an instrument. In particular, this table utilizes the cumulative average of of SSRIs and SNRIs antidepressants as an instrument to estimate the proportion of individuals with diagnosed depression. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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.

	Panel A: First-Stage Regression				
	Dependent Variable: Have Depression (t)				
	(1)	(2)	(3)	(4)	(5)
Selected Drugs (t-1)	0.3349***	0.4655***	3.0978***	2.8514***	2.6762***
	(0.073)	(0.108)	(0.748)	(0.734)	(0.796)
First-stage F-statistic	21.08	18.56	17.17	15.10	11.31
Adj. R^2	0.28	0.34	0.45	0.46	0.52
# of Obs.	45,627	45,627	45,627	45,584	44,934
	Panel B: Second-Stage Regression				
	Dependent Variable: Absolute Forecast Error (t)				
$\widehat{\text{Have Depression}}$ (t-1)	-0.1965	-2.8102***	-2.1207***	-3.4404***	-2.6876***
	(0.622)	(0.750)	(0.723)	(0.893)	(0.727)
# of Obs.	45,627	45,627	45,627	45,584	44,934
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table A3. IV Analysis: Precipitation

The table uses the quarterly change in average precipitation as an instrument to estimate the proportion of individuals with depression. Panel A reports the estimation results for the first-stage regression (analogous to Equation (3)). Panel B shows the estimation results for the second-stage regression (analogous to Equation (4)). Precipitation data from the National Centers for Environmental Information (NCEI). Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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.

	Panel A: First-Stage Regression				
	Dependent Variable: Have Depression (t)				
	(1)	(2)	(3)	(4)	(5)
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 $\widehat{\text{Depression}}$ (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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table A4. Effect of Depression among Optimism Analysts

The table examines the role of reduced optimism in generating higher forecast accuracy among the most and the least optimistic analysts in Panel A and Panel B, respectively. Analysts' level of optimism is determined by sorting analysts into quartile groups based on the average forecast errors in the previous quarter, where the highest (lowest) quartile contains the most (least) optimistic analysts. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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: Most Optimistic Analysts				
Have Depression (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
	Panel B: Least Optimistic Analysts				
	(1)	(2)	(3)	(4)	(5)
Have Depression (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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table A5. Effect of Depression beyond Economic Uncertainty

The table repeats the baseline analysis 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 identical to those used in Table 2. The sample period is from 2011 to 2016. 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: VIX				
	(1)	(2)	(3)	(4)	(5)
Have Depression (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 (t-1)	-0.2694***	-0.2137***	-0.1684**	-0.2714***	-0.2595***
	(0.085)	(0.079)	(0.080)	(0.072)	(0.067)
Macroeconomic Uncertainty (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 (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 (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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

B Additional Evidence and 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. We also rule out major depression as a driver of our findings. Moreover, we 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.

B.1 Alternative Measure of Forecast Accuracy

In our baseline analysis, we measured analysts' forecast inaccuracy using the absolute deviation of their earnings forecasts from the actual earnings of a firm (i.e., Equation (1)), similar to previous studies (Hong et al., 2000; Da and Huang, 2019). 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 are not sensitive to this choice, we further define an alternative measure of forecast inaccuracy as:

$$\text{Standardized Absolute Forecast Error}_{i,f,t} = \frac{|\text{User Forecast}_{i,f,t} - \text{Actual Earnings}_{f,t}|}{\text{Price}_{f,t}}, \quad (8)$$

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. Next, we re-estimate Regression (2) and replace the main independent variable with the above measure. Table B1 reports the estimation results.[39] As shown, our point estimates remain consistent with those in Table 2.

B.2 Clustering Standard Errors and Weighting Observations

In our baseline test, we rely on a time-series specification that generates variation from 21 quarters of depression levels. Since we include forecasts from many analysts for each quarter, we need to account for correlation in the residuals. As mentioned earlier, we cluster the standard errors at the analyst level. We do so, because double-clustered standard errors might be downward-biased when a panel's period is short. However, to ensure that our results remain robust, we repeat our baseline analysis, altering the clustering of the standard errors. Table B2 shows the results for analyst-quarter and analyst-firm clustering in Panels A and B, respectively. Both panels show that including time or firms in the standard error clusters does not affect the statistical significance of our findings.

We further recognize that the distribution of Estimize forecasts is heavily skewed. Therefore, earnings surprises to stocks with a large number of contributors may generate highly correlated absolute forecast errors. To address this issue, we repeat our baseline regression but use a different weighting scheme for the observations. In particular, we calculate the number of forecasters for each firm-quarter and then weight each observation by the inverse of this number. In untabulated results, we find that in the most conservative case that includes all control variables and FEs, the estimated coefficient for the main variable of interest equals a statistically significant value of -0.1705.

B.3 Effects of Severe Depression

As previously discussed, depression ranges from mild to major episodes, 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

[39] The fewer number of observations in this panel is driven by the availability of price information two days prior to firms' earnings announcement date.

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 severe depression. Specifically, one could argue that individuals who are majorly 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 unable to directly identify the severeness of individuals' depression. Therefore, we indirectly estimate the proportion of majorly depressed individuals as those who report loss of interest in activities. Specifically, we rely on the question "Over the last two weeks how often have you been bothered by the following problem? Little interest or pleasure in doing things." From the responses, we measure the proportion of the individuals who choose "Nearly Every Day" as a proxy for those who suffer from major depression. A similar question has been widely used in various studies that screen major depression disorder (e.g., Manus et al., 2005; Macmillan et al., 2005).

Next, we repeat our baseline regression but replace our main independent variable with the above measure (i.e., *No Interest in Activities*).[40] As shown in Panel A of Table B3, and unlike the estimates in Table 2, an increase in the proportion of individuals with major depression does not significantly affect the absolute value of forecast error. This result suggests that our previous results are less likely to be affected by individuals who may suffer from severe depression. In Panel B, we further interact the proxy for major depression with the main independent variable and rerun the analysis. We find that, while depression maintains a negative and significant impact on analysts' absolute forecast error, our proxy for major depression or its interaction with depression do not have a similar effect.

B.4 Effects of Anxiety

Another concern relates to the impact of anxiety. Studies find that anxiety and depression are highly comorbid (Kessler et al., 2015). An argument can be made that if anxiety ac-

[40] Gallup only collects data on the above question from 2013, reducing the number of observations in Table B3 relative to the baseline estimates.

companies depression it may be the driver for the improved forecast outcomes. While it is difficult to distinguish between anxiety and depression directly, the Gallup survey provides questions that can proxy for levels of anxiety. Specifically, following the DSM-IV criteria for diagnosing anxiety, worry and stress, represent an appropriate proxy.[41] Based on this evidence, we measure anxiety analogously to *Have Depression* using the following two questions "*Experience Stress Yesterday: Yes*" and "*Experience Worry Yesterday: Yes.*"

Using the quarterly time series for our sample, the correlation between "Experience Stress (Worry) Yesterday: Yes" and *Have Depression* is 0.3381 (-0.1776) with corresponding p-values of 0.51 and 0.74, respectively. Next, we repeat our baseline regression using the strictest specifications and include our new measures of anxiety as additional control variables. If anxiety accounts for our findings, then we do not expect our baseline results to remain in the presence of these variables.

Table B4 displays our findings. We show throughout Columns (1) to (6) if only including each of "*Experience Stress Yesterday: Yes*" and "*Experience Worry Yesterday: Yes*," or including both variables into the regression at the same time, the economic or statistical significance of *Have Depression* on the absolute forecast errors is not impacted.

B.5 Earnings Management

Firms that are covered by analysts on the Estimize platform have different information environments. Given that poor earnings quality can create information asymmetry (Eames and Glover, 2003; Francis et al., 2004), one may argue that such asymmetry can contribute to the differences in earnings forecast accuracy of analysts. To control for the potential impact of earnings quality, we follow Kothari et al. (2005) and measure discretionary accruals as a proxy for the information environment of firms. Next, we include this variable in our model and rerun our baseline test.

Table B5 displays the results. Although the coefficient on discretionary accruals is positive and significant, implying a relationship between absolute forecast error and the information

[41] The generalized anxiety disorder criteria provided by the National Library of Medicine.

environment (Salerno, 2014), the coefficient on our variable of interest remains negative and statistically significant throughout all specifications.

B.6 Impact of Depression Among Professional Analysts

Most previous studies have focused on professional sell-side analysts when examining the effect of mood on their forecast accuracy. Among other characteristics, the professional analyst status may provide incentives that affect judgement differently relative to other contributors on the Estimize platform. Therefore, ex-ante, it is not clear whether the documented impact of depression is the same among professional and non-professional forecasters. Moreover, we recognize that managers and market participants focus most heavily on the forecasts provided by professional or Wall Street analysts. Therefore, the professional analyst characteristic may moderate the influence of depression on decision-making. Such a possibility makes it important to understand whether analysts' job characteristics affect the previous results.

To investigate this idea, we perform two tests. First, we divide the Estimize sample into two sub-samples 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 B6 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 depression is not restricted to non-professionals only and that depression impacts both groups of professional and non-professional analysts similarly by raising the average forecast accuracy.

B.7 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. As shown in Table 1, 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.[42]

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, winsorized 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.

[42] 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: Estimize.

Table B1. Alternative Measure of Forecast Accuracy

The table repeats our baseline analysis but uses the standardized absolute forecast errors (Equation (8)) as the main independent variable. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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: Standardized Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Have Depression (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	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table B2. Alternative Method of Clustering the Standard Errors

The table repeats the baseline analysis but uses different clustering of the standard errors. Panel A and Panel B cluster the standard errors at analyst-quarter and analyst-firm levels, respectively. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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: Analyst-Time Clustering				
	(1)	(2)	(3)	(4)	(5)
Have Depression (t-1)	-0.2485***	-0.1890**	-0.1412	-0.2141***	-0.1999***
	(0.083)	(0.075)	(0.086)	(0.070)	(0.063)
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: Analyst-Firm Clustering				
Have Depression (t-1)	-0.2485***	-0.1890***	-0.1412*	-0.2141***	-0.1999***
	(0.065)	(0.062)	(0.074)	(0.063)	(0.066)
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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table B3. Effect of Severe Depression on Forecast Accuracy

The table examines the effect 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 have declared having little to no interests in activities (i.e., *No Interest in Activities*). Panel B shows the results using the interaction of this variable and *Have Depression*. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2013 to 2016. 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				
	(1)	(2)	(3)	(4)	(5)
No Interest in Activities (t-1)	0.1309	0.2724	-0.7485	-0.2221	-0.1486
	(0.120)	(0.366)	(0.536)	(0.440)	(0.414)
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				
Have Depression ×	0.3744***	0.4866***	0.2552	0.5506***	0.5345***
No Interest in Activities (t-1)	(0.110)	(0.184)	(0.184)	(0.116)	(0.125)
Have Depression (t-1)	-0.3983***	-0.1247	-0.2177**	-0.2603***	-0.2035**
	(0.110)	(0.184)	(0.184)	(0.116)	(0.125)
No Interest in Activities (t-1)	1.0856***	0.7548*	0.0115	0.9743*	0.8839
	(0.317)	(0.415)	(0.685)	(0.577)	(0.555)
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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table B4. Effect of Depression beyond Anxiety

The table repeats the baseline analysis but additionally controls for two proxies of anxiety: *Experience Stress Yesterday* and *Experience Worry Yesterday*. Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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)					
	(1)	(2)	(3)	(4)	(5)	(6)
Have Depression (t-1)	-0.2142***	-0.1950***	-0.2055***	-0.1872***	-0.2124***	-0.1896***
	(0.068)	(0.067)	(0.068)	(0.066)	(0.067)	(0.066)
Stressed (t-1)	0.0017	-0.0842			0.1861	0.0824
	(0.094)	(0.096)			(0.113)	(0.115)
Worried (t-1)			-0.3153**	-0.3492***	-0.4657***	-0.4148***
			(0.126)	(0.122)	(0.152)	(0.146)
Adj. R^2	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
Controls	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Analyst FEs		✓		✓		✓

Table B5. Earnings Management

The table repeats the baseline analysis but additionally controls for discretionary accruals as a proxy for firms' earnings management. Firms' discretionary accruals are measured following the method of Kothari et al. (2005). Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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)				
	(1)	(2)	(3)	(4)	(5)
Have Depression (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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table B6. Depression among Professional Analysts

The table repeats the baseline analysis on 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 identical to those used in Table 2. The sample period is from 2011 to 2016. 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: Estimize Non-Professionals				
	(1)	(2)	(3)	(4)	(5)
Have Depression (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 (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 (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
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table B7. Analysts with Large Number of Covered Firms

The table repeats the baseline analysis but winsorizes the number of firms covered at the 1% level in Column (1); at the 2% level in Column (2); at the 1% of right-tail in Column (3); and trimmed at the 1% level in Column (4). Table A1 describes all control variables in detail. Control variables and their sources are identical to those used in Table 2. The sample period is from 2011 to 2016. 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)			
	1% winsorized	2% winsorized	1% right-tail winsorized	1% trimmed
	(1)	(2)	(3)	(4)
Have Depression (t-1)	-0.2048***	-0.1992***	-0.2048***	-0.1763
	(0.068)	(0.068)	(0.068)	(0.127)
Adj. R^2	0.54	0.54	0.54	0.49
# of Obs.	44,934	44,934	44,934	18,101
Controls	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓