The Up Side of Being Down: Depression and Crowdsourced Forecasts

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Abstract

We examine the impact of non-severe depression on crowdsourced financial judgments using earnings forecasts from Estimize. Our findings reveal that an increase in the proportion of the U.S. population with depression is associated with improved forecast accuracy among users. This effect remains consistent across different measures and is distinct from the influence of temporary seasonal depression or other sentiment measures on decision-making. We identify two mechanisms, namely slow information processing and reduced optimism, that contribute to explaining our results. Overall, our research establishes a link between depression and crowdsourced financial evaluations.

Keywords: non-severe depression; crowdsourced earnings forecasts; forecast accuracy; cognition; Estimize

JEL Classification: G00, G24

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1 Introduction

The increasing importance of online platforms, such as crowdsourced websites, blogs, and social media, in capital markets has led to a shift in investor behavior (Chen et al., 2014). These platforms offer easy access, aggregated opinions, and potentially more accurate information compared to traditional sources.[1] As a result, investors are relying more on online sources (Grennan and Michaely, 2021), making it crucial to understand the factors influencing the outputs on these platforms.[2]

Recent research has highlighted the significance of crowd sentiment as a key determinant of financial outcomes (Hirshleifer et al., 2020). Building on this work, we ask whether persistent non-severe depression affects the financial decisions of online crowdsourced earnings forecasters, and if so, whether the mechanisms underlying this effect differ from those associated with short-term negative affect, such as seasonal depression.

Examining these questions is crucial for several reasons. First, while the effects of transient affect on financial decisions have been studied (e.g., Dolvin et al., 2009; Dehaan et al., 2016), the impact of persistent mood changes such as depression has received limited attention. The enduring nature of depression sets it apart from shorter-term moods, making it essential to investigate whether depression enhances or impairs decision-making abilities.

Second, previous research in the field of earnings forecasts has primarily focused on behavioral factors influencing professional analysts, and it remains unclear whether these factors affect the opinions of crowds and professionals alike. Last, the rising prevalence of depression in society, with projections indicating it could become the leading cause of the global burden of disease by

[1] See Jame et al. (2016); Bartov et al. (2018); Jame et al. (2022); and Drake et al. (2023).

[2] For instance, Bloomberg's licensing of Estimize data gave over 300,000 investment professionals access to crowdsourced earnings and revenue consensuses, emphasizing the importance of crowdsourced opinions in financial markets (source: Business Wire).

2030, underscores the importance of understanding its effects on decision-making (WHO, 2012; Hidaka, 2012).

To investigate the relationship between depression and crowdsourced earnings forecasts, we utilize a dataset from Estimize.com, a platform where users submit their earnings and revenue forecasts for listed firms. The level of depression is measured using data from Gallup Analytics, which includes responses from over 2 million households at the national level. We specifically focus on the question “Have depression?" which captures the quarterly proportion of the population reporting a diagnosis of depression by a healthcare professional.

Our baseline analysis reveals that, between 2011 and 2016, higher levels of depression among the U.S. population are associated with reduced absolute forecast errors of Estimize users. This effect holds even after accounting for various firm and analyst characteristics and controlling for fixed effects. Our finding is economically significant, with a 1-standard-deviation increase in the proportion of the population with depression leading to a 0.25% (i.e., 3% of the sample's mean) improvement in future earnings forecast accuracy. This improvement is equivalent to over five quarters of firm-specific experience for the average analyst and is comparable to other determinants of performance on Estimize, such as experience, and professional status.

To address concerns of omitted variable bias, we employ an instrumental variable (IV) analysis and use the prescribed antidepressants as an IV. We find a significantly positive association between our depression measure and the cumulative average of prescribed antidepressants, validating the instrument's economic relevance. We rely on recent research that highlights the randomness in physicians' and hospitals' propensities to diagnose and prescribe medications to satisfy the exclusion restriction for the IV (Dalsgaard et al., 2014; Buason et al., 2021). Results from a two-stage least squares (2-SLS) regression provide further support for our baseline findings.

Measuring persistent depression over a short time series of available data may affect the inference of our results. Our estimates will be less reliable if the depression measure exhibits time trends, or if either forecast errors or the depression series exhibit serial correlation. To assess the impact of these issues, we use a demeaned and de-trended measure of depression as the independent variable and conduct a dynamic regression by including the lagged dependent variable in the models. We do not find significant changes in the statistical inference of our estimates, alleviating concerns about a spurious relationship between forecast accuracy and depression.

To address concerns about the timing of depression diagnosis in the Gallup survey, we utilize data from two alternative nationally representative surveys that are more likely to capture the current depressive status of respondents.[3] Using these alternative proxies, we replicate our previous findings. We also recognize that respondents' choice in answering the survey questions subjects our depression measure to selection bias. To address this concern, we employ a user-generated measure of depression by constructing a Google Trend Search Volume Index (SVI) and continue to find consistent results.

We extend our findings to the state level by taking advantage of the larger variation in non-severe depression across U.S. regions. First, we repeat our baseline analysis using annual depression levels across states. Second, we use state-level data to compare Estimize users' accuracy in high-depression areas relative to those in low-depression areas. Third, we repeat the analysis using alternative surveys and Google Trends data to proxy for local depression. Fourth, we replicate the IV analysis at the state level. These cross-sectional tests support our key finding that earnings forecasts are more accurate following periods of high depression.

[3]The data are from the Centers for Disease Control and Prevention and the Medical Expenditure Panel Survey.

To explore the economic mechanisms behind our findings, we investigate the role of increased ruminating as a potential explanation. We construct a follower-leader ratio to measure the information-processing time of analysts. Specifically, we estimate the cumulative follow- and lead-time for the number of days it takes an analyst to issue forecasts relative to other analysts covering the same firms (Cooper et al., 2001). Consistent with the increased ruminating channel, we find that analysts with slower processing time during periods of high depression have lower absolute forecast errors compared to their counterparts. We also demonstrate that the likelihood of being a slow processor is higher during quarters with higher depression.

We investigate the role of reduced analyst optimism as another explanation. Prior research suggests that analysts have incentives to issue optimistic forecasts, and a condition like depression that dampens this optimism may improve forecast accuracy (Dolvin et al., 2009; Moore and Fresco, 2012). To test this hypothesis, we examine signed forecast errors and find that higher levels of depression specifically reduce errors in optimistic forecasts. This result suggests that mood moderation remains an important channel via which behavioral factors affect financial forecasts.

A potential confounding factor in our analyses is the impact of economic downturns. Prior studies such as Loh and Stulz (2018) show that forecast errors are lower in bad economic times, and one might be concerned that psychological depression is also high during these periods. To mitigate this concern, we incorporate variables that proxy for economic depression following the approach of Loh and Stulz (2018). Our analysis shows that the influence of psychological depression on forecast accuracy remains robust. Moreover, we find that the impact of psychological depression on forecast accuracy is statistically identical during or outside of economic downturns. This result further suggests a distinct impact of psychological depression.

We also investigate whether the channels through which economic downturns affect forecast accuracy are driving our results. Specifically, we directly test the influence of career concern, analyst reliance, and increased analyst effort, and find that these channels have a muted effect in our setting. These collective results suggest a distinct impact of psychological depression on Estimize users' forecast quality compared to the influence of economic downturns.

We acknowledge that persistent depression shares some underlying mechanisms with other effects that have been previously documented in the literature. For example, seasonal affective disorder (SAD) may have a similar impact on analyst forecasts. However, our study goes beyond seasonal variations and demonstrates that the influence of depression on forecast accuracy remains significant even when considering de-trended data, low-SAD months, and states with more sunlight. While both depression and SAD affect optimism, we find that the slow information processing channel is specific to depression and does not impact forecasts during high-SAD months.

To distinguish our measure of non-severe depression from major depressive disorder (MDD), we employ alternative survey questions related to lack of interest in daily activities. Utilizing this measure as the independent variable in the baseline regression, we find no significant effect of MDD on forecast accuracy, supporting the distinct impact of non-severe depression on forecasts' quality of Estimize users.

We also address the concern that depression may capture market sentiment by controlling for various sentiment proxies such as the Baker and Wurgler's (2006) Investor Sentiment Index, Consumer Confidence Index, and Gallup Economic Confidence Index. Despite including these controls, we consistently find support for the independent effect of depression on forecast accuracy.

We conclude our analyses with several robustness tests. First, we confirm that our results hold when using alternative measures of forecast accuracy and different estimation methods. Second, we demonstrate that anxiety is not driving our results by including alternative survey questions and proxies in our analysis. Third, we account for differences in firm earnings quality and find consistent outcomes. Fourth, we explore the moderating effect of analysts' professional experience and observe consistent results across different user groups. Last, we address concerns related to the skewed distribution of variables in Estimize, as well as firm earnings and prices.

Our paper adds to the growing literature in accounting and finance that examines the quality of crowdsourced information. One line of research focuses on the value of content and opinions on crowdsourced platforms (Jame et al., 2016; Bartov et al., 2018; Grennan and Michaely, 2021), exploring their impact on research quality from traditional sources (Chen et al., 2014; Jame et al., 2022). Another line investigates factors that influence the quality of content and opinions on these platforms. For instance, previous research has shown that limited access to public information can lead to more accurate consensus on platforms like Estimize (Da and Huang, 2020). Studies have also demonstrated how events such as the Gamestop short-squeeze can affect the investment quality of due diligence recommendations on platforms like Reddit's Wallstreetbets (Bradley et al., 2024).

We contribute to this literature by highlighting the impact of a non-conventional factor, specifically non-severe depression, on the forecast accuracy of users on Estimize. This extends the existing research by emphasizing the significance of emotional factors in understanding the dynamics of crowdsourced information in financial markets.

Our paper also contributes to the literature on the behavioral factors influencing analyst outcomes. For instance, studies find that, among other factors, meteorological conditions from unpleasant weather (Dehaan et al., 2016) to hurricanes (Bourveau and Law, 2021), SAD (Dolvin et al., 2009; Lo and Wu, 2018), and air pollution (Dong et al., 2021) influence analyst optimism and forecast accuracy, mediated through mood. Despite some similarities, our distinct and robust research design includes an instrumental variable to measure depression and demonstrates information processing speed as a new mechanism. We also highlight that, unlike SAD, the role of depression is over and above seasonal or temporary mood changes.

Our research also adds to the existing literature on the impact of psychological health conditions on economic outcomes. While previous studies have explored the effects of depression on life satisfaction (Buason et al., 2021), poverty (Ridley et al., 2020), and economic decision-making (Meckel and Shapiro, 2021), we contribute by investigating its influence on financial outcomes. Specifically, we demonstrate that non-severe depression can enhance financial evaluations by counterbalancing optimism and influencing information processing.

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 the seriousness of this mental disorder.

2 Hypothesis Development

Depression is a prevalent mental illness and a significant contributor to the global disease burden, ranking second among the top-20 causes (Vigo et al., 2016). This is a diagnosable health condition that has been shown to affect cognition and is distinct from feelings of sadness, stress, or fear (WHO, 2017).

Depression encompasses two main sub-categories: major depressive disorders (MDD) and dysthymia, also known as non-severe depression (American Psychiatric Association, 1994). MDD is characterized by five or more separate recurring severe depressive episodes lasting at least two weeks, while dysthymia involves continuous symptoms lasting several months.

In our study, we specifically investigate the impact of non-severe depression (used interchangeably with “depression" in this paper) on the quality of forecasts made on a crowd-sourced platform. This research question is significant as it explores the influence of persistent mood changes on financial decision-making. While there is existing evidence on the effects of transitory affect (e.g., weather-induced moods or seasonal depressive disorder) on financial choices, the impact of persistent mood changes such as non-severe depression has not been thoroughly explored. Furthermore, it is unclear whether non-severe depression enhances or impairs the quality of financial judgment.

The psychology literature suggests that depression can have contrasting effects on cognition. On one hand, the mood congruency effect indicates that negative information becomes more salient during depression, leading to poorer cognition (Isen, 2008). On the other hand, there is evidence that depressive individuals exhibit better problem-solving abilities due to increased rumination, attention to detail, and processing of information in smaller increments, resulting in a realistic reasoning style (Andrews and Thomson, 2009; Barbic et al., 2014).

To understand the impact of depression on forecast quality, we test whether analysts' errors decrease or increase with higher levels of depression. A decrease (increase) in errors would support the idea of improved (degraded) cognition. This leads to our first hypothesis.

H1: Higher levels of depression reduce forecast errors relative to lower levels of depression.

We propose several testable hypotheses to explore the potential mechanisms underlying the impact of depression on forecast errors. Specifically, we examine two channels: the speed of information processing and reduced optimism.

For the first channel, research suggests that individuals with depression tend to process information at a slower pace and in smaller increments (Andrews and Thomson, 2009). This slower processing may lead to more accurate and less biased judgments, as depressed individuals are less likely to rely on heuristics and cognitive biases such as the fundamental attribution error (e.g., Alloy and Abramson, 1979). Previous studies have also shown that depressive individuals exhibit improved cognition and outperform non-depressed individuals in complex tasks, due to their persistent and distraction-resistant cognitive analysis (Barbic et al., 2014). These dynamics drive our priors.

H2-a: Higher levels of depression reduce forecast errors for slow processing forecasters.

H2-b: Higher levels of depression increase chances of being a slow-processing forecaster.

The second channel we consider is the lower relative optimism among individuals experiencing depression. Depressed individuals tend to provide less optimistic forecasts compared to non-depressed individuals, even when presented with the same information. This cautious approach may lead them to assume the occurrence of an event only when they are highly confident about it (Moore and Fresco, 2012).

The lower optimism observed in depressed individuals can influence their forecasting behavior and contribute to more accurate forecasts. In the context of equity analysts, various factors such as career incentives and promotion goals contribute to their tendency to issue optimistic forecasts (e.g., Hong and Kubik, 2003). Although, in the case of Estimize users, these traditional incentives may not apply directly, users may still have a bias toward optimism due to their choice to cover specific firms (Malmendier and Shanthikumar, 2014). In this regard, non-severe depression can act as a mitigating factor by dampening the user's tendency towards excessive optimism. This evidence motivates our last hypothesis as follows.

H3: Higher levels of depression reduce forecast errors of optimistic forecasts.

3 Data and Variables

3.1 Estimize

We gather individual forecasts from Estimize.com, a company that crowdsources quarterly earnings and revenue predictions. Estimize contributors include professional analysts, students, academics, and industry professionals. Estimize benefits from a diverse range of contributors, resulting in higher forecast accuracy compared to the Wall Street consensus (Jame et al., 2016). The use of pseudonymous handles on Estimize creates a level playing field, avoiding biases faced by Wall Street professionals. We analyze I/B/E/S data and compare the effects of depression on professional analysts and Estimize users in Section 6.5.[4]

We focus on earnings forecasts, removing any duplicate observations and refining our sample by considering only users' most recent estimates, excluding estimates issued 90 days before or after the actual earnings announcement (Jame et al., 2016; Li et al., 2020).[5] If a user issues multiple forecasts for a firm on the same day, we use the average values of these forecasts. To obtain details 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 $US 5 at the beginning of each quarter (Harford et al., 2019), although our results are robust to using an alternative cutoff (e.g., $1).

[4]Similar to Amazon reviewers or Wikipedia contributors, Estimize users have various incentives to contribute, including accessing peer-generated data, comparing their accuracy to others on the platform, and being part of a published consensus sold to institutional investors. For more information, see this article on Estimize.com.

[5]To ensure our results are not affected by herding effects, we tested various window lengths of 10, 30, 45, 120, 150, and 180 days before the announcements. Our results remain consistent across these lengths.

3.2 Gallup Analytics

Gallup Analytics provides information about individuals' depression through their representative and ongoing assessments of Americans' health. With daily interviews conducted with at least 500 adults, the data from Gallup offer a nationally representative sample that has been utilized in prior economics literature.[6]

The measure of depression used in this study is based on responses to the question asked by Gallup Analytics: "Have you ever been told by a physician or nurse that you have depression?" Respondents can choose from three options: "Yes," "No," or "Don't Know/Refuse." Gallup aggregates the responses in each category and calculates the daily proportion of individuals who report having or not having depression, taking into account various characteristics of the respondents.[7] This measure is used as a construct of non-severe depression and aligns with the definition of mild depression commonly used in the psychology literature.

The use of Gallup survey data provides several advantages in measuring depression prevalence. First, Gallup employs survey methods similar to those used in epidemiological studies, providing a national and international scale of depression prevalence and treatment measurement (Markkula et al., 2015). Second, the use of representative survey data ensures a more accurate reflection of individuals' mental health status. Therefore, these data are superior to measures of general sentiment derived from market information (Baker and Wurgler, 2006) or non-representative user-generated data from platforms like Twitter (Bartov et al., 2018) and Google Trends (Da et al., 2015).

[6]These studies include examining well-being and economic policy across time and U.S. states (Deaton, 2018), GDP and income (Stevenson and Wolfers, 2013), and equity portfolio composition (Pan et al., 2023).

[7]The Gallup Panel uses a rigorous sampling method to ensure the representativeness of the U.S. population. It randomly selects about 100,000 U.S. adults using random-digit dialing of landline and cellphone numbers, along with demographic information. These individuals participate in surveys through various methods like phone interviews, web surveys, or mail surveys. Further information about the methodology can be found on www.Gallup.com.

Third, the inclusion of multiple questions in the Gallup survey provides a comprehensive assessment of depression without the need for post-classification (Moore and Fresco, 2012). Researchers have utilized similar questions as instruments for measuring depression levels, as these questions capture random variation in depression compared to other measures (Buason et al., 2021). The exogeneity of the likelihood of a diagnosis by a physician to the patient further supports the validity of using such questions as reliable indicators of depression prevalence.

Fourth, relative to other national surveys that measure individuals' well-being, data from Gallup is more suitable for assessing the psychological depression of Estimize users. According to Pew Research Center and Gallup data, during our sample, over half of the American households in the Gallup survey are stock market participants.[8] This statistic suggests that the Gallup survey is more likely to capture the psychological depressive state of an American investor, which an Estimize user is more likely to qualify for.[9]

We align the data from Gallup with the Estimize information by aggregating the daily measures to a quarterly frequency. This is done by merging Gallup's daily values with the Estimize data using the date when users create an estimate. We then compute the average of the daily measures within each quarter to obtain the quarterly measure of depression. Our findings remain consistent if we first compute the quarterly values of depression in Gallup and then merge them with the Estimize database. Our final sample comprises 1,754 users, covering 1,364 firms over the reporting period of 2011-Q4 (when the Estimize sample begins) to 2016-Q4 (when Gallup well-being survey data ends).

[8]See Pew Research Center and Gallup.

[9]We acknowledge that the sample of users on Estimize may not be representative of U.S. households compared to the Gallup Analytics sample. We address this concern in Section 6.4 with several cross-sectional tests.

3.3 Variables and Summary Statistics

We use *Absolute Forecast Error* as our main dependent variable, which measures the absolute difference between an Estimize user's most recent earnings forecast and the actual earnings of a firm in a given reporting quarter similar to Da and Huang (2020). We confirm the robustness of our results when standardizing the forecast error using either firms' stock prices or assets per share.

Our main independent variable is *Have Depression*, representing the proportion of individuals in the Gallup survey diagnosed with depression. We control for analyst and firm characteristics, following prior research (Clement and Tse, 2005; Jame et al., 2016). For analysts, we consider *Number of Covered Industries*, *Number of Covered Firms*, *Forecast Horizon*, *Firm-specific Experience*, *Estimize Experience*, and *Professional Status*. For firms, we incorporate *Institutional Ownership*, *Size*, and *Market-to-Book Ratio* as explanatory variables. We also control for the quarterly average of national-level *Income per Capita* as a proxy for underlying economic factors (Walther and Willis, 2013). Appendix Table A1 reports detailed definitions of variables.

Table 1 provides a summary of key variables. In Panel A, the mean of *Absolute Forecast Error* is 0.0858 with a standard deviation of 0.1447. This value and the interquartile range mirror the consensus forecast error in Da and Huang (2020). Estimize users cover 42 firms and 4 industries per quarter on average. They make forecasts about 8 days before the actual announcement date. The average firm on Estimize has 30% institutional holdings, a firm size of 5.4 billion (logarithmically transformed to 8.6), and a market-to-book ratio of 2.54.

On average, 17.3% of respondents in Gallup report experiencing depression, consistent with the 12.7% of the U.S. population prescribed antidepressants between 2011 and 2014 (Pratt et al., 2017). The depression variable's standard deviation is 0.45%, indicating low variation. This is anticipated due to the Gallup survey capturing both lifetime and short-term prevalence, resulting in relatively stable reports over time.[10] To address the issue of limited variation in the depression variable, we conduct cross-sectional tests in Section 4.5.

We provide a temporal perspective of this variable in Figure 1. The solid line in the upper plot in the figure illustrates the quarterly time-series distribution of the variable, showcasing an upward trend from 17.4% in late 2011 to nearly 18% in late 2016. This trend reflects the increased likelihood of depression diagnoses that stems from several nationwide policy changes in the early years of the sample.[11]

To explore the association between depression values and specific periods, the bottom plot of the figure displays the distribution of high- and low-depression quarters. High-depression (low-depression) quarters are those that exceed (fall under) the median value of *Have Depression*. The number of depression states spreads almost evenly across quarters. Additionally, the number of forecasts issued per quarter in our sample is balanced: 12,084 in Q1, 13,406 in Q2, 11,487 in Q3, and 8,650 in Q4, indicating even forecasting activity throughout the year.

In Panel B of Table 1, we present the within Pearson correlations between our main variables. The results show that the depression variable is negatively and significantly correlated with forecast accuracy. We also find that forecast inaccuracy is positively correlated with forecast horizon and negatively correlated with attributes such as experience and professional status, which can proxy for analysts' ability (e.g., Clement and Tse, 2005). Importantly, the main independent variable,

[10]Limited variation in depression measures may also result from slow-moving factors discussed by Hidaka (2012), such as drug and alcohol abuse, declining mental health, societal modernization, changes in living environments, and shifts in the social environment.

[11]For example, the Affordable Care Act expansion of mental health coverage in 2014 increased access to services, leading to more diagnoses (see National Alliance on Mental Illness). Apart from the general time trend, the number of depression diagnoses is generally higher in the third calendar quarter. This may result from seasonal depression diagnosed in the first two quarters or from public health campaigns that increase mental health awareness in the first half of the year. To mitigate the influence of these time patterns, our analyses include specifications with different time fixed effects. We also provide robust evidence using the demeaned and detrended version of the depression series in Section 4.3.

Have Depression, has low correlations with other control variables, indicating a lower risk of multicollinearity in our setup.

4 Depression and Forecast Accuracy

4.1 Baseline Results

To test whether higher depression levels reduce forecast errors, we run the following pooled ordinary least squares (OLS) regression:

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

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. *Have Depression*$_{t-1}$ shows the proportion of the population who declared a depression diagnosis in quarter $t-1$. We control for analyst and firm characteristics ($Analyst\ Char$ and $Firm\ Char$), explained in Section 3.3. We also include calendar year and quarter fixed effects (δ_y and δ_q), firm fixed effects (λ_f), and analyst fixed effects (γ_i), ensuring that our estimate is an average of the depression effect obtained across analysts and firms. We cluster standard errors at the analyst level to address the correlation of analysts' earnings forecast errors.[12]

Table 2 presents the estimation results. We report standardized coefficients in percentage points for easier comparison. Without fixed effects, results in Column (1) show a negative and statistically significant coefficient for *Have Depression*, indicating that higher depression levels are associated

[12]Results are consistent across different specifications of fiscal year and quarter FEs or calendar year and fiscal quarter FEs. The estimated coefficient for *Have Depression* is -0.2490 (t-statistic = -3.557) in the former specification and -0.1183 (t-statistic = -1.740) in the latter. Alternative clustering methods, such as analyst-by-time or analyst-by-firm, yield consistent outcomes.

with lower forecast errors in the subsequent period, in line with *H1*. This pattern persists when adding time, firm, or analyst fixed effects in Columns (2) to (5).[13]

Macroeconomic and political events can drive depression and account for our results. In Column (6), we incorporate several variables that capture these events, including *Economic Policy Uncertainty Index*, *Macro Uncertainty*, *VIX*, *Financial Distress*, and *Geopolitical Risk*. We provide the definition of these variables in Table A1 and report their summary statistics in Table 1. Our findings remain consistent after controlling for these variables.[14]

Economically, our estimate in Column (1) shows that a 1-standard-deviation increase in the proportion of the U.S. population with depression is associated with a 0.25% increase in forecast accuracy, which accounts for 3% of the sample mean. This effect is comparable to other factors that influence forecast accuracy, such as professional status or experience. To put it into perspective, the impact of depression on accuracy is equivalent to having an additional five quarters of firm-specific experience for the average analyst.[15]

4.2 Instrumental Variable Analysis

Endogeneity is a significant concern in studies that investigate the effects of mental health conditions. While we assume the exogeneity of our independent variable in Regression (1) based on the argument of Buason et al. (2021), we recognize potential issues, including selection biases where

[13] To explore potential asymmetry in depression, we examine three indicators from the Gallup survey: (1) not feeling stressed, (2) expecting life to thrive in the future, and (3) rating current life highly. We include these measures as independent variables in our analysis but find no statistically significant relationship with forecast accuracy. This suggests that our measure of depression may not exhibit a symmetric pattern.

[14] When we regress depression on these macroeconomic and political variables, together with time trend and calendar quarter indicators, we find that only macroeconomic uncertainty is associated with depression.

[15] In the strictest model, we find that the effect of depression on accuracy is 2.25 (0.1999/0.0888 = 2.25) times larger than the effect of firm-specific experience. This translates to an additional five ($2.25 \times 2.24 = 5$) quarters of experience, relative to the standard deviation of firm-specific experience. Untabulated Wald tests show that the impact of depression on accuracy is comparable to an analyst's professional status and significantly greater than the effect of the forecast horizon, highlighting its economic significance.

disclosure of depression may vary over time. Additionally, the variable may primarily represent treated individuals or reflect older diagnoses due to its dependency on seeking treatment.

Instrumental variable (IV) analysis has been widely used to address such endogeneity concerns. However, the typical instruments used, such as personal characteristics and social support variables such as religiosity or parental alcohol dependency, are not suitable for our analysis.[16] Instead, to estimate the proportion of individuals with a depression diagnosis, we use the dosage of prescribed antidepressants as our instrument. This choice is supported by studies such as Buason et al. (2021), which utilize the propensity of receiving treatment from a hospital as an instrument for measuring those diagnosed with depression.[17]

To construct the IV, $Mild\ Drugs$, we utilize data on prescribed antidepressants, between 2002 to 2017, from the Medical Expenditure Panel Survey (MEPS), a nationally representative survey of the U.S. population that provides data on the type and dosage of prescribed medications. Detailed information in MEPS allows us to capture the specific antidepressants commonly associated with the treatment of non-severe depression, such as selective serotonin reuptake inhibitors (SSRIs).

We test the economic relevance of our instrument in Panel A of Table 3. As shown, the cumulative average doses of SSRIs are positively and significantly correlated with the proportion of individuals diagnosed with depression. The estimated F-statistics (e.g., 16.24 in the most conservative specification) indicate that our analysis does not suffer from the weak IV problem (Stock et al., 2002).

We also report the partial R-squared in this panel. Across all columns, we find that the IV contributes significantly to explaining the variation in our depression measure compared to all

[16]These variables are subject to issues of reverse causality and omitted variable bias, as highlighted in recent studies (e.g., Peng et al., 2016). Social support variables (e.g., weekly religious service attendance) may also pose problems as they could simultaneously capture depression and an individual's network informativeness.

[17]Studies in health economics adopt this instrumental approach based on the idea that the propensity to treat an individual's mental disorders is more likely to be exogenous (Duggan, 2005; Dalsgaard et al., 2014).

other control variables, ranging from 4% to 7%. This additional explanatory power is notable, considering the adjusted R-squared of the most conservative specification is 67%.

To satisfy the exclusion restriction, we rely on the assumption that the differences in doctors' prescription practices make receiving antidepressant treatment exogenous to patients seeking it. While we cannot directly test this criterion, prior studies (e.g., Dalsgaard et al., 2014) have made similar arguments to support the validity of this assumption. Our approach also acknowledges that different doctors or hospitals may have varying tendencies when prescribing antidepressants. By using an aggregate national measure of antidepressant prescription, our IV captures the overall treatment patterns rather than being driven by biases of individual physicians.

Motivated by this reasoning, in Panel B of Table 3, we test and report the results from the second stage of the 2-SLS regression. We find that the results remain economically significant, with a 1-standard-deviation increase in depression predicting a 1.34% (i.e., 16% of the sample mean) increase in forecast accuracy.[18]

Finally, we mitigate any impact on forecast accuracy that could be attributed to depressive individuals' familiarity with the companies from which they receive their medications. We do so by excluding pharmaceutical firms from our sample, specifically those with SIC codes 2831 and 5122. Our results remain consistent in untabulated analysis, with a coefficient of -1.3458 and a *t*-statistic of -3.860.

[18] The economic effect in the IV analysis is significantly larger than in the baseline test. This increase can be attributed to mitigating potential omitted variable bias and reducing noise in the Gallup responses, strengthening the observed effect. Our 2SLS estimate is about 6.5 times larger than the OLS estimate (-1.34 in Column (5) of Panel B of Table 3, versus -0.19 in Column (5) of Table 2). This ratio falls within the range of average ratios of IV to OLS estimates (3.5 to 18.8) reported in over 200 previous studies by Jiang (2017).

4.3 Temporal Dependencies in Depression Measure

In our baseline analysis, we use the time-lagged value of depression as the main independent variable for several reasons. First, it allows us to estimate the predictive power of depression on Estimize users' forecast inaccuracy. Second, it aligns with DSM-IV criteria, which require depressive episodes to last at least two weeks and non-severe depression symptoms to persist for a minimum of two months (American Psychiatric Association, 1994). Third, it provides a time-series identification of the effect and captures variability in individuals' depression status, including new diagnoses.

Despite this approach, we also examine the contemporaneous impact of depression on analysts' forecasts and find consistent results (coefficient = -0.1387; t-statistic = -2.720). We also include additional lags of the depression variable in the baseline regression and find consistent results for estimates in $t-1$ and $t-2$ (coefficient = -0.1370 and -0.2004; t-statistic = -2.107 and -3.285, respectively).

However, the persistent effect of depression on analyst forecasts raises concerns about a downward bias in standard error estimation due to our short sample period. Leveraging a large panel dataset, as in our case, helps mitigate such limitations (Wooldridge, 2010). Our approach also aligns with Loh and Stulz (2018), who explore the impact of macroeconomic depression on analyst forecasts.

To further address potential inference issues caused by a short sample, we proceed with several tests. First, a short sample raises a concern that our findings are driven by a few outlier periods when depression was abnormally high, while the true relation between forecast accuracy and depression might be flat most of the time. We address this concern by visually inspecting potential time discrepancies in the depression effect on forecast accuracy in Figure 2. The plot illustrates the consistent negative relationship between the *Have Depression* and the *Absolute Forecast Error* variables, after removing year-by-quarter fixed effects. This evidence indicates that the effect of depression on forecast accuracy is less likely influenced by outliers and time-varying unobserved factors.

Second, potential non-stationary features (e.g., time trends) in Gallup survey responses can bias the statistical significance of our estimates. We alleviate this concern by employing demeaned and de-trended daily time-series values for *Have Depression* (Granger and Newbold, 1974). The results in Panel A of Table 4 demonstrate that our conclusion remains.

Third, the usual t-test will be less reliable if the regression residuals are correlated due to a potentially spurious relation between forecast errors and the depression measure. If the regression residuals from Regression 1 exhibit serial correlation, including the lagged value of forecast errors should nullify our main estimates (Granger and Newbold, 1974). In Panel B, we include the lagged absolute forecast errors, repeat our baseline analysis, and continue to find our results robust.[19] Overall, these tests suggest that the inference of our findings is less likely affected by time dependency in the depression measure.

4.4 Assessing the Timing of Depression Diagnoses

4.4.1 Alternative National Surveys

Given concerns about the impact of past depression diagnoses on our results, we used the current prescription of depression-related medication as an IV. In this section, we incorporate data from two alternative sources that are more likely to capture current mild depression. The first variable, *Have*

[19]The coefficient estimates on the lagged dependent variable are positive, as in prior studies (e.g., Brown et al., 1987). However, due to the inclusion of fixed effects in the dynamic regressions, these estimates are inconsistent (see Angrist and Pischke, 2009). Despite this, the estimates for our main variable, i.e., depression, remain consistent across all specifications, mitigating concerns from including fixed effects in dynamic regression models.

Depression: CDC, uses data from the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (CDC-BRFSS). It captures the percentage of the population recently experiencing depressive states based on responses to the question: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"

We create a second variable, *Have Depression: MEPS*, utilizing the Medical Conditions Files sourced from MEPS. Each entry in these files corresponds to a response to the question "What [medical condition] did you/PERSON have?" Instances with a reported code matching 311 (ICD9CDX variable) are categorized as individuals experiencing depression (Zhang and Sullivan, 2007). To ensure recent diagnoses are captured, we determine the timing of depression diagnosis based on the condition round (CONDRD variable) during which the condition was initially reported.[20]

The mean of the CDC-BRFSS's measure exceeds that of the Gallup measure (see Table 1), likely due to the broader nature of the CDC-BRFSS question, which includes individuals with recent experiences of negative emotions beyond depression. In contrast, the mean of the MEPS's measure is smaller, possibly because MEPS surveys the same households over a more extended time interval. Despite variations in the average values of these alternative proxies, we expect a high co-movement in their time-series patterns if their fluctuations are influenced by a common component reflecting current depression. This alignment is evident in the upper plot in Figure 1. Furthermore, the Gallup measure shows a strong correlation with the CDC-BRFSS and MEPS measures, at 0.3741 (p-value=0.095) and 0.4901 (p-value=0.024), respectively.

Panel A of Table 5 presents the outcomes of the depression effect on forecast accuracy using these alternative measures. Columns (1) and (2) display results using *Have Depression: CDC*, while

[20]Institutional details on these variables can be found at CDC-BRFSS's and MEPS's websites.

Columns (3) and (4) report outcomes with *Have Depression: MEPS* as the primary independent variable. Across both alternative measures, we find that a heightened level of depression correlates with lower forecast errors. Moreover, we observe no significant variations in economic magnitudes across the measures. This suggests that distinct measures from large-scale U.S. surveys on depressive status share a common factor, reflecting the prevalent and recent depressive status of the U.S. population.

4.4.2 Non-Survey Measures of Depression

To further ensure our findings are not driven solely by past diagnoses of non-severe depression, we introduce a measure of depression based on non-survey data using information from Google Trends. This non-survey measure also helps mitigate selection bias arising from survey responses and treatment-seeking behavior. We generate two Google Trends SVI indices as follows. Appendix Table A2 explains the steps in detail.

First, we create a depression-related word list by filtering the General Inquirer's Harvard IV-4 Psychological Dictionary for the Psychological Well-Being and Negative categories. Next, we narrow down the list by selecting words that have a positive correlation with *Have Depression* over a 180-day rolling window, following Da et al. (2015). Finally, we aggregate the daily SVIs of the selected words into an index and calculate a quarterly average value, aligning with our methodology for the *Have Depression* measure.[21]

We repeat Regression (1), replacing our main variable of interest with one of the two SVI indices. As displayed in Panel B of Table 5, our coefficient of interest remains negative and statistically

[21] Our first Google Trends SVI index uses 7 words, including *melancholy, neurosis, confident, relaxation, figure, afraid, unhappily*. Our second index selects words that are either positively or negatively correlated with *Have Depression* and 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*.

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.

4.5 Cross-Sectional Tests

In this section, we complement the main analysis with state-level cross-sectional tests. This analysis allows us to account for the low variation in the drivers of depression and consider the influence of aggregate moods in individuals' immediate geography.

To create the state-level depression variable, we request users' region and county information from Estimize and gather Gallup data available annually at the Metropolitan Statistical Area (MSA) level.[22] We average the depression values across all MSAs within each state, representing the average proportion of individuals in each state who reported a diagnosis of depression. The state-level measure of depression exhibits greater variability compared to the national-level measure (average value of 0.167 and a standard deviation of 0.017). We also observe that Estimize users are not heavily concentrated in a few specific states, indicating a dispersed geographic distribution.

We re-run Regression (1) but replace the quarterly national *Have Depression* with the above annual state-level variable. We align the timing of control variables by taking the average across four quarters. In addition to previous regressors, we account for state-level characteristics, including the percentage of male population, college or bachelor degree holders, age range (18 to 24), income, and the unemployment rate.

[22]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. The largest shares of users are in the Southern, Northeast, and Western regions of states, having a 41.6%, 22.9%, and 21.3% proportion of the users, respectively. The Midwest region has 14.3% of the sample of Estimize users.

Column (1) in Table 6 reports the estimation result. The magnitude of the coefficient on the state-level *Have Depression* is greater than those in Table 2, indicating a stronger effect. In Column (2), we examine whether analysts' forecast accuracy differs based on the depression levels in their local areas. We create an indicator variable, *Depressed State*, which takes the value of 1 if a state's depression level exceeds the median depression level across all states in the previous year, and 0 otherwise. Analysts in highly depressed states tend to have slightly lower absolute forecast errors, although the result is not statistically significant.[23] We also conduct the tests with alternative measures of local non-severe depression, integrating location information from CDC-BRFSS and MEPS. We find consistent results in Columns (3) and (4).

To ensure comparability, we modify our annual state-level depression specification to measure quarterly state-level depression using the short word list from Google Trends. The results in Column (5) remain consistent with our previous findings. Lastly, in Column (6), we conduct a cross-sectional IV analysis using the same instrument described earlier. The results confirm the robustness of our findings using a local measurement of depression with a larger variation.[24]

5 Economic Channels

5.1 Speed of Information Processing

To test *H2-a*, which suggests a link between higher levels of depression and slow information processing, we use analysts' forecasting time as a proxy for the processing period. While the actual

[23]With firm-year fixed effects and the continuous measure of depression, we find that the estimated coefficient for *Have Depression* is -2.5423 (t-statistic = -3.127). The estimated coefficient for *Depressed State* is -0.1545 (t-statistic = -0.445), consistent with findings from other specifications.

[24]The results remain robust when we additionally control for state-level economic and political variables, including *Economic Policy Uncertainty*, *Economic Confidence Index*, *Standard of Living*, *President Approval*, *Political View*, and *Ideological Distance between Parties* (see their description in Table A1 of the Appendix). The estimated coefficient for the depression measure, beyond these controls, equals -0.8418 (t-statistic = -3.263).

time it takes for analysts to process information is not directly observed, this metric is commonly used in previous research to provide an indirect measure of processing speed. Similar to Cooper et al. (2001), we calculate the forecasting time for an analyst relative to other analysts covering the same firm.

$$FLR = \frac{T_1}{T_0}, \tag{2}$$

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

$$T_0 = \sum_{k=1}^{K} \sum_{i=1}^{N} t_{ik}^0, \text{ and } T_1 = \sum_{k=1}^{K} \sum_{i=1}^{N} t_{ik}^1. \tag{3}$$

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 that the analyst takes longer to issue forecasts compared to other analysts covering the same firm. We categorize the FLR variable into quartiles and create an indicator variable, *Slow Processor*, which takes the value of 1 if the analyst is in the top quartile and 0 otherwise.[25]

Next, we include an indicator variable for slower processing analysts and its interaction with *Have Depression* in our baseline regression model. Supporting *H2-a*, Table 7 shows a negative coefficient on this interaction. This result suggests that slower processing analysts have smaller absolute forecast errors during periods of high depression compared to faster processors.

In the most stringent specification in Column (5), the effect becomes statistically insignificant, while the main effect is marginally significant. Nevertheless, the total effect (i.e., the sum of the two

[25]We confirm the robustness of our results by using alternative sorting methods, such as tertiles or quintiles, and by redefining the indicator to be 0 for analysts in the bottom quartile only.

effects) remains statistically significant at the 1% level (coefficient = -0.3083, t-statistic = -2.980). We also observe that the main effect becomes insignificant in several of the specifications. This suggests that the effect of higher depression does not manifest in more accurate forecasts for analysts who are not slow processors.

5.1.1 Depression and Speed of Information Processing

To test *H2-b*, we examine whether depression increases the probability of an analyst being classified as a slow or fast processor. We calculate the median value of the FLR variable for each analyst's portfolio every quarter and sort these median values into quartiles. We then define two indicator variables, *Slow Processor* and *Fast Processor*, which take a value of 1 for analysts in the top and bottom quartiles, respectively, and 0 for others.

We regress these indicator variables on the *Have Depression* variable while controlling for the same set of variables as in our baseline model. The results in Panel A of Table 8 show that across OLS and Logit estimations, analysts are more likely to be categorized as slow processors during periods of higher depression. In contrast, the effect of depression on being classified as a fast processor is not statistically significant, although the direction of the effect is negative (Panel B). These results support our assumption that depression is linked to slower information processing, as Estimize users are more likely to be classified as slow processors during higher depression periods.

5.1.2 Slow Information Processing vs. Procrastination

An alternative explanation is the possibility of procrastination in forecast issuance. Users may issue forecasts closer to announcement dates when there is a higher probability of information leakage. This is a valid concern since forecasts from Estimize users tend to cluster around firms' earnings announcement dates, with approximately 70% of forecasts issued within a 10-day window surrounding the announcement date.

To address this concern, we conduct two tests. First, we narrow our analysis to forecasts issued within the 10 days before an earnings announcement, removing the impact of forecasts issued further in advance. Despite this restriction, the results in Panel A of Table 9 show the same pattern as before.

Second, we consider the herding behavior of analysts. Delaying forecast issuance implies that the propensity of analysts' herding behavior may increase as procrastinating analysts have access to the forecasts of their early peers. To test this idea, we define *Herding* as an indicator variable equal to 1 if an analyst's forecast is between the consensus forecast and her previous forecast, and 0 otherwise (Hirshleifer et al., 2020). We then revisit the analysis in Table 7, but replace the dependent variable with *Herding*.

Panel B of Table 9 presents the results. The results show no statistically significant association between depression and users' herding behavior. The interaction term is also not statistically different from zero. This null result indicates that slow processors during high periods of depression do not exhibit significantly different herding behavior relative to other users.

5.2 Reduced Optimism

To examine *H3*, we analyze Estimize users' signed earnings forecast errors and divide the sample into two sub-samples: forecasts with non-negative errors, which indicate optimistic forecasts, and forecasts with negative errors. If depression indeed reduces analysts' optimism, we expect the impact of depression on forecast accuracy to be more pronounced in the former sub-sample.

Focusing on non-negative forecast errors in Panel A of Table 10, we observe that higher levels of depression are associated with a reduction in forecast errors, supporting *H3*. Across various specifications, except for Column (3), we consistently find a negative and statistically significant coefficient on the variable *Have Depression*. This suggests that experiencing depression is linked to more accurate forecasts with fewer optimistic biases.[26] On the contrary, the effect of depression is absent when testing the sub-sample of negative forecast errors in Panel B of Table 10, as the coefficient on the *Have Depression* is not statistically different from zero across most specifications.

In addition, we introduce an indicator variable, $Pessimism_{i,f,t-1}$, which takes a value of 1 if analyst i's earnings forecast for firm f at time $t-1$ is below the management guidance, and 0 otherwise. We consider management guidance as a strict benchmark for pessimism since it is likely intended to counter analysts' optimistic forecasts and set beatable targets (e.g., Matsumoto, 2002). Thus, forecasts below the guidance can be considered pessimistic. We include the interaction between this indicator variable and *Have Depression* as our primary independent variable in both forecast error sub-samples. In Column (6) of Panel A, we find that the interaction term is negative and statistically significant, further suggesting that depressed individuals exhibit higher relative pessimism, as their forecasts are more likely to be below management guidance.[27]

[26] The sign change in the coefficient after including quarter fixed effects in Column (3) is not a major concern. First, it occurs in one specification among many others that consistently show a negative and statistically significant coefficient on the main variable. Second, the characteristics of non-negative forecast errors differ from negative ones, and factors such as the walk-down of forecasts may influence the results (Richardson et al., 2004). Third, the interpretation of the positive coefficient in the non-negative forecast errors sub-sample does not strictly imply increased optimism, because the sub-sample includes errors equal to zero.

[27] We also redefine the pessimism variable to compare forecasts to the consensus forecast, defined as the median of earnings forecasts from all analysts covering the same firm in a quarter. This new definition categorizes forecasts as pessimistic if they are below the consensus, and optimistic otherwise. This alternative measure yields consistent results. We also ensure that the distribution of the pessimism variable does not bias our findings, as the number of analysts classified as pessimistic is similar in both panels of our analysis (p-value of difference = 0.4629).

5.3 Alternative Mechanism: Economic Depression

An important factor that could contribute to our findings is the influence of economic downturns. Previous research has indicated that periods of economic depression can impact the forecast accuracy of financial analysts. For instance, Loh and Stulz (2018) demonstrate that during economic downturns, analysts tend to intensify their efforts in response to increased market demand for their insights, resulting in enhanced earnings forecasts.

As shown in earlier sections, our primary findings, along with those derived from the instrumental variable (IV) and state-level tests, remain robust after accounting for various economic and political control variables. Furthermore, in Section 5.2, we illustrated that periods of heightened psychological depression are associated with decreased optimism in forecasts. This finding contrasts with the findings of Loh and Stulz (2018), who observed an increase in the issuance of positively biased forecasts during economic downturns.

To further investigate the influence of economic and psychological depression on the forecast accuracy of Estimize users, we conducted additional tests. First, we show that our results are not limited to periods of economic depression. Additionally, we examine the economic mechanisms explored by Loh and Stulz (2018) and demonstrate that these mechanisms play a less significant role in driving forecast accuracy during periods of high psychological depression

We begin by following Loh and Stulz (2018) and introduce two binary variables, *Economic Policy Uncertainty Indicator* and *Recessionary States*, into our baseline regressions. These variables are constructed to capture different aspects of economic depression. The time-series correlation between our measure of non-severe depression with *Economic Policy Uncertainty Indicator* and *Recessionary States* is -0.2155 (p-value = 0.098) and 0.0693 (p-value = 0.598), respectively. Detailed information on the construction of these variables is available in Table A1.

Panel A of Table 1 reports the results. In Column (1) of the panel, we report the same estimate from Column (5) of Table 2 to facilitate comparison with other specifications. In Columns (2) and (3) of the panel, we add the above binary variables to our baseline test. Consistent with the main findings of Loh and Stulz (2018) and extending them to the Estimize sample, we find negative coefficient estimates for these economic depression measures. Importantly, the conditional effect of psychological depression remains significant in all models, indicating that economic depression does not diminish the impact of psychological depression

We also incorporate the interaction between economic and psychological depression measures into our model. If the impact of psychological depression is solely driven by higher economic depression, we would expect the estimated interaction term to be negative and statistically significant. However, our results show that the influence of psychological depression on forecast accuracy is consistent across different economic states. The coefficient estimate for the interaction term is economically small and statistically insignificant, indicating that economic depression does not significantly alter the effect of psychological depression.[28]

To further show that economic conditions do not solely drive the influence of psychological non-severe depression on forecast accuracy, we mitigate the potential confounding impact of economic depression. We regress the variable *Have Depression* on the economic policy uncertainty index, the unemployment rate, and the GDP growth rate, and use the residual values (*Residual Depression*) as the key variable. As shown in Column (4), we find consistent results, indicating that economic conditions do not significantly affect the relationship between psychological non-severe depression and forecast accuracy.

[28]As robustness tests, we construct another variable to capture firms' market uncertainty, defined as the standard deviation of the market component of firms' daily stock returns. The results are consistent with our main findings (coefficient for *Have Depression* = -0.1431, *t*-stat = -1.811). We also conduct the above test at the state level and obtain a similar conclusion. Specifically, the untabulated coefficient estimate of the interaction term for two measures of economic states is -2.203 (*t*-statistic = -1.725) and -1.152 (*t*-statistic = -1.244), respectively.

Together, these results suggest that the impact of psychological and economic depression on forecast accuracy is distinct. In the following section, we further explore whether the mechanisms through which adverse economic environments influence earnings forecasts also apply during periods of psychological depression. Specifically, we examine three analyst hypotheses as investigated by Loh and Stulz (2018): the reliance hypothesis, the career concern hypothesis, and the effort hypothesis.

5.3.1 Analyst Reliance Hypothesis

According to Loh and Stulz (2018), changes in firms' information environment during economic downturns may increase the market demand for more accurate forecasts. Therefore, the increase in forecast accuracy of analysts during these times is shown to be more pronounced for opaque firms. To test this hypothesis, we construct four measures of firm opaqueness, including lack of management earnings guidance, low institutional ownership, high idiosyncratic volatility, and low I/B/E/S coverage. We include these measures in our baseline regressions. If the psychological depression measure captures the times when firms' information environment changes due to economic uncertainty, we would expect the interaction between the measure and the four measures of firm opaqueness to be statistically significant.

Panel B of Table 11 reports the results. Contrary to our expectations, the interaction terms are inconsistent and statistically insignificant across all four measures of opaqueness, while the main effect of *Have Depression* remains consistent. These results suggest that the measure of mental depression is less likely to solely capture time-varying changes in firms' information environment induced by bad economic periods.

5.3.2 Analyst Career Concern Hypothesis

Bad economic conditions may increase employment risks, incentivize analysts to work harder, and issue more accurate forecasts. However, we posit that the career concern channel is not significant in our context. This is because two-thirds of our Estimize sample consists of non-professional analysts, whose employment is unlikely to depend on the value of their work on a crowd-sourced platform. Moreover, in all our tests, we directly control for professional status of Estimize users to account for its impact on our results.

Nevertheless, we directly test the career concern hypothesis by separately analyzing the impact of non-severe depression on the forecast accuracy of non-professional and professional users. If mental depressive times capture the same factors that trigger career concerns, we would expect our results to be primarily driven by the professional users' sub-sample.

Panel C of Table 11 reports results from this test for the non-professional (Columns (1) and (2)) and professional (Columns (3) and (4)) sub-samples. Contrary to the career concern conjecture, we observe that the influence of non-severe depression is persistent among both sub-samples. Although the economic magnitude of the effect is slightly larger among the former group, the difference between the estimated coefficients of *Have Depression* among these samples is statistically identical (p-value of the difference between Columns (1) and (3) (Columns (2) and (4)) is equal to 0.811 (0.849)). Similar to Panel A, we also find the interaction of economic and psychological depression measures statistically insignificant across both sub-samples.

5.3.3 Analyst Effort Hypothesis

Lastly, we examine whether, similar to economic downturns, Estimize users increase their efforts during high periods of non-severe mental depression. Following Loh and Stulz (2018), we proxy for analyst activity by taking the natural logarithm of one plus the number of forecasts in each period, and regress this measure on different economic and psychological depressive states.

Panel D of Table 11 reports the results. Columns (1) and (2) of the table use *Economic Policy Uncertainty Indicator* and *Recessionary States* as proxies for economic depression. Consistent with Loh and Stulz (2018), we find that bad economic times are associated with higher analyst activity. However, these results are not observed when using Gallup's measure of psychological depression. Specifically, Column (3) shows that the coefficient estimate for *Have Depression* is both economically small and statistically insignificant. In Column (4), we repeat the test using *Mental Depressive Times* as an indicator variable, equal to one (zero) if *Have Depression* is above (below) the sample median, and obtain a similar finding. These results suggest that increasing efforts is not a significant channel linking mental depression and improved forecast accuracy.

6 Additional Tests and Robustness Checks

6.1 Distinguishing Depression from Seasonal Affective Disorder

Previous studies explore the impact of affective states on financial outcomes, including the role of optimism and pessimism (e.g., Dehaan et al., 2016). Recent studies by Dolvin et al. (2009) and Lo and Wu (2018) focus on SAD and find that reduced optimism during certain periods leads to more accurate forecasts by analysts.

Despite similarities, non-severe depression and SAD are distinct conditions with different underlying causes and manifestations (Michalak et al., 2002). Therefore, it is important to understand how depression differs from the effects observed in SAD-related studies. To examine this, we modify and re-run our baseline test in two different ways.

First, we narrow down the sample to only include months during the low-SAD seasons, which are the second and third quarters of the year. By doing so, we aim to isolate the effect of depression from the effects of SAD. The findings in Panel A of Table A3 support our hypothesis that depression is distinct from SAD.

Second, we replicate our baseline analysis for the low-SAD seasons and further restrict the sample to southern states where Dolvin et al. (2009) did not find an effect of SAD. The results in Panel B of Table A3 once again support our conjecture, reinforcing the notion that depression has a unique impact on forecast accuracy.[29]

Third, we investigate whether the mechanisms driving the impact of SAD on forecast accuracy are distinct from depression. To do so, we revisit our analysis in Section 5.1 and include a triple interaction term between the indicators for slow processing, depression, and SAD in our regression analysis. We define *SAD* as an indicator variable that equals 1 for forecasts issued during high-SAD months (i.e., the first and the fourth calendar quarters), and 0 otherwise.

The results in Panel C of Table A3 reveal that the interaction between slow processing and depression remains consistently negative and statistically significant across all specifications, reaffirming our previous results. Moreover, the coefficient on the triple interaction term is positive and statistically significant in the strictest specification. This indicates that the mechanism through which depression affects judgments differs from SAD's, providing further evidence for their distinct impacts on forecast accuracy.

[29] To address concerns about the selection of southern states, we use an objective measure based on estimated sunlight time as in Gibson and Shrader (2018) to select southern states. We find that even with this alternative approach, the impact of depression on forecast accuracy remains significant (coefficient = -0.5171; *t*-statistic = -2.030). We appreciate Jeffrey Shrader for providing the code for estimating sunlight duration.

6.2 Distinguishing Non-Severe Depression from Major Depressive Disorder

Given that Gallup's question does not specify a time frame or severity for which the individual has received a diagnosis of depression, one might be concerned about the impact of MDD on our results. To mitigate this issue, we estimate the proportion of individuals experiencing major depression indirectly using Gallup data to examine the relationship between major depression symptoms and forecast accuracy.

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." Based on the responses, we identify those who choose "Nearly Every Day" as a proxy for individuals with major depression symptoms, following the approach of Macmillan et al. (2005). We perform a regression analysis using the measure of *No Interest in Activities* as a proxy for major depression symptoms, replacing our main independent variable in the baseline model.

In Panel A of Table A4, we find that an increase in the proportion of individuals with major depression symptoms does not have a significant effect on the absolute forecast error. This suggests that our previous findings are unlikely to be influenced by individuals with severe depression. In Panel B of the table, we include an interaction term between the proxy for major depression and our main independent variable. The results indicate that while depression continues to have a negative and significant impact on forecast error, the proxy for major depression or its interaction with depression does not have a similar effect.

6.3 Distinguishing Depression from Known Sentiment Measures

We examine the relationship between depression and various sentiment indices to ensure that our measures of depression capture distinct dimensions of individuals' emotions. We include the Baker and Wurgler's (2006) Investor Sentiment Index, Consumer Confidence Index, and Gallup Economic Confidence Index as control variables in our baseline analysis.

The correlations between our depression measure and these indices do not exhibit a clear pattern, suggesting that our depression measures capture different aspects of individuals' emotions.[30] Additionally, Table A5 presents the results of including each index separately and concurrently in our regression analysis. We find that the impact of depression on forecast accuracy is distinct from the effects of other known sentiment measures, indicating that depression has a unique influence on financial decisions.

6.4 Gallup Participants vs. Estimize Users

Next, we address concerns related to the representativeness of Gallup surveys to assess the mental status of Estimize users. While it is true that the sample of thousands of active users on Estimize may not be representative of U.S. households in comparison to the Gallup Analytics sample, it is important to note the wide range of Estimize's sample and its relatively larger representation compared to other traditional databases, such as I/B/E/S. This suggests that the responses in the Gallup survey primarily capture the mental health state of the users or, at the very least, likely capture the mental state of their immediate environment.

Despite this, we draw from research on the demographic distribution of stock market participants and perform additional tests. Assuming that Estimize users are more likely to be market participants, we identify their highest demographic likelihood based on available sources (e.g., Gallup Survey, 2016; and Bhagwat et al., 2023).

[30]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.

Specifically, we assume that Estimize users are more likely to be non-Hispanic white males who have higher education and higher incomes. Because Gallup data only allows us to measure the depressed population for each demographic characteristic separately, we further utilize the details in CDC-BRFSS data to identify the sub-population that matches these characteristics jointly. Subsequently, we conduct robustness tests by repeating our baseline analysis on each sub-sample, reporting our findings in Table A6. The results across all sub-samples consistently align with our main findings.

Moreover, we examine whether the Gallup Survey, which presumably has a better distribution across states, would be representative of Estimize users that could be more concentrated in the major cities with strong finance industry representation. In this test, we narrow down our sample to states with a higher likelihood of significant finance industry representation. Following Dougal et al. (2022), we identify 24 states encompassing 32 cities where firms headquartered create substantial market value.[31] In untabulated results, we find that depression remains negatively associated with forecast errors (coefficient = -3.3734; t-statistic = -3.117). These additional tests contribute to a more robust understanding of the geographic representation of Estimize users.

6.5 Robustness Tests

In this section, we conduct multiple robustness tests to strengthen our main argument. We provide a summary of these tests without presenting the detailed tables. However, we report the estimated coefficients and corresponding t-statistics from our strictest specifications as a reference.

We address concerns about the inclusion of time fixed effects given the low variation of our main independent variable over time. By excluding time fixed effects from the analysis, we find

[31]These states include Arizona, California, Colorado, Cincinnati, District of Columbia, Florida, Georgia, Illinois, Indiana, Massachusetts, Maryland, Michigan, Minnesota, Missouri, North Carolina, New York, Ohio, Oregon, Pennsylvania, Rhode Island, Texas, Virginia, Washington, and Wisconsin.

consistent evidence (coefficient = -0.3166; t-statistic = -5.458). To account for the heterogeneity in analysts' selection of covered firms, we introduce analyst-by-firm fixed effects into the model. We continue to find the same evidence (coefficient = -0.2026; t-statistic = -3.321).

To address the concern that non-severe depression might be a fixed trait of analysts, we estimate β_1 from Regression (1) using random effects and find similar results (coefficient = -0.2259; t-statistic = -3.586). We conduct a cluster bootstrapping test to further alleviate this concern. In this test, we randomly sample clusters, defined as unique analyst-firm pairs, from our original sample with replacement, and replicate our baseline analysis 10,000 times. The mean (standard error) of the bootstrapped β_1 is approximately -0.1868 (0.065), which is comparable in magnitude to the estimate from Table 2.

Next, we address the concern of selection bias resulting from the voluntary nature of user contributions on Estimize. If individuals who are mildly depressed withhold issuing forecasts, our results could be driven by the non-depressed population. However, as depicted in the bottom plot of Figure 1, we find no significant evidence that the number of forecasts during low-depression times is greater than that during high-depression periods (average of 1,139 vs. 3,423 with one-sided p-value of 0.98).

To account for the potential impact of Estimize's switch to a blind model in November 2015, we include a 2016 dummy variable and its interaction with *Have Depression* in our baseline regression. Consistent with Da and Huang (2020), we find larger absolute forecast errors in 2016, moderated by depression; that is, a negative coefficient on the interaction term (coefficient = -3.0053; t-statistic = -3.701). We also note that the economic magnitude of this coefficient is larger, indicating a larger impact of depression when other public signals are muted.

Next, we run Regression (1) with alternative measures of forecast accuracy. We follow Edmans (2011) (Malmendier and Shanthikumar, 2014) and standardize analyst absolute forecast error using total assets (price per share). We find consistent results when scaling with either assets (coefficient = -0.0058; *t*-statistic = -2.071) or price (coefficient = -0.0176; *t*-statistic = -5.867).[32]

To address potential correlation in the residuals in our baseline analysis, we re-estimate the model while double-clustering the standard errors at the analyst-time or analyst-firm levels. The results remain consistent with our previous findings (coefficient = -0.1999; *t*-statistic = -3.173 and -3.029, respectively). Accounting for the potential correlation between analyst absolute forecast errors in the Estimize sample, we re-estimate our baseline analysis while weighting each observation by the inverse of the number of forecasters for each firm quarter. This weighting accounts for the skewness in forecasts generated by earnings surprises to stocks with a large number of contributors. We find that our results remain consistent (coefficient = -0.1705; *t*-statistic = -2.234).

Another concern is that our results might be driven by periods with a larger number of respondents who had depression in previous periods. To address this, we aggregate the number of respondents to the survey question for each period, weight each observation by the inverse of this number, and re-estimate our baseline models. We find that the association between depression and forecast accuracy remains consistent (coefficient = -0.2168; *t*-statistic = -3.097).

To account for the potential influence of anxiety on our findings, we explicitly control for it in our baseline regression using the responses to the Gallup survey's questions "Experience Stress Yesterday" and "Experience Worry Yesterday" as indicators of anxiety, based on previous studies that highlight worry and stress as central features of anxiety disorders (Fichter et al., 2010). Even

[32]Using price as a scalar may create a spurious relationship through economic states that mechanically drive both prices and depression. Mitigating this concern, we perform several regressions using *Have Depression* as the independent variable on various measures of firm valuation. We find statistically insignificant results when using the natural logarithm of price, stock return, market-to-book ratio, and institutional ownership as the dependent variables, and only marginally significant results using the natural logarithm of firm size.

after including controls for anxiety in our analysis, we find that our results remain consistent (coefficient = -0.1896; *t*-statistic = -2.873).

To account for potential differences in firm earnings quality, which can create information asymmetries affecting analyst forecasts, we control for discretionary accruals as a proxy for the information environment (e.g., Kothari et al., 2005). Our results remain robust in this model (coefficient = -0.2183; *t*-statistic = -3.210).

We investigate whether being a professional analyst moderates the relationship between depression and forecast accuracy. We analyze a sample of sell-side analysts on I/B/E/S and find similar results (coefficient = -0.2316; *t*-statistic = -3.262). These findings suggest that the relationship between depression and forecast accuracy holds regardless of professional status.

Finally, we address concerns about the skewed distributions of the number of firms covered by Estimize users, actual firm earnings, and underlying stock prices. First, we winsorize the sample at different levels and find consistent results at the 1% level (coefficient = -0.2048; *t*-statistic = -3.012) and the 2% level (coefficient = -0.1992; *t*-statistic = -2.929). Second, we ensure that the distribution of the underlying earnings does not impact our results by trimming the sample of actual earnings before defining the absolute forecast error variable (coefficient = -0.2194; *t*-statistic = -3.597), as well as the standardized absolute forecast error variable (coefficient = -0.0137; *t*-statistic = -4.567). Third, we trim the distribution of stock prices used as the scalar in the standardized absolute forecast error variable and find results consistent with our baseline findings (coefficient = -0.0160; *t*-statistic = -5.333).

7 Summary and Conclusion

This paper investigates the impact of depression on financial judgments using quarterly earnings forecasts from Estimize users. By analyzing data from the Gallup survey, we find that higher levels of depression in the U.S. population are associated with more accurate earnings forecasts. Our research reveals that the improvement in forecast accuracy during high depression periods is driven by slower information processing and a reduction in forecasters' optimism.

These findings contribute to the existing literature on crowdsourced market information and productivity by highlighting depression as a driver of crowdsourced forecast accuracy. We also add to studies on mental health and economic outcomes by establishing a connection between depression, a mental disorder, and financial outcomes. However, it is important to note that our study does not diminish the seriousness or economic and social costs of depression. Overall, our research provides valuable insights into the influence of depression on financial judgments and contributes to a better understanding of the complex relationship between mental health and economic decision-making.

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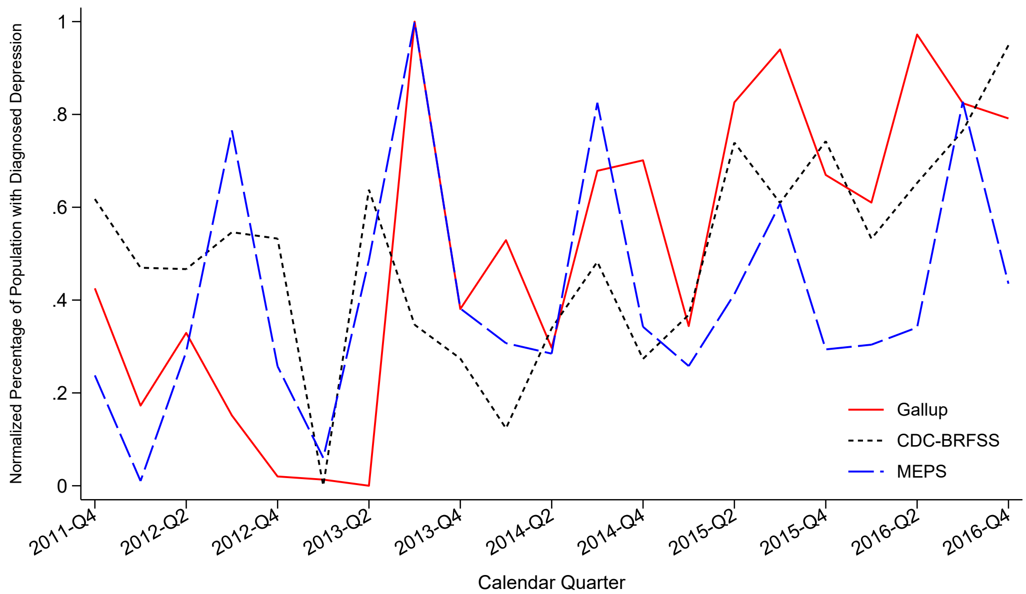
Figure 1. Time-Series Distribution of Depression

The upper plot shows the percentage of individuals with diagnosed depression per quarter sourced from three surveys over the sample period of 2011 to 2016. The time series are normalized for visual clarity. The lower plot shows the distribution of high and low depression states across the four calendar quarters. Using the median of quarterly depression measure over the full sample, we assign each calendar quarter into either a low (lower than the median) or high (higher than the median) depressive state. The bars show the total times each quarter belongs to either state.



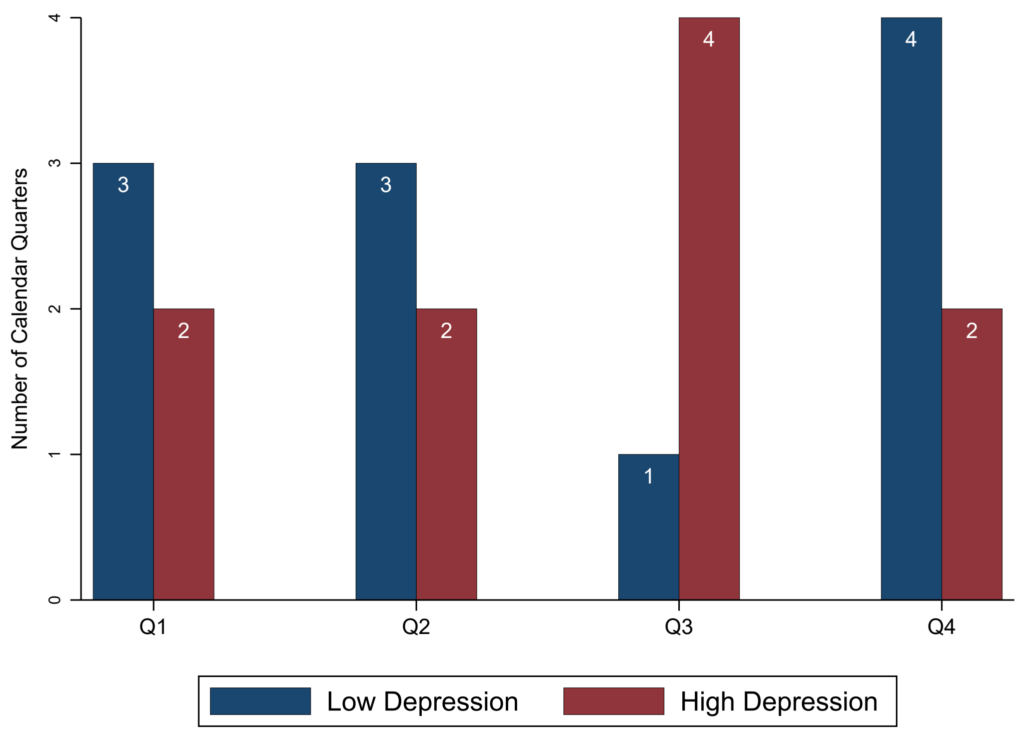


Figure 2. Time-series of Adjusted Depression and Forecast Accuracy

The figure plots the boxplot for *Absolute Forecast Error (t)* and the mean *Have Depression (t-1)* from 2012 Q1 to 2016 Q4. The solid black line connects the median of adjusted *Absolute Forecast Error*, and the dashed red line connects the mean of adjusted *Have Depression* in the sample. Adjusted *Absolute Forecast Error* are residuals obtained from the regression of *Absolute Forecast Error* on the year-by-quarter and firm FEs, while adjusted *Have Depression* are residuals obtained from the regression of daily *Have Depression* on the year-by-quarter FE and then aggregate to the quarter level. Variables are scaled for visual clarity.

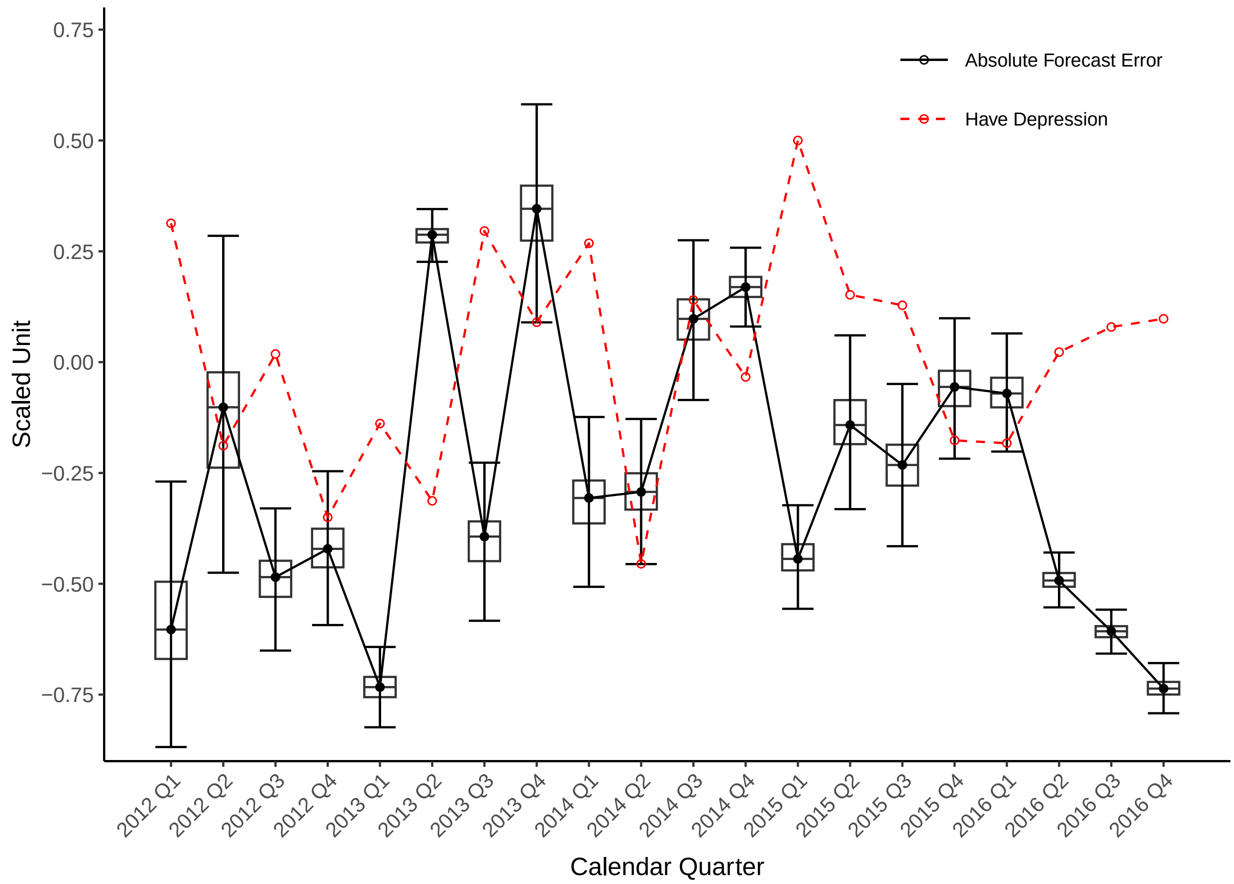


Table 1. Summary Statistics and Correlation

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, firm, income, and depression data are from Estimize, CRSP combined with Thomson 13F, FRED, and Gallup Analytics, respectively. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Descriptive Statistics							
	Mean	Std.	1 Pctl.	25 Pctl.	Median	75 Pctl.	99 Pctl.	# of Obs.
Dependent Variable								
Absolute Forecast Errors	0.0858	0.1447	0.0000	0.0200	0.0400	0.0900	0.6900	45,627
Main Independent Variable								
Have Depression: Gallup	0.1731	0.0045	0.1638	0.1690	0.1744	0.1763	0.1816	21
Have Depression: CDC	0.3022	0.0092	0.2843	0.2965	0.3002	0.3082	0.3180	21
Have Depression: MEPS	0.0172	0.0036	0.0114	0.0149	0.0162	0.0211	0.0241	21
Control Variables								
Number of Firms Covered	42.0882	130.1049	1	3	8	27	649	4,195
Number of Industries Covered	3.7676	2.7483	1	1	3	6	10	4,195
Forecast Horizon (Days)	7.7140	15.1204	0	0	2	7	8	45,627
Firm-Specific Experience (Quarters)	2.6400	2.2422	1	1	2	3	10	45,627
Estimize Experience (Quarters)	5.0133	3.7534	0	2	4	7	16	45,627
Professional Status	0.3300	0.4704	0	0	0	1	1	1,606
Institutional Holdings	0.3177	0.1049	0.0488	0.2532	0.3210	0.3825	0.5708	7,634
Firm Size	8.6560	1.5504	5.6727	7.4877	8.5062	9.6635	12.4303	7,634
Market-to-Book Ratio	2.5393	1.7969	0.7775	1.3915	1.9780	3.0367	9.6289	7,634
Income Per-Capita (in 2012 $US)	40,373	1,175	38,704	39,299	40,180	41,610	42,104	110
Macro. & Political Control Variables								
Economic Policy Uncertainty Index	0.0223	1.0359	-1.0953	-0.8110	-0.1906	0.8175	2.1976	21
Macro. Uncertainty	-0.5427	0.3552	-1.0177	-0.7076	-0.6724	-0.2518	0.0612	21
VIX	-0.5794	0.3123	-1.0453	-0.7780	-0.6200	-0.4490	0.3541	21
Financial Distress	-0.6619	0.3000	-1.1619	-0.8497	-0.7148	-0.5903	-0.1142	21
Geopolitical Risk	0.5249	1.2350	-1.2192	-0.1934	0.5347	0.8600	3.4773	21
Price and Earnings per Share								
Beginning-of-Quarter Stock Price	62.08	68.97	6.88	26.66	46.31	76.85	323.5	7,634
Actual Earnings per Share	0.71	0.93	-0.85	0.26	0.55	1.01	3.61	7,634

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. **Non-Severe Depression and Forecast Accuracy**

The table shows the estimation results from Regression (1), which tests the impact of depression on the absolute earnings forecast errors of Estimize users. *Have Depression* is the main independent variable and shows the national percentage of individuals with diagnosed depression. Macroeconomic and political control variables include the time series of Macro Uncertainty, VIX Index, Economic Policy Uncertainty Index, Financial Distress, and Geopolitical Risk. Table A1 describes all variables in detail. Analyst, firm, income, and depression data are from Estimize, CRSP combined with Thomson 13F, FRED, and Gallup Analytics, respectively. 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)	-0.2485***	-0.1890**	-0.1412*	-0.2141***	-0.1999***	-0.1711**
	(0.081)	(0.075)	(0.076)	(0.069)	(0.068)	(0.077)
Number of Covered Firms (t-1)	-0.1422	-0.2428**	-0.2384**	-0.0001	-0.2158	-0.1314
	(0.109)	(0.109)	(0.110)	(0.085)	(0.152)	(0.166)
Number of Covered Industries (t-1)	-0.9520***	-0.9501***	-0.9561***	-0.2744***	0.0821	0.0299
	(0.129)	(0.129)	(0.128)	(0.075)	(0.151)	(0.149)
Firm-Specific Experience (t-1)	-0.1822	-0.1353	-0.1143	-0.1904**	-0.0888	-0.0951
	(0.156)	(0.163)	(0.163)	(0.081)	(0.065)	(0.064)
Estimize Experience (t-1)	-0.1732	-0.2891**	-0.2449*	-0.0041	4.2914	4.4683
	(0.139)	(0.140)	(0.143)	(0.106)	(4.053)	(4.048)
Forecast Horizon (t-1)	-0.0055	-0.0528	-0.0346	0.1410**	0.0076	0.0407
	(0.107)	(0.108)	(0.106)	(0.056)	(0.059)	(0.060)
Professional Status	-0.4967**	-0.3713	-0.4102*	0.0680		
	(0.226)	(0.238)	(0.229)	(0.126)		
Institutional Ownership (t-1)	-0.1899***	-0.1903***	-0.2019***	0.3566**	0.2465	0.2559
	(0.071)	(0.071)	(0.071)	(0.164)	(0.161)	(0.160)
Firm Size (t-1)	0.4612***	0.4641***	0.4272***	6.4201***	5.8089***	5.7379***
	(0.109)	(0.110)	(0.109)	(0.981)	(1.001)	(0.990)
Market-to-Book Ratio (t-1)	-0.1462	-0.1271	-0.1343	-2.2238***	-1.9689***	-1.9807***
	(0.099)	(0.101)	(0.100)	(0.246)	(0.233)	(0.233)
Income Per Capita (t-1)	1.5233***	-0.5269**	-0.0586	0.4959**	0.5106*	1.4608***
	(0.106)	(0.219)	(0.254)	(0.248)	(0.262)	(0.328)
Adj. R^2	0.02	0.02	0.02	0.52	0.54	0.54
# of Obs.	45,627	45,627	45,627	45,584	44,934	44,934
Year FEs		✓	✓	✓	✓	✓
Quarter FEs			✓	✓	✓	✓
Firm FEs				✓	✓	✓
Analyst FEs					✓	✓
Macro. & Political Controls						✓

Table 3. Instrumental Variable Analysis

The table uses the cumulative average of mild antidepressant prescriptions (i.e., *Mild Drugs*) as an instrument to examine the impact of depression on forecast accuracy. Panel A reports the results of the first-stage regression, while Panel B shows the results of the second-stage regression. Antidepressant data is obtained from the Prescribed Medicines files of the Medical Expenditure Panel Survey. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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)					
	(1)	(2)	(3)	(4)	(5)	(6)
Mild Drugs (t-1)	0.3489***	0.4877***	4.6445***	4.4768***	4.4364***	4.3846***
	(0.069)	(0.104)	(0.972)	(0.972)	(1.101)	(0.663)
First-stage F-statistic	25.82	22.21	22.84	21.21	16.24	43.78
Adj. R^2	0.28	0.35	0.48	0.48	0.54	0.67
Partial R^2	0.04	0.05	0.06	0.06	0.06	0.07
# of Obs.	45,627	45,627	45,627	45,584	44,934	44,934
	Panel B: Second-Stage Regression					
	Dependent Variable: Absolute Forecast Error (t)					
Have $\widehat{\text{Depression}}$ (t-1)	-0.1519	-2.6396***	-1.1699***	-1.7671***	-1.3421***	-1.7044***
	(0.578)	(0.673)	(0.394)	(0.441)	(0.340)	(0.331)
# of Obs.	45,627	45,627	45,627	45,584	44,934	44,934
Controls	✓	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓	✓
Quarter FEs			✓	✓	✓	✓
Firm FEs				✓	✓	✓
Analyst FEs					✓	✓
Macro. & Political Controls						✓

Table 4. Temporal Dependencies in Depression

Panel A repeats the baseline analysis but demeans and de-trends the main independent variable. Panel B repeats the baseline regression but adds the lagged dependent variable to control for time series dependence. *Have Depression* is the main independent variable and shows the national percentage of individuals with diagnosed depression. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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: De-trended Depression				
	Dependent Variable: Absolute Forecast Error (t)				
	(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: Dynamic Regression				
	Dependent Variable: Absolute Forecast Error (t)				
Have Depression (t-1)	-0.2596***	-0.2064***	-0.1565**	-0.2414***	-0.2007***
	(0.084)	(0.076)	(0.078)	(0.069)	(0.069)
Absolute Forecast Errors (t-1)	6.4143***	6.4117***	6.4122***	0.2126	0.2980
	(0.377)	(0.377)	(0.377)	(0.216)	(0.222)
Adj. R^2	0.20	0.20	0.21	0.53	0.55
# of Obs.	43,590	43,590	43,590	43,544	43,544
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 5. **Alternative Measures of Depression**

Panel A repeats the baseline regression using alternative measures of national depressive states. Columns (1) and (2) of the panel use data from the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (CDC-BRFSS) to construct a measure of recent experience of depression, while Columns (3) and (4) use data from the Medical Expenditure Panel Survey to construct a measure of recent diagnoses of depression. Panel B examines the impact of depression on forecast accuracy by using the Google Trend Search Volume for depression-related words from the short (long) list as described in Table A2. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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: Alternative Survey Measures			
	Dependent Variable: Absolute Forecast Errors (t)			
	(1)	(2)	(3)	(4)
Have Depression: CDC (t-1)	-0.1939**	-0.1892**		
	(0.079)	(0.086)		
Have Depression: MEPS (t-1)			-0.3050*	-0.3588*
			(0.184)	(0.194)
Adj. R^2	0.52	0.54	0.52	0.54
# of Obs	45,584	44,934	45,584	44,934
	Panel B: Non-Survey Measures			
	Dependent Variable: Absolute Forecast Errors (t)			
Google Index: Short List (t-1)	-0.2742**	-0.2438*		
	(0.134)	(0.131)		
Google Index: Long List (t-1)			-0.3600***	-0.2780***
			(0.098)	(0.099)
Adj. R^2	0.53	0.55	0.53	0.55
# of Obs.	43,291	42,659	43,291	42,659
Controls	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
Analyst FEs		✓		✓

Table 6. State-Level Tests

This table tests the impact of state-level depression on the earnings forecast accuracy of Estimize users. In Column (1), *Have Depression* is the proportion of the population with depression in each state year. In Column (2), *Depressed State* is an indicator variable that equals 1 if a state has a depression value above the sample median and 0 otherwise. Columns (3) to (5) repeat the same analysis as in Column (2), but use the CDC-BRFSS, MEPS, and Google Trend data to identify depressed states, respectively. In Column (6), $\widehat{Have\ Depression}\ (t-1)$ is the second stage measure of the IV test in Table 3, where the IV is the state-level cumulative average of the most common antidepressant prescriptions. Columns (1) and (2) (Columns (3) to (6)) use data at the annual (quarterly) frequency. Control variables include those in Table 2, as well as the state-level population, gender, age, income, education, and unemployment rate. The sample period is from 2011 to 2016. Adjusted R^2 for the IV specification is from the first-stage regression. 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)	-2.3424***					
	(0.868)					
Depressed State: Gallup (t-1)		-0.3647				
		(0.416)				
Depressed State: CDC (t-1)			-0.2175			
			(0.200)			
Depressed State: MEPS (t-1)				-0.3563*		
				(0.182)		
Depressed State: Google Trends (t-1)					-0.3456***	
					(0.123)	
$\widehat{\text{Have Depression}}$ (t-1)						-6.8529***
						(2.197)
Adj. R^2	0.62	0.61	0.54	0.54	0.54	0.96
# of Obs.	8,796	8,796	44,934	44,934	44,934	44,934
Controls	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓	✓	✓

Table 7. **Speed of Information Processing and Forecast Accuracy**

The table repeats the baseline analysis but further includes *Slow Processor* and its interaction with *Have Depression* to the regression, where *Slow Processor* is an indicator variable equal to 1 if a user belongs to the top-quartile of follower-leader ratio sorted value in a quarter, and 0 otherwise. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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. **Depression, Slow and Fast Processors**

The table examines the relationship between slow processing and depression levels at the analyst-quarter level. *Slow Processor* (*Fast Processor*) is an indicator variable equal to 1 if a user belongs to the top (bottom) quartile of analyst-quarter follower-leader ratio sorted value and 0 otherwise. *Have Depression* and other control variables are measured as the average within each quarter. Panel A (Panel B) reports the regression results of *Slow Processor* (*Fast Processor*) on *Have Depression* and other control variables. Columns (1) and (2) (Columns (3) and (4)) report the results using OLS (Logit) estimation. Control variables and their sources are identical to those used in Table 2, and described in Table A1 in detail. The sample period is from 2011 to 2016. *Have Depression* and continuous control variables are standardized to have a mean and standard deviation equal to 0 and 1, respectively. $***$, $**$, 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: Slow-Processor Sub-sample			
	Dependent Variable: Slow Processor (t)			
	(1)	(2)	(3)	(4)
Have Depression (t)	0.0265***	0.0269**	0.1265***	0.1655***
	(0.009)	(0.011)	(0.044)	(0.063)
Adj. (Pseudo) R^2	0.19	0.07	0.16	0.28
# of Obs.	2,724	2,724	2,724	2,724
	Panel B: Fast-Processor Sub-sample			
	Dependent Variable: Fast Processor (t)			
Have Depression (t)	-0.0070	-0.0026	-0.0303	-0.0218
	(0.009)	(0.011)	(0.044)	(0.063)
Adj. (Pseudo) R^2	0.20	0.08	0.17	0.28
# of Obs.	2,674	2,674	2,674	2,674
Controls	✓	✓	✓	✓
Analyst FEs		✓		✓
Model	OLS	OLS	Logit	Logit

Table 9. Information Processing vs. Procrastination

The table repeats the test of the information processing channel from Table 7 but restricts forecasts to those issued in the ten days before announcements (Panel A) and uses *Herding* as a dependent variable (Panel B). *Herding* is an indicator variable equal to 1 if the analyst forecast is between the consensus forecast and the analyst's previous forecast, and 0 otherwise. *Slow Processor* is defined as in Table 7. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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: Short-Horizon Forecasts Dependent Variable: Absolute Forecast Error (t)					Panel B: Herding Behavior Dependent Variable: Herding (t)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Have Depression (t-1)	-0.1986**	-0.1346	0.0208	-0.0296	-0.0293	-0.0298	0.2740	0.0253	0.2734
	(0.088)	(0.093)	(0.097)	(0.070)	(0.080)	(0.395)	(0.310)	(0.393)	(0.327)
Slow Processor (t-1)	-0.1950	-0.2341	-0.2481	-0.2192**	-0.2793**			-1.0118	-0.5317
	(0.194)	(0.199)	(0.198)	(0.108)	(0.109)			(0.894)	(0.521)
Have Depression ×	-0.4117**	-0.3654**	-0.3988**	-0.3619***	-0.3116**			-0.2090	0.0050
Slow Processor (t-1)	(0.172)	(0.180)	(0.177)	(0.139)	(0.141)			(0.750)	(0.672)
Adj. R^2	0.01	0.02	0.02	0.57	0.58	0.04	0.13	0.04	0.13
# of Obs.	31,236	31,236	31,236	31,165	30,683	45,627	44,934	45,627	44,934
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓	✓	✓	✓	✓
Quarter FEs			✓	✓	✓	✓	✓	✓	✓
Firm FEs				✓	✓		✓		✓
Analyst FEs					✓		✓		✓

Table 10. Reduced Optimism and Forecast Accuracy

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. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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: Non-Negative Forecast Error Dependent Variable: Signed Forecast Error (t)					
	(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 (t-1)						-0.1939
						(0.284)
Have Depression ×						-0.4589***
Pessimism (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 Dependent Variable: Signed Forecast Error (t)					
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 (t-1)						-0.3003*
						(0.181)
Have Depression ×						0.1760
Pessimism (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 11. Alternative Mechanism: Economic Depression

Panel A estimates the impact of psychological depression on forecast accuracy beyond the impact of economic depression. Column (1) uses the Gallup measure of non-severe depression. Columns (2) and (3) add Baker et al.'s (2016) economic policy uncertainty (EPU) indicator and a proxy of recessionary periods, respectively. Column (4) uses *Residual Depression* as the main independent variable. This variable is the residual value obtained by regressing *Have Depression* on the EPU index, the unemployment rate, and the GDP growth rate. Panel B repeats the baseline regressions but adds four measures of stock opaqueness, including lack of management guidance (Column (1)), low institutional ownership (Column (2)), high idiosyncratic volatility (Column (3)), and low I/B/E/S analyst coverage (Column (4)). Panel C repeats the baseline regressions on sub-samples of non-professional (Columns (1) and (2)) and professional (Columns (3) and (4)) Estimize users. Panel D uses analyst-time level panel regressions to estimate the effect of economic (Columns (1) and (2)) and psychological (Columns (3) and (4)) depression on analyst efforts. Table A1 of the Appendix shows the definition of variables in detail. Additional control variables are identical to those 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.

	Panel A: Psychological vs. Economic Depression			
	Dependent Variable: Absolute Forecast Error (t)			
	(1)	(2)	(3)	(4)
Have Depression (t-1)	-0.1999***	-0.1895**	-0.2075***	
	(0.068)	(0.079)	(0.069)	
EPU Indicator (t-1)		-0.7258***		
		(0.148)		
Have Depression × EPU Indicator (t-1)		-0.0009		
		(0.120)		
Recessionary States (t-1)			-0.9360***	
			(0.326)	
Have Depression × Recessionary States (t-1)			0.0588	
			(0.178)	
Residual Depression (t-1)				-0.2011***
				(0.071)
Adj. R^2	0.54	0.54	0.54	0.54
# of Obs.	44,934	44,934	44,934	44,934

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Table 11 (*continued*)

	Panel B: Analyst Reliance			
	Dependent Variable: Absolute Forecast Error (t)			
Have Depression (t-1)	-0.2208**	-0.2246***	-0.1640**	-0.1995***
	(0.101)	(0.069)	(0.066)	(0.068)
No Guidance (t-1)	4.1858***			
	(0.553)			
No Guidance × Have Depression (t-1)	0.0497			
	(0.105)			
Low IO		-0.4153		
		(0.268)		
Low IO × Have Depression (t-1)		0.1000		
		(0.140)		
High IVOL			-0.7537***	
			(0.204)	
High IVOL × Have Depression (t-1)			-0.1853	
			(0.141)	
Low Coverage				-0.8351
				(2.122)
Low Coverage × Have Depression (t-1)				-0.1740
				(1.071)
Adj. R^2	0.54	0.54	0.54	0.54
# of Obs.	44,934	44,934	44,934	44,934
	Panel C: Analyst Career Concern			
	Dependent Variable: Absolute Forecast Error (t)			
Have Depression (t-1)	-0.2373*	-0.1937*	-0.1248	-0.2196**
	(0.124)	(0.103)	(0.108)	(0.098)
EPU Indicator (t-1)	-0.8085***		-0.5585***	
	(0.188)		(0.210)	
Have Depression × EPU Indicator (t-1)	0.1866		-0.2189	
	(0.158)		(0.160)	
Recessionary States (t-1)		-1.6057***		-0.5480
		(0.411)		(0.472)
Have Depression × Recessionary States (t-1)		0.0369		0.2328
		(0.330)		(0.198)
Sub-sample	Non-professional	Non-professional	Professional	Professional
Adj. R^2	0.55	0.55	0.52	0.52
# of Obs.	25,938	25,938	18,777	18,777
Controls	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓

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Table 11 (*continued*)

	Panel D: Analyst Effort			
	Dependent Variable: Log (1+ Number of Forecasts (t))			
EPU Indicator (t-1)	0.2754***			
	(0.024)			
Recessionary States (t-1)		0.3311***		
		(0.034)		
Have Depression (t-1)			0.0159	
			(0.011)	
Mental Depressive Times (t-1)				0.0208
				(0.022)
Adj. R^2	0.65	0.65	0.64	0.79
# of Obs.	4,195	4,195	4,195	3,329
Controls	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓

Internet Appendix

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 Covered Firms	The total number of firms each unique Estimize user covers in each quarter	Estimize
Number of Covered Industries	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 Ownership	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)
Depressive Times	An indicator of 1 if *Have Depression* is above the sample's median, and 0 otherwise	
Mild Drugs	The national cumulative average of antidepressant prescription	Medical Expenditure Panel Survey
Depression Index	Google Trends Search Volume Index (SVI) from depression-related words	Google Trends
State-level Have Depression	The yearly average proportion of respondents who declared having depression in each MSA in a state	Gallup Analytics
Depressed State: Gallup (CDC) (MEPS)	An indicator of 1 if Gallup (CDC) (MEPS) depression level exceeds the median depression level across all states, and 0 otherwise	
Depressed State: Google Trends	An indicator of 1 if state-level Google Trends SVI exceeds the median level across all states, and 0 otherwise	
Slow (Fast) Processor	An indicator of 1 if an analyst belongs to the top (bottom) quartile of the follower-leader ratios, and 0 otherwise	
Pessimism Dummy	An indicator of 1 if an analyst's forecast is below the management guidance, and 0 otherwise	
Herding	An indicator of 1 if an analyst's forecast is between the consensus forecast and her previous forecast, and 0 otherwise	
SAD	An indicator of 1 if an analyst's forecast is created during the first and the fourth calendar quarters, and 0 otherwise	
LN(Price)	End-of-quarter natural logarithm of stock price	CRSP
Return	The quarterly stock return	CRSP
Economic Policy Uncertainty Index	Index generated by measuring list of terms on Access World News database of more than 2,000 newspapers in the US related to uncertainty	Policy Uncertainty

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Table A1 (*continued*)

Variable	Definition	Source
Macro Uncertainty	A time-series measure of macroeconomic uncertainty extracted from hundreds of macroeconomic and financial indicators	www.sydneyludvigson.com
VIX	Chicago Board Options Exchange's CBOE Volatility Index	www.cboe.com
Financial Distress	Index generated by measuring a list of newspaper-based negative terms in the US related to financial markets	Policy Uncertainty
Geopolitical Risk	Index generated by measuring a list of newspaper articles related to geopolitical tensions	Policy Uncertainty
Economic Policy Uncertainty Indicator	An indicator of 1 if the national economic policy uncertainty index is in the top tercile over the sample period, and 0 otherwise	Policy Uncertainty
Recessionary States	An indicator of 1 if a period is recessionary, and 0 otherwise. We define a month to be recessionary if relative to the prior month, the national unemployment increases and GDP decreases	Federal Reserve (FRED)
Residual Depression	The residual values of *Have Depression* after regressing the variable on the economic policy uncertainty index, the unemployment rate, and the GDP growth rate	
Economic Confidence Index	An index summarizing the responses of Gallup's Economic Conditions and Economic Outlook measures	Gallup Analytics
Standard of Living	Percentage indicating "Getting Better" to the question of standard of living	Gallup Analytics
President Approval	Percentage answering do not approve to question of presidential approval	Gallup Analytics
Political View	Measures percentage answering very conservative, moderate, and very liberal political viewpoints	Gallup Analytics
Ideological Distance between Parties	Distance between party median ideology in state House and Senate	The Correlates of State Policy
No Guidance	An indicator of 1 if a firm does not have earnings guidance in the prior period, and 0 otherwise	I/B/E/S
Low IO	An indicator of 1 if a firm's institutional ownership is in the lowest quintile, and 0 otherwise	
High IVOL	An indicator of 1 if a firm's idiosyncratic volatility estimated from the Fama-French 3-factor model is in the highest quintile, and 0 otherwise. Idiosyncratic volatility is estimated using daily return data over 3-month periods.	
Low Coverage	An indicator of 1 if the number of I/B/E/S analysts covering a stock is in the lowest quintile, and 0 otherwise	I/B/E/S

Table A2. Google Trends Indices

The table defines the procedure used to obtain both Google Trends depression indices.

Word List	Procedure	Number of Words
Short List	1. Filter the General Inquirer's Harvard IV-4 Psychological Dictionary for the Psychological Well-Being and the Negative categories	164 words
	2. Obtain Google Trends Search Volume Index (SVI) for each word	
	3. Perform 180-day rolling regression of each word SVI on *Have Depression*	
	4. Keep words with resulting positive t-statistic greater than 1.3 for each regression period	7 words
	5. Construct the depression index by aggregating daily SVIs into index and obtaining a quarterly average	
Long List	1. Filter the General Inquirer's Harvard IV-4 Psychological Dictionary for the Psychological Well-Being and the Negative categories	164 words
	2. Obtain Google Trends Search Volume Index (SVI) for each word	
	3. Perform 180-day rolling regression of each word SVI on *Have Depression*	
	4. Keep words with resulting positive or negative t-statistic greater than 1.3 for each regression period	25 words
	5. Construct the depression index by aggregating daily SVIs into index and obtaining a quarterly average	

Table A3. Depression vs. SAD

The table examines whether seasonality moderates the impact of depression on forecast accuracy. Panel A repeats the baseline regression but restricts the sample to the low-SAD seasons, i.e., the second and the third calendar quarters. Panel B repeats the baseline regression but restricts the sample to the southern states during the low-SAD seasons. Panel C 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. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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: Low-SAD Seasons Dependent Variable: Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
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 B: Southern States During Low-SAD Seasons Dependent Variable: Absolute Forecast Error (t)				
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
	Panel C: SAD and Speed of Information Processing Dependent Variable: Absolute Forecast Error (t)				
Slow Processor × SAD × Have Depression (t-1)	0.2465	-0.1413	0.0900	0.3819*	0.5116**
	(0.219)	(0.182)	(0.185)	(0.176)	(0.174)
Slow Processor × Have Depression (t-1)	-0.5352***	-0.2521*	-0.3797**	-0.4422***	-0.4620***
	(0.162)	(0.145)	(0.140)	(0.122)	(0.123)
Slow Processor × SAD (t-1)	0.8981***	0.4297*	-0.3975	-0.3418	-0.2598
	(0.213)	(0.219)	(0.265)	(0.214)	(0.205)
Have Depression × SAD (t-1)	0.7451***	0.3415	0.5565**	0.5187***	0.5342***
	(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 A4. Non-Severe vs. Severe Depression

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 interest in activities. Panel B shows the results using the interaction of this variable and *Have Depression*. Table A1 describes all control variables. 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.

	Panel A: Severe Depression				
	Dependent Variable: Absolute Forecast Error (t)				
	(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: Non-Severe vs. Severe Depression				
	Dependent Variable: Absolute Forecast Error (t)				
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 A5. Depression Effect vs. Sentiment Measures

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 (Column (1)), Consumer Confidence Index (Column (2)), Gallup Economic Confidence Index (Column (3)). Column (4) reports the results controlling for all sentiment measures jointly. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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	✓	✓	✓	✓

Table A6. Non-Severe Depression and Forecast Accuracy: Demographic Sub-samples

The table repeats the baseline regression using alternative demographic sub-samples of Gallup and CDC-BRFSS to construct depression measures. Columns (1) to (5) report the results using the sub-samples from Gallup data. Column (6) reports the result using the sub-sample from CDC-BRFSS that matches on these demographic characteristics. Control variables and their sources are identical to those used in Table 2. Table A1 describes all control variables in detail. The sample period is from 2011 to 2016. 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)	-0.1999***					
	(0.068)					
Have Depression (t-1)		-0.5683***				
		(0.086)				
Have Depression (t-1)			-0.4238***			
			(0.112)			
Have Depression (t-1)				-0.2309**		
				(0.110)		
Have Depression (t-1)					-0.6906***	
					(0.232)	
Have Depression (t-1)						-0.1065**
						(0.046)
Adj. R^2	0.54	0.54	0.54	0.54	0.54	0.54
# of Obs.	44,934	44,934	44,934	44,934	44,934	44,934
Controls	✓	✓	✓	✓	✓	✓
Time FEs	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓	✓	✓
Sample	Gallup Full Sample	Non-Hispanic White	Male	Some College	Monthly Income > than $3,000	CDC: Joint Demographic Char.