The Up Side of Being Down: Depression and Crowdsourced Forecasts

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Abstract

This study examines the role of non-severe depression as a psychological anchor against overoptimism. Using earnings forecasts from Estimize, we find that an increase in the proportion of the U.S. population with depression is associated with improved forecast accuracy among users. This effect is concentrated among forecasts that are optimistic and analysts who take longer time to issue forecasts, highlighting reduced optimism and slow information processing as economic mechanisms that explain our results. We also show that this effect is distinct from the influence of temporary seasonal depression or other sentiment measures on decision-making. 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

Conventional economic theories assume rational actors operating in efficient markets. However, a large body of research suggests that economic agents are influenced by cognitive biases that can distort their decision-making (e.g., Kahneman and Tversky, 1979). One of the most pervasive of these is optimism bias, a tendency to overestimate favorable outcomes and underestimate unfavorable ones (Weinstein, 1980).[1]

The optimism bias affects various market participants, including retail investors (e.g., Odean, 1999; Barber and Odean, 2000; Merkle, 2017), equity analysts (e.g., Easterwood and Nutt, 1999; Michaely and Womack, 1999), and corporate executives (e.g., Ben-David et al., 2013; Ge et al., 2024). It has meaningful implications for market outcomes, contributing to speculative bubbles (Mei et al., 2009), inflating asset prices ahead of earnings announcements (Ertan et al., 2016), and generating systematic mispricing (De Bondt and Thaler, 1985; La Porta, 1996; Daniel et al., 1998). Therefore, identifying factors that temper this bias is important for improving market efficiency.

In this study, we examine persistent and non-severe depression as a condition that may act as a psychological anchor against the optimism bias. Psychological research suggests that individuals with depression are less susceptible to self-serving or overly optimistic biases and may exhibit better problem-solving abilities due to increased rumination and more incremental information processing (Andrews and Thomson, 2009; Barbic et al., 2014).

We test this prediction using data from Estimize.com, a crowdsourced platform where users submit earnings and revenue forecasts for publicly listed firms. In addition to the growing influence of online platforms in shaping investor behavior (Chen et al., 2014), this setting allows us to examine how sentiment affects financial judgment in a broader population of forecasters, beyond the professional analysts that have been the focus of prior research (e.g., Dolvin et al., 2009; Moore and Fresco, 2012). Importantly, Estimize provides a context

[1]See Barberis and Thaler (2003) and Hirshleifer (2015) for surveys on cognitive and behavioral biases affecting decision-making process in finance.

in which forecasts can be directly compared to ex-post realizations, allowing us to isolate a belief-based mechanism from preference-driven explanations.

To measure depression, we use data from Gallup Analytics, which conducts nationally representative surveys of U.S. households' well-being. We construct a quarterly measure based on the proportion of respondents who report having received a clinical diagnosis of depression.

Our baseline analysis reveals that, between 2011 and 2016, higher levels of depression among the U.S. population reduced absolute forecast errors of Estimize users, beyond the effect of various firm and analyst characteristics and 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 positive association between our depression measure and the cumulative average of prescribed antidepressants, validating the instrument's economic relevance. We rely on research that highlights the randomness in physicians' 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 further support our main results.

Next, we test whether reduced optimism is indeed an economic mechanism through which depression improves forecast accuracy. Specifically, we examine signed forecast errors and find that higher levels of depression reduce errors in optimistic forecasts. This result suggests that mood moderation is an important channel via which behavioral factors affect financial forecasts. We replicate these findings using the above IV, further supporting the role of depression in reducing analysts' overoptimism.

Additionally, we investigate whether increased ruminating serves as another 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). Supporting 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. Again, we replicate these results using the IV analysis.

Recently, Loh and Stulz (2018) show that forecast errors are lower in bad economic times. Hence, one might be concerned that psychological depression is also high during these periods. To mitigate this, 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. We also test the influence of career concern, analyst reliance, and increased analyst effort, and find that these channels have a muted effect in our setting.

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 (Dolvin et al., 2009; Lo and Wu, 2018). However, our study goes beyond seasonal variations and demonstrates that the influence of depression on forecast accuracy remains significant even when considering detrended 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 a lack of interest in daily activities. We find no significant effect of MDD on forecast accuracy, supporting the distinct impact of non-severe depression on the quality of forecasts of Estimize users.

We conclude our analyses with several robustness tests. We address the potential time trends in our depression measure using a demeaned and detrended measure of depression, as well as conducting a dynamic regression by including the lagged dependent variable in the models. We repeat our tests using measures of depression from alternative national surveys, as well as a non-survey-based measure of depression based on Google Trends data. Moreover, we conduct a state-level test, allowing for a larger variation in the depression measure. All these tests replicate our main findings.

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

Our paper contributes to the growing literature in accounting and finance that examines factors mitigating the influence of cognitive and behavioral biases on market participants (Barberis and Thaler, 2003; Hirshleifer, 2015). Prior studies identify various mitigating forces, including feedback from past outcomes (Merkle, 2017), regulatory interventions such as Regulation Fair Disclosure (Heflin et al., 2012), and experience (Victoravich, 2010; Drake and Myers, 2011). More recently, Back et al. (2023) show that robo-advisors incorporating social design elements can improve investor decision-making. Additionally, short-term negative affect, induced by weather conditions, seasonal depression, or environmental conditions, has been found to influence sentiment and reduce optimism in forecasts (Dolvin et al., 2009; Dehaan et al., 2016; Lo and Wu, 2018; Bourveau and Law, 2021; Dong et al., 2021). We extend this literature by showing that persistent, non-severe depression is associated with lower earnings forecast errors among Estimize users. This suggests that underlying psychological conditions, rather than transient mood shifts, can meaningfully temper overoptimism in financial judgments.

We also contribute to the literature on the quality and dynamics of crowdsourced financial information (Chen et al., 2014; Bartov et al., 2018; Jame et al., 2022). Prior studies have shown that limited access to public information can lead to more accurate consensus estimates on platforms like Estimize (Da and Huang, 2020), and that extreme market events, such as the GameStop short squeeze, can affect the quality of investment discussions on forums like Reddit's WallStreetBets (Bradley et al., 2024). We add to this body of work by highlighting the role of a non-traditional factor, i.e., non-severe depression, in shaping forecast accuracy. This underscores the importance of emotional and psychological factors in understanding the behavior of contributors on crowdsourced platforms.

Finally, our research contributes to the broader literature on the economic consequences of psychological health conditions. 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 provide evidence that non-severe depression can also influence financial decision-making. Specifically, we show that it may enhance forecast quality 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

Optimism bias is a systematic tendency to overestimate favorable outcomes and underestimate unfavorable ones (Weinstein, 1980). Psychological research suggests that this tendency manifests through mechanisms such as self-attribution bias (Miller and Ross, 1975) and the illusion of control (Langer, 1975).

In financial contexts, the optimism bias represents a prevalent manifestation of overconfidence, which has been widely documented across major groups of market participants

(Odean, 1998). Among retail investors, Odean (1999) and Barber and Odean (2000) show that excessive trading stems from overconfidence in the precision of private information, resulting in subpar returns. Professional investors are similarly prone to the bias as Heaton (2002) and Ben-David et al. (2013) document that senior financial managers systematically overestimate their firms' future cash flows and underestimate return volatility, leading firms to invest more and use more debt financing. Related work shows that overconfident executives increase default risk (Hackbarth, 2008, 2009). Among equity analysts, the optimism bias is reflected in earnings forecasts and stock recommendations (De Bondt and Thaler, 1990; Michaely and Womack, 1999), attributed to their overreactions to positive information (Easterwood and Nutt, 1999).

Previous research has proposed various mitigating factors to subdue the effect of overoptimism, including feedback from prior outcomes, regulatory changes like Regulation Fair Disclosure, and greater experience (Victoravich, 2010; Drake and Myers, 2011; Heflin et al., 2012). Recent work highlights the role of design-based interventions, such as robo-advisors with social features (Back et al., 2023), as well as temporary mood shifts induced by weather or environmental factors (Lo and Wu, 2018; Dong et al., 2021). We extend this literature by examining the role of non-severe depression (referred to as "depression" for brevity in some sections) as a potential psychological condition that mitigates the optimism bias and enhances forecast accuracy on a crowdsourced platform.[2] This leads to our first hypothesis.

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

Moore and Fresco (2012) show that depressed individuals offer less optimistic forecasts than non-depressed peers, even when presented with identical information. This suggests that depressed individuals may only predict the occurrence of an event when they are highly confident, leading to more conservative and potentially accurate forecasting behavior. Korn

[2]According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5-TR), depression includes various sub-types, such as major depressive disorder (MDD) and persistent depressive disorder (PDD, also known as non-severe depression), among others (American Psychiatric Association, 2022). MDD is characterized by at least five severe depressive symptoms that last at least two weeks, whereas PDD is marked by only a non-severe depressed mood that persists significantly longer.

et al. (2014) also find that individuals with depressive symptoms display reduced optimism in long-term outcome predictions, likely due to heightened attention to potential negative outcomes and diminished cognitive capacity to simulate positive futures.

This reduced optimism can shape forecasting tendencies in a way that enhances accuracy. Among equity analysts, the optimism bias is often driven by career concerns and promotional incentives (e.g., Hong and Kubik, 2003). While such institutional pressures may be less relevant for users on crowdsourced platforms like Estimize, a bias toward optimism may still exist, particularly if users self-select into forecasting firms they view favorably (Malmendier and Shanthikumar, 2014). In this regard, non-severe depression may dampen users' inclination toward excessive optimism, potentially improving forecast accuracy. This motivates our second hypothesis.

H2: Higher levels of depression reduce forecast errors of optimistic forecasts.

Further, research suggests that depressed individuals tend to process information more slowly and incrementally (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 for our last hypothesis.

H3: Higher levels of depression reduce forecast errors for slow processing forecasters.

3 Data and Variables

3.1 Estimize

We collect individual forecasts from Estimize.com, a platform that crowdsources quarterly earnings and revenue predictions from professional analysts, students, academics, and industry professionals. Estimize's diverse contributor base leads to more accurate forecasts than the Wall Street consensus (Jame et al., 2016). Pseudonymous handles help level the playing field, avoiding biases faced by Wall Street professionals.[3]

D'Acunto and Weber (2024) further emphasize the value of large-sample survey data in behavioral research. Relative to traditional survey-based settings, Estimize offers a richer and more granular set of observations from a broader population of forecasters, making it an ideal environment to examine how individual-level sentiment, such as persistent depressive symptoms, affects forecast accuracy. Moreover, the platform enables direct comparisons between forecasts and ex-post realizations, allowing us to isolate belief-based mechanisms from preference-based explanations.

We focus on earnings forecasts, keeping only the most recent estimates and excluding those issued 90 days before or after the earnings announcement (Li et al., 2020).[4] For multiple forecasts on the same day, we use the average. We merge forecast data with Center for Research on Security Prices (CRSP) and Thomson Reuters' Institutional 13F holdings and exclude firms with fewer than three distinct users or stock prices below $5 at the start of each quarter (Harford et al., 2019), though results hold with a $1 cutoff.

3.2 Gallup Analytics

Gallup Analytics provides nationally representative measures of depression through daily interviews with at least 500 U.S. adults. Our measure of depression is based on responses to the question, "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

[3]Like Amazon reviewers or Wikipedia contributors, Estimize users are motivated by access to peer data, performance comparisons, and participation in a consensus sold to institutional investors (see this article).

[4]Our results are robust to alternative windows of 10, 30, 45, 120, 150, and 180 days before announcements.

the respondents.[5] 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.

Gallup data offers several advantages. First, it mirrors epidemiological study methods, providing reliable, large-scale mental health data (Markkula et al., 2015). Second, it captures mental health status more accurately than sentiment indices based on market data (Baker and Wurgler, 2006) or non-representative user data from Twitter (Bartov et al., 2018) and Google Trends (Da et al., 2015). Third, Gallup's multi-question format allows for a richer assessment of depression without post-survey classification (Moore and Fresco, 2012), and physician-diagnosed measures introduce random variation that improves causal identification (Buason et al., 2021).

Finally, Gallup's sample aligns well with our study. 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.[6] 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. Nonetheless, we recognize potential differences between Estimize users and the broader U.S. population and address this in Appendix B.

We combine 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. Results are consistent if we first aggregate Gallup measures to the quarter and then merge. Our final sample includes 1,754 users covering 1,364 firms from 2011-Q4 (when the Estimize sample begins) to 2016-Q4 (when Gallup well-being survey data ends).

[5] Gallup data have been widely used in economics research (e.g, Deaton, 2018; Pan et al., 2023). It uses a rigorous sampling method to ensure the representativeness of the population. It selects adults using random-digit dialing of landline and cellphone numbers, along with demographic information. Further information about the methodology can be found on www.Gallup.com.

[6] See Pew Research Center and Gallup.

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 0.09 with a standard deviation of 0.14. 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, 17.31% of respondents in Gallup report experiencing depression, consistent with the 12.70% 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.[7] To address the issue of limited variation in the depression variable, we conduct cross-sectional tests in Section 6.4.

We provide a temporal perspective of this variable in Figure 1. The upper plot illustrates the quarterly time-series distribution, revealing an increase in the variable from almost 17.5% in late 2011 to nearly 18.0% by late 2016. As mentioned in the previous section, Gallup employs random sampling in its surveys so that each wave samples different individuals. Therefore, the survey should not consistently reflect an increasing number of people diagnosed with depression simply due to the passage of time. Instead, the observed upward trend likely reflects a growing incidence of depression diagnoses, potentially influenced by several nationwide policy changes implemented during the early years of the sample period.[8]

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

[7] 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.

[8] For example, the 2014 Affordable Care Act expansion improved access to mental health services, increasing diagnoses (see National Alliance on Mental Illness). Depression diagnoses also tend to peak in Q3, potentially due to 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 address these patterns, we include time fixed effects and use a demeaned, detrended depression series in Section 6.1.

4 Depression and Forecast Accuracy

4.1 Baseline Results

We begin by visually examining the time-series relationship between *Have Depression* and *Absolute Forecast Error* over the sample period. Figure 2 shows both series after controlling for year-by-quarter and firm fixed effects, revealing a consistently negative co-movement. To formally test this finding, we run the following pooled ordinary least squares (OLS) regression:

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

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.[9]

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

[9]Results are robust to using concurrent depression diagnosis. Moreover, the estimates are consistent across different specifications of fiscal year and quarter FEs or calendar year and fiscal quarter FEs. Alternative clustering methods, such as analyst-by-time or analyst-by-firm, yield consistent outcomes.

Macroeconomic and policy-related 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.

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.[10]

4.2 Instrumental Variable Analysis

Endogeneity is a key concern in studies examining the effects of mental health conditions. While we follow Buason et al. (2021) in assuming the exogeneity of our main independent variable, we recognize potential issues, including selection biases where 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 is commonly used to address endogeneity concerns. To estimate the proportion of individuals with a depression diagnosis, we use the dosage of prescribed antidepressants as our instrument. Our approach is supported by studies like Buason et al. (2021), which use the propensity of receiving treatment from a hospital as an instrument for measuring those diagnosed with depression.[11]

[10] In the strictest model, we find that the effect of depression on accuracy is 2.22 ($-0.20/-0.09 = 2.22$) times larger than the effect of firm-specific experience. This translates to an additional five ($2.22 \times 2.24 \approx 5$) 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.

[11] Health economics literature supports this approach, arguing that the propensity to treat mental health conditions is more likely to be exogenous (Duggan, 2005; Dalsgaard et al., 2014).

To construct the IV, *Mild Drugs*, we use data on prescribed antidepressants from the Medical Expenditure Panel Survey (MEPS), from 2002 to 2017. MEPS is a nationally representative survey of the U.S. population that provides detailed information on the type and dosage of prescribed medications. This allows us to isolate antidepressants commonly used to treat non-severe depression, such as selective serotonin reuptake inhibitors (SSRIs).

We test the economic relevance of our instrument in Panel A of Table 3, using a linear model to estimate the likelihood of having depression. 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).

To satisfy the exclusion restriction, we assume that variation in doctors' prescribing practices makes receiving antidepressant treatment exogenous to patients seeking it. Although this assumption cannot be directly tested, it is supported by prior studies (e.g., Dalsgaard et al., 2014). Our approach further accounts for heterogeneity in treatment propensities across providers by using a national aggregate measure of antidepressant prescriptions. This allows our IV to reflect overall treatment patterns rather than idiosyncratic prescribing behaviors of individual physicians. Motivated by this reasoning, we present the second-stage results of the 2-SLS regression in Panel B of Table 3. The findings remain economically significant, with a 1-standard-deviation increase in depression predicting a 1.34% improvement in forecast error accuracy, equivalent to 16% of the sample mean.[12]

To further rule out confounding influences, we exclude pharmaceutical firms from the sample, specifically those with SIC codes 2831 and 5122. This addresses the concern that depressed individuals might be more familiar with firms from which they receive medications, potentially biasing forecast accuracy. Our findings remain consistent in this untabulated analysis (coefficient = -1.35; t-statistic = -3.86).

[12] The larger economic effect in the IV analysis may reflect a reduction in omitted variable bias and measurement error in the Gallup survey responses (see Jiang, 2017).

5 Economic Channels

5.1 Reduced Optimism

We next test *H2*. If depression mitigates the optimism bias, its impact on forecast accuracy should be concentrated among non-negative forecast errors. Figure 3 explores this relationship. Panel A plots residualized non-negative forecast errors (i.e., optimistic forecasts) against residualized depression. The two series move in opposite directions, indicating that higher depression levels are associated with less optimistic forecasts. This negative relationship is consistent over time, suggesting it is not driven by isolated events or short-term shocks. Panel B, by contrast, shows no systematic relationship between depression and negative forecast errors (i.e., pessimistic forecasts). The lack of persistent co-movement and occasional alignment in direction further highlights the asymmetric influence of depression across forecast types.

Additionally, Panel A of Table 1 presents summary statistics for both groups, while Panel B reports their correlations with *Have Depression*. As expected, non-negative forecast errors show a significant negative correlation with depression, whereas negative forecast errors exhibit no significant relationship, providing initial support for our hypothesis.[13]

Turning to the regression analyses, we focus on non-negative forecast errors in Panel A of Table 4. Across various specifications, except for Column (3), we find a negative and statistically significant coefficient on *Have Depression*, suggesting that individuals experiencing depression issue more accurate forecasts with reduced optimistic bias.[14] In contrast, results

[13]As shown in Panel A of Table 1, the two sub-samples are similarly sized, with slightly more observations for negative forecast errors (25,911 vs. 19,716). The upper tail of the non-negative distribution (99^{th} percentile: 0.66) and the lower tail of the negative distribution (1^{st} percentile: -0.73) exhibit comparable absolute magnitudes, and this symmetry holds across other distributional statistics.

[14]The sign change in Column (3) is not a major concern as it occurs in only one specification, while others consistently show negative and significant coefficients. Moreover, non-negative forecast errors differ in nature from negative ones and may be influenced by dynamics such as forecast walk-downs (Richardson et al., 2004). Additionally, a positive coefficient in this subsample does not necessarily imply increased optimism, as it includes cases with zero forecast error.

for the negative forecast error subsample, reported in Panel B of Table 4, show no significant relationship between depression and forecast accuracy across most specifications.[15]

In addition to the above tests, 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, given its role in anchoring analyst expectations and creating beatable targets (e.g., Matsumoto, 2002). Forecasts that fall below this benchmark can thus be interpreted as 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.[16]

To further support these findings, we employ the IV described in Section 4.2 and replicate the above analysis using a 2-SLS framework. For brevity, we report only the second-stage results, while confirming the relevance and strength of the instrument in untabulated first-stage estimates.[17] Panel A of Table 5 presents the second-stage IV estimates for the non-negative forecast error sub-sample. Across most specifications, the results mirror those of the baseline analysis, with depression associated with lower forecast error, reinforcing the argument that reduced optimism drives the improvement in forecast accuracy. In contrast, Panel B reports results for the negative forecast error sub-sample, where the estimated coefficients remain statistically insignificant in all specifications.

[15]For the analysis of this section, we double-clustered standard errors to account for the significant serial correlation of the forecast errors in the non-negative (coefficient $=-0.31$, t-statistic $=-2.83$) and negative sub-sample (coefficient $=-0.10$, t-statistic $=-1.31$). The serial correlation in the full sample is low (coefficient $=-0.07$, t-statistic $=-0.88$), and our baseline results remain robust with the same double-clustering.

[16]The proportion of analysts classified as pessimistic is similar across both sub-samples (p-value = 0.46). We also define the consensus forecast as the median of earnings forecasts from all analysts covering the same firm in a quarter, and consider a forecast as pessimistic if it is below the consensus, and optimistic otherwise. This measure produces consistent results.

[17]In the most restrictive specification, the estimated coefficient for the *Mild Drugs* instrument is 4.06 (t-statistic = 4.17) for the non-negative forecast error sub-sample, and 4.39 (t-statistic = 3.13) for the negative forecast error sub-sample. The first-stage F-stat (adjusted R^2) is 17.37 (0.59) and 9.76 (0.52), respectively.

5.2 Speed of Information Processing

To test *H3*, we use analysts' forecasting time as a proxy for their information processing period. Although the actual duration of processing is unobservable, forecasting time is widely used in prior research as an indirect measure of processing speed. Following Cooper et al. (2001), we calculate each analyst's forecasting time relative to the forecasting times of 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,

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

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. Accordingly, higher values of the *FLR* variable indicate that the analyst tends to issue forecasts later than their peers, suggesting slower information processing. We categorize the *FLR* variable into quartiles and construct an indicator variable, *Slow Processor*, which equals 1 if the analyst falls into the top quartile, and 0 otherwise.[18]

We start this analysis by visually examining the relationship between *FLR* and depression, accounting for the time- and firm-invariant factors in both series. Figure 4 shows that *Have Depression* appears to exhibit a positive co-movement with *FLR*, suggesting that periods of higher depression are often associated with longer forecasting time. We perform the statistical test for this finding by incorporating the indicator variable for slower-processing analysts and its interaction with *Have Depression* into our baseline model.

[18] We confirm the robustness of our results using alternative sorting methods, including tertiles and quintiles, and by redefining the indicator to equal 0 only for analysts in the bottom quartile.

As shown in Panel A of Table 6, the interaction term yields a negative coefficient, supporting *H3*. In the most stringent specification (Column 5), the interaction effect becomes statistically insignificant, while the main effect of *Have Depression* is only marginally significant. Nonetheless, the total effect, calculated as the sum of the main and interaction terms, remains statistically significant at the 1% level (coefficient = -0.31, t-statistic = -2.98).

An alternative explanation for the observed effect is that it may reflect procrastination in forecast issuance. Specifically, users might delay issuing forecasts until closer to the earnings announcement date, when the probability of information leakage is higher. This is a valid concern, as Estimize forecasts are known to cluster near announcement dates, with approximately 70% submitted within a 10-day window surrounding the announcement. To address this concern, we restrict our analysis to forecasts issued within the 10 days before the earnings announcement, thereby eliminating the influence of earlier-issued forecasts. As shown in Panel B of Table 6, our results remain consistent under this restriction.[19]

We replicate the analysis in Table 6 using the same IV described in the previous sections. As before, we report the results from the second stage of the 2-SLS regressions and confirm the economic relevance of the IV in untabulated tests for brevity.[20] The results, presented in Table 7, show that higher levels of depression continue to exert a stronger effect on reducing forecast errors among analysts classified as slow processors.

5.3 Alternative Channels

5.3.1 Economic Depression

An alternative explanation for our findings is the potential influence of economic downturns. Loh and Stulz (2018) show that during economic downturns, analysts often respond

[19] We also consider whether procrastination may reflect herding behavior, as delayed forecasts give users greater access to earlier peer forecasts. To explore this, we define *Herding* as an indicator variable equal to 1 if an analyst's forecast falls between the consensus forecast and their prior forecast, and 0 otherwise (Hirshleifer et al., 2020). Re-estimating the models in Table 6 with *Herding* as the dependent variable, we find no statistically significant association between depression and analysts' herding behavior.

[20] In the most restrictive specification, the estimated coefficient for the *Mild Drugs* instrument is 4.44 (t-statistic = 4.03) for the full sample, and 4.47 (t-statistic = 3.61) for the short-horizon sample. The first-stage F-stat (adjusted R^2) is 8.11 (0.54) and 6.49 (0.60), respectively.

to heightened market demand by increasing their effort, which in turn leads to improved earnings forecasts. However, our baseline and IV results remain robust even after controlling for several economic and policy-related conditions. Moreover, in Section 5.1, we provided evidence that higher levels of psychological depression are linked to reduced optimism in earnings forecasts. This contrasts Loh and Stulz (2018), who find that analysts tend to issue more positively biased forecasts during economic downturns.

To further disentangle the effects of economic versus psychological depression on the forecast accuracy of Estimize users, we follow Loh and Stulz (2018) and introduce two binary variables, *Economic Policy Uncertainty Indicator* and *Recessionary States*, into our regressions. These variables are constructed to capture different aspects of economic depression.[21] Panel A of Table 8 shows the results. Column (1) replicates the baseline estimate from Table 2. Columns (2) and (3) add the economic depression variables. Consistent with Loh and Stulz (2018), both variables are negatively associated with forecast errors, suggesting improved accuracy during downturns. Importantly, psychological depression remains significant in all models, indicating that its effect is distinct from and not driven by economic conditions.

We also include an interaction between economic and psychological depression. If psychological depression were simply a proxy for economic downturns, the interaction should be negative and significant. Instead, we find a small and insignificant coefficient, suggesting that the effect of psychological depression holds across economic conditions.[22] Additionally, 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-

[21] The time-series correlation between our measure of non-severe depression with *Economic Policy Uncertainty Indicator* and *Recessionary States* is -0.22 (p-value $= 0.10$) and 0.07 (p-value $= 0.60$), respectively. Detailed information on the construction of these variables is available in Table A1.

[22] As an additional robustness check, we use firm-level market uncertainty, measured as the standard deviation of the market component of daily returns, and find consistent results (*Have Depression* $= -0.14$, t-statistic $= -1.81$).

severe depression and forecast accuracy. Together, these results suggest that the impact of psychological and economic depression on forecast accuracy is distinct.

5.3.2 Analyst Reliance

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 8 reports the results. Contrary to the above conjecture, the interaction terms are inconsistent and statistically insignificant across all four measures, 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.

5.3.3 Career Concern

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 the 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 8 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 0.81 (0.85)). Similar to Panel A, we also find the interaction of economic and psychological depression measures statistically insignificant across both sub-samples.

5.3.4 Analyst Effort

Last, 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 8 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 Temporal Dependencies in Depression Measure

Non-stationarity features (e.g., time trends) in Gallup survey responses may bias the statistical significance of our estimates. We mitigate this issue by using demeaned and detrended daily time-series values for *Have Depression* (Granger and Newbold, 1974). As shown in Panel A of Table A2, our findings remain robust.

We further acknowledge that standard t-tests may be unreliable if regression residuals exhibit serial correlation, which could indicate a spurious relationship between forecast errors and depression. If serial correlation is present in the residuals from Regression (1), including lagged forecast errors should attenuate our main estimates (Granger and Newbold, 1974). We directly test this in Panel B of Table A2 by incorporating lagged absolute forecast errors and find that our results persist. These tests suggest that our inferences are unlikely to be distorted by time-series dependencies in the depression measure.

6.2 Alternative National Surveys

To mitigate concerns about the impact of past depression diagnoses on our results, we supplement our analysis with two alternative depression measures. First, we use CDC-BRFSS data to measure the percentage of respondents reporting poor mental health (including stress, depression, or emotional problems) in the past 30 days. Second, we construct a clinical depression measure using MEPS medical condition records, classifying respondents with a reported code matching 311 (ICD9CDX variable) as individuals experiencing depression (Zhang and Sullivan, 2007). We track initial reporting dates through the survey's condition rounds to identify recent diagnoses.[23]

The CDC-BRFSS measure exhibits a higher mean prevalence (mean = 30.22%, standard deviation = 0.92%) than the Gallup measure, as expected given its inclusion of broader negative emotional states beyond clinical depression. The MEPS measure shows lower preva-

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

lence (mean = 1.72%, standard deviation = 0.36%) due to its stricter diagnostic criteria. Despite these differences in magnitude, all three measures demonstrate significantly positive co-movement, supported by the statistically significant correlation of the Gallup measure with the CDC-BRFSS measure (0.37, p-value = 0.10) and the MEPS measure (0.49, p-value = 0.02). These statistics suggest that the three survey-based measures capture a common underlying depression component.

Panel A in Table A3 reports the estimated effects of depression on forecast accuracy using our alternative measures. Columns (1) and (2) present results using the CDC-BRFSS measure, while Columns (3) and (4) use the MEPS measure. Both measures consistently show that higher depression levels are associated with greater forecast errors. The economic magnitudes remain stable across specifications, indicating that different depression proxies capture a common underlying construct of current depressive conditions in the U.S. population.

6.3 Non-Survey Measures of Depression

To ensure our findings are not restricted to survey-based measures, we construct an alternative depression index using Google Trends search volume data. Specifically, we construct a depression-related word list using the General Inquirer's Harvard IV-4 Psychological Dictionary, focusing on terms classified under the Psychological Well-Being and Negative categories. We then refine this list by selecting words that exhibit a positive correlation with the *Have Depression* variable over a 180-day rolling window, following Da et al. (2015).

Using the filtered set of words, we construct a daily Google Trends Search Volume Index (SVI), which we aggregate into a quarterly average to match the frequency of the *Have Depression* measure.[24] We repeat Regression (1), replacing our main variable of interest

[24]Our primary Google Trends SVI index includes 7 words: *melancholy, neurosis, confident, relaxation, figure, afraid, unhappily.* A secondary, expanded index incorporates both positively and negatively correlated terms, resulting in a set of 25 words: *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.*

with one of the two SVI indices. As displayed in Panel B of Table A3, our coefficient of interest remains negative and statistically significant throughout all specifications.

6.4 State-Level Tests

To address the limited variation in national-level depression measures, we complement our main analysis with state-level cross-sectional tests, focusing on the influence of aggregate mood within individuals' immediate geographic context.

We construct a state-level depression variable by merging users' location data, requested information from Estimize, with Gallup's annual MSA-level depression data. We average depression values across MSAs within each state, capturing the proportion of individuals reporting a depression diagnosis. This measure shows greater cross-sectional variability than the national measure (mean = 16.7%, standard deviation = 1.7%). Estimize users are geographically dispersed, reducing concerns about regional concentration.

We re-estimate Regression (1) using the state-level depression variable and include additional state-level controls: gender composition, education, age (18-24), income, and unemployment. Column (1) of Table A4 shows a larger coefficient on state-level *Have Depression*, suggesting a stronger effect. In Column (2), we test whether analysts' accuracy varies with local depression levels using an indicator, *Depressed State*, equal to 1 if a state's depression exceeds the previous year's median. Analysts in more depressed states have slightly lower absolute forecast errors, though not statistically significant. Results using alternative local depression measures from the CDC-BRFSS and MEPS (Columns 3 and 4) are consistent.

For comparability, we also create a quarterly state-level measure using the Google Trends word list. Results (Column 5) align with prior findings. Lastly, Column (6) presents a cross-sectional IV analysis using our earlier instrument, confirming robustness with a more variable local depression measure.

6.5 Depression vs. Seasonal Affective Disorder

Studies such as Dolvin et al. (2009) and Lo and Wu (2018) show that reduced optimism during periods associated with Seasonal Affective Disorder (SAD) leads to more accurate analyst forecasts. While related, non-severe depression and SAD are distinct conditions with different causes and manifestations (Michalak et al., 2002), making it important to differentiate their effects.

To do so, we re-estimate our baseline model using three modifications. First, we restrict the sample to the low-SAD seasons (Q2 and Q3) to isolate the effect of depression. The findings in Panel A of Table A5 support our hypothesis that depression is distinct from SAD. Second, we limit the sample to southern states, where Dolvin et al. (2009) found no SAD effect. Panel B results again support our conjecture. To address concerns about state selection, we use sunlight duration estimates—defined as the difference between sunrise and sunset time for a location on a given day—from Gibson and Shrader (2018) to objectively define southern states as states that have average sunlight time greater than the median across all states and find consistent results (coefficient = -0.52; t-statistic = -2.03).

Third, we investigate whether the mechanisms driving the impact of SAD on forecast accuracy are distinct from depression. To do so, we add a triple interaction between indicators for slow processing, depression, and SAD (defined as 1 during Q1 and Q4, and 0 otherwise) to the model in Section 5.2. Panel C shows that the depression–slow processing interaction remains negative and significant across specifications. The triple interaction is positive and significant in the strictest model, suggesting that the mechanism through which depression affects judgments differs from SAD's, providing further evidence for their distinct impacts on forecast accuracy.[25]

[25] We also control for the Baker and Wurgler's (2006) Investor Sentiment Index, Consumer Confidence Index, and Gallup Economic Confidence Index as control variables in our baseline analysis. We find that the impact of depression on forecast accuracy remains statistically significant, beyond the influence of these sentiment measures.

6.6 Non-Severe Depression vs. Major Depressive Disorder

Given that Gallup's depression question does not specify a time frame or severity, one might be concerned about the impact of MDD on our results. To address this, we indirectly estimate the prevalence of major depression and examine its relationship with forecast accuracy using several proxies.

We first use Gallup data 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." Following Macmillan et al. (2005), we use responses of "Nearly Every Day" as a proxy for major depression symptoms and substitute this measure into our baseline regression. To ensure robustness, we construct two alternative proxies for MDD using CDC-BRFSS and MEPS data. The CDC-BRFSS measure is based on responses indicating chronic depressive disorders, while the MEPS measure identifies survey respondents with a diagnostic code of 296, which corresponds to MDD.

Panel A of Table A6 shows that the share of individuals with major depression symptoms does not significantly affect absolute forecast error, suggesting that our results are not driven by severe depression. In Panel B, we include interaction terms between each MDD proxy and the *Have Depression* measure. Across specifications, *Have Depression* consistently predicts lower forecast errors, while the MDD proxies and their interactions are not significant, reinforcing the distinct role of non-severe depression.

7 Summary and Conclusion

This paper examines the impact of depression on financial judgment by analyzing quarterly earnings forecasts submitted by users of the Estimize platform. Using data from the Gallup survey, we find that higher levels of depression in the U.S. population are associated with improved forecast accuracy. Our analysis suggests that this improvement stems from a reduction in optimism bias and slower, more deliberate information processing during periods of elevated depressive symptoms.

These findings contribute to the literature on crowdsourced forecasting and behavioral finance by identifying depression as a psychological condition that may counteract excessive optimism, thereby enhancing forecast quality. Importantly, our study does not minimize the serious social and economic burdens of depression. Rather, it offers new insights into how mental health can influence economic decision-making, underscoring the nuanced relationship between psychological states and financial behavior.

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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 the Gallup surveys over the sample period of 2011 to 2016. 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.

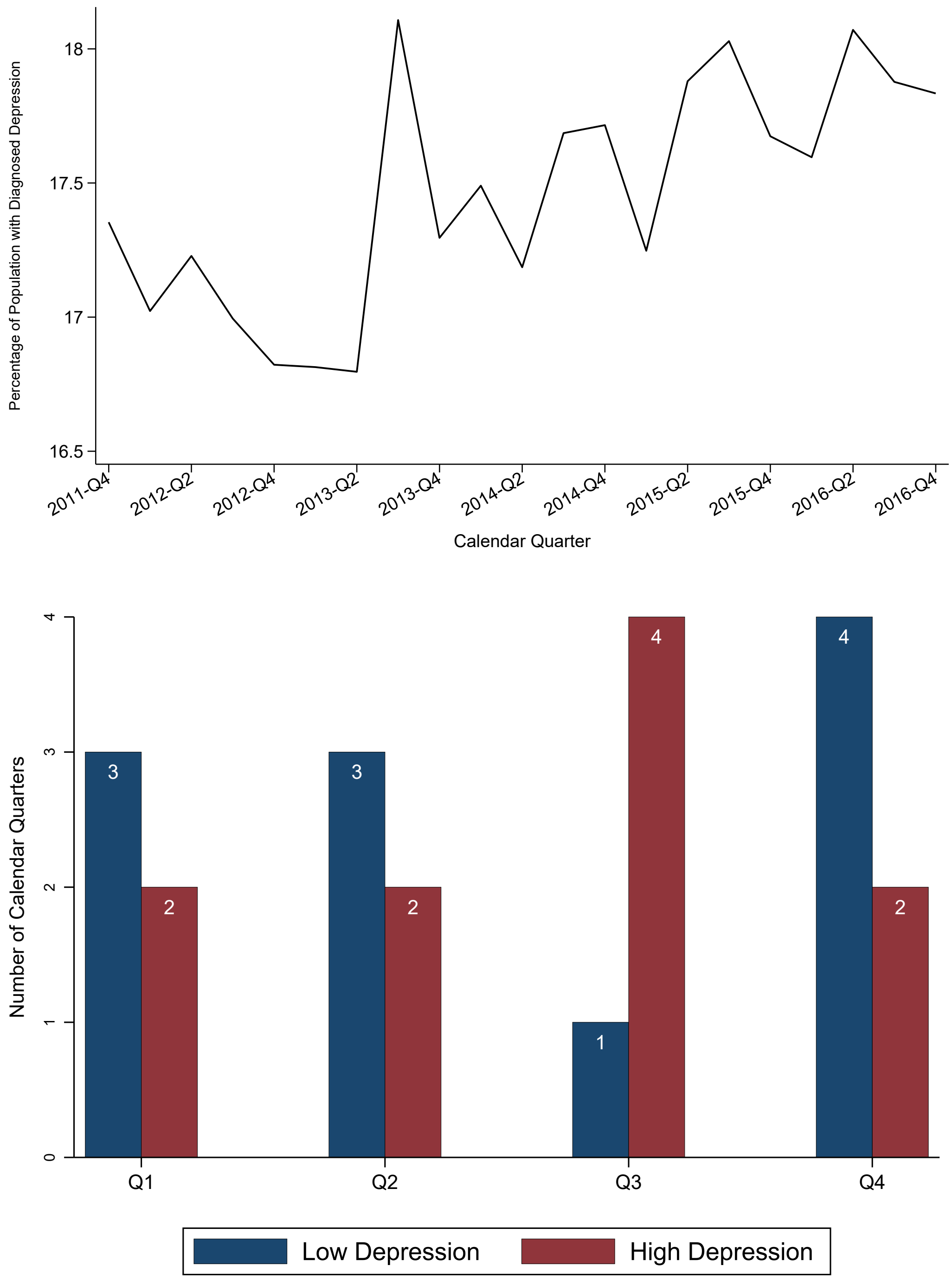

Figure 2. Time-series of Adjusted Depression and Forecast Accuracy

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.

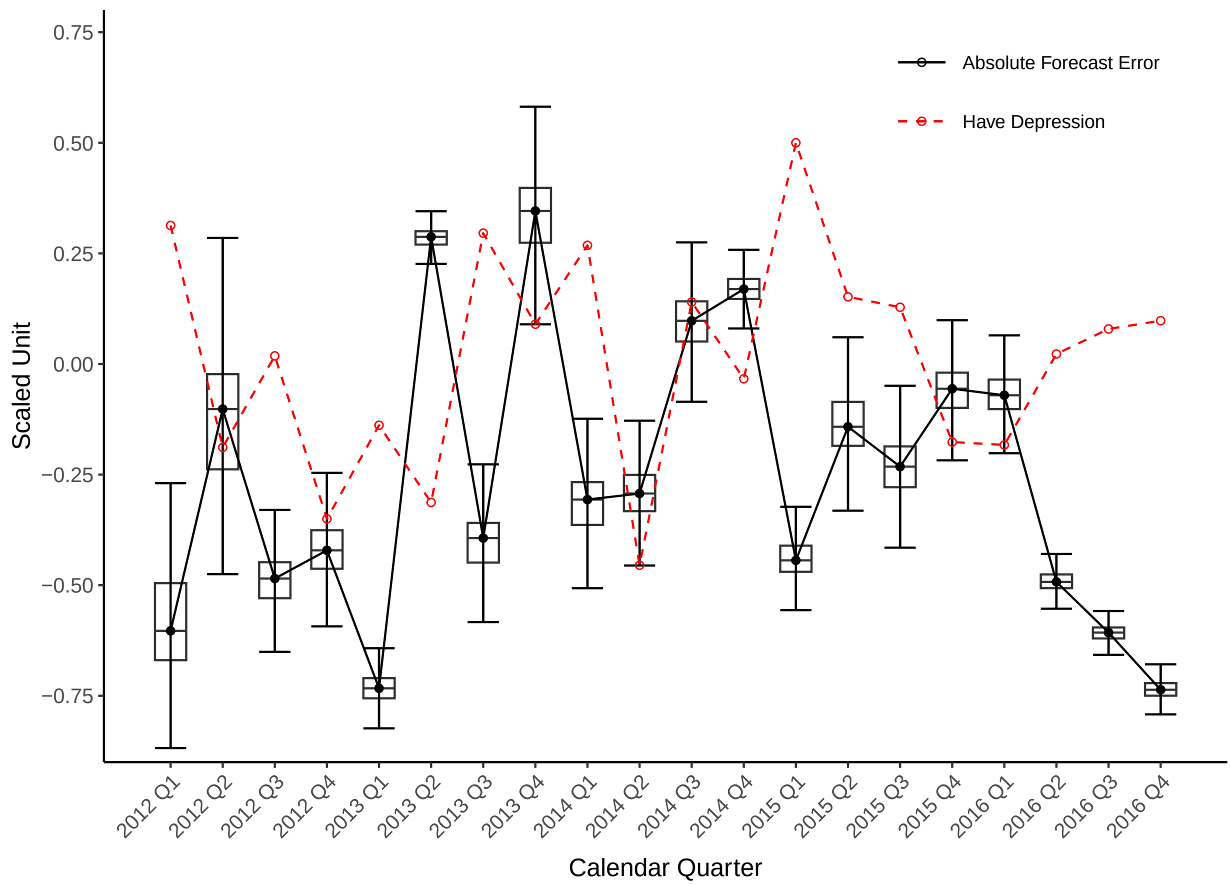

Figure 3. Time-series of Adjusted Depression and Signed Forecast Error

The figure plots the boxplot for the *Signed Forecast Error (t)* (non-negative and negative) and the mean *Have Depression (t-1)* from 2012 Q1 to 2016 Q4. Panels A and B plot the non-negative and negative forecast errors, respectively. The solid black line connects the median of adjusted *Signed Forecast Error*, and the dashed red line connects the mean of adjusted *Have Depression* in the sample. Adjusted *Signed Forecast Error* are residuals obtained from the regression of *Signed 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 aggregated to the quarter level. Variables are scaled for visual clarity.

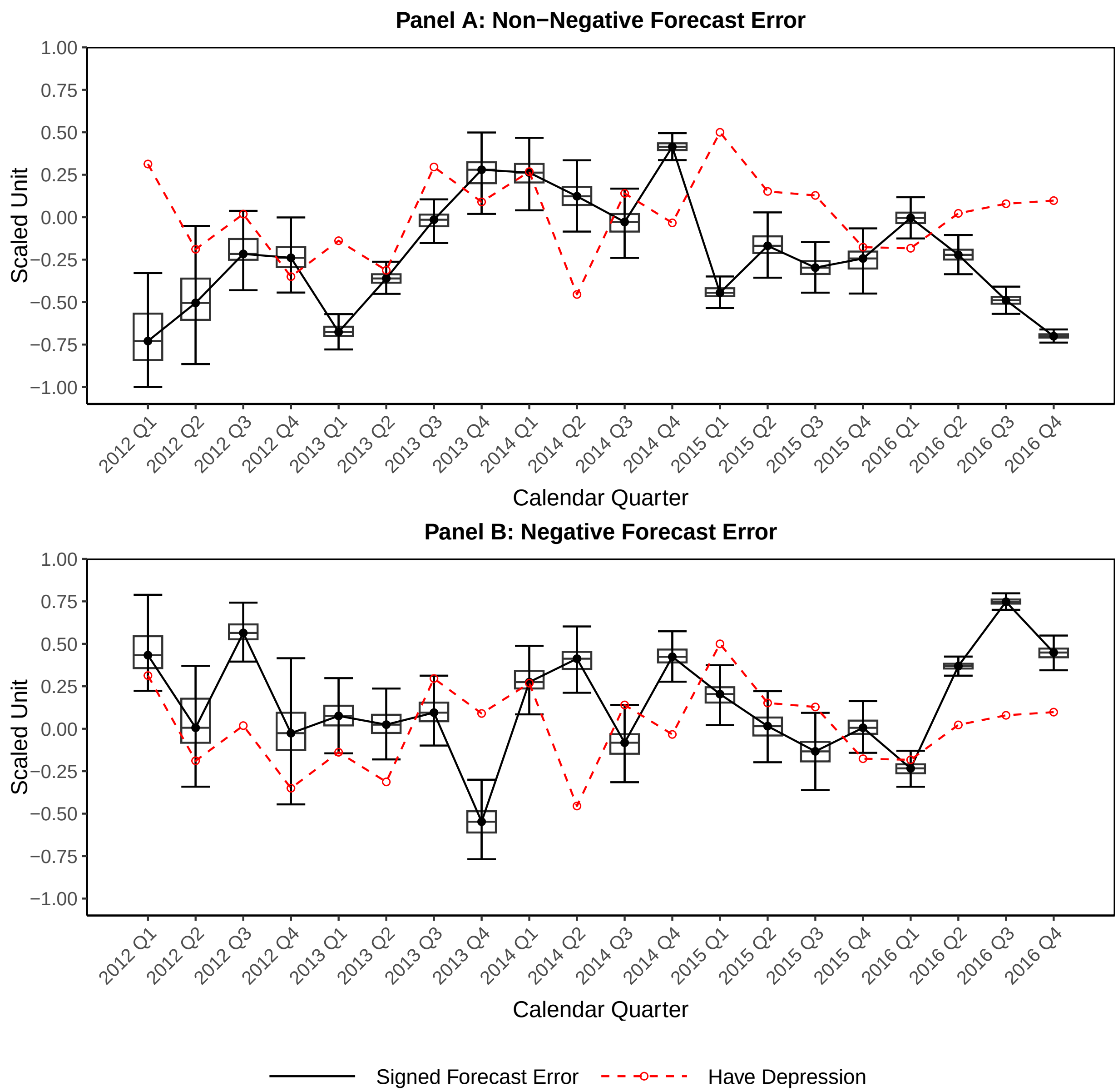

Figure 4. Time-series of Adjusted Follower-Leader Ratio and Forecast Accuracy
The figure plots the boxplot for *Follower-Leader Ratio (t)* and the mean *Have Depression (t)* from 2012 Q1 to 2016 Q4. The solid black line connects the median of adjusted *Follower-Leader Ratio*, and the dashed red line connects the mean of adjusted *Have Depression* in the sample. Adjusted *Follower-Leader Ratio* are residuals obtained from the regression of *Follower-Leader Ratio* 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.

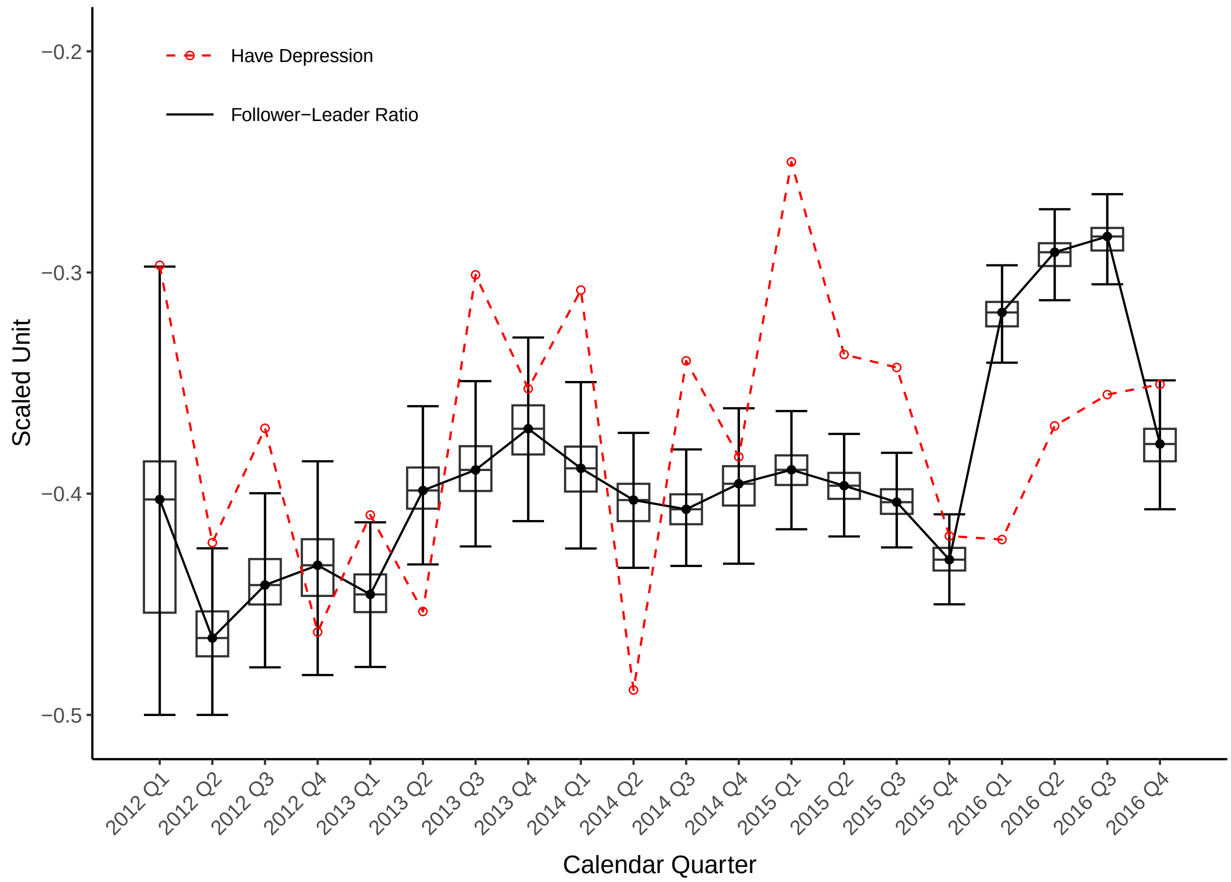

Table 1. Summary Statistics and Correlation

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	0.09	0.14	0.00	0.02	0.04	0.09	0.69	45,627
Non-Negative Forecast Errors	0.07	0.14	0.00	0.01	0.03	0.08	0.73	19,716
Negative Forecast Errors	−0.09	0.15	−0.66	−0.10	−0.05	−0.02	−0.01	25,911
Main Independent Variable								
Have Depression: Gallup (%)	17.31	0.45	16.38	16.90	17.44	17.63	18.16	21
Control Variables								
Number of Firms Covered	42.09	130.10	1.00	3.00	8.00	27.00	649.00	4,195
Number of Industries Covered	3.77	2.75	1.00	1.00	3.00	6.00	10.00	4,195
Forecast Horizon (Days)	7.71	15.12	0.00	0.00	2.00	7.00	80.00	45,627
Firm-Specific Experience (Quarters)	2.64	2.24	1.00	1.00	2.00	3.00	10.00	45,627
Estimize Experience (Quarters)	5.01	3.75	0.00	2.00	4.00	7.00	16.00	45,627
Professional Status	0.33	0.47	0.00	0.00	0.00	1.00	1.00	1,606
Institutional Holdings	0.32	0.10	0.05	0.25	0.32	0.38	0.57	7,634
Firm Size	8.66	1.55	5.67	7.49	8.51	9.66	12.43	7,634
Market-to-Book Ratio	2.54	1.80	0.78	1.39	1.98	3.04	9.63	7,634
Income Per-Capita (in 2012 $US)	40,373	1,175	38,704	39,299	40,180	41,610	42,104	110
Macro. & Policy-related Control Variables								
Economic Policy Uncertainty Index	0.02	1.04	−1.10	−0.81	−0.19	0.82	2.20	21
Macro. Uncertainty	−0.54	0.36	−1.02	−0.71	−0.67	−0.25	0.06	21
VIX	−0.58	0.31	−1.04	−0.78	−0.62	−0.45	0.35	21
Financial Distress	−0.66	0.30	−1.16	−0.85	−0.71	−0.59	−0.11	21
Geopolitical Risk	0.52	1.24	−1.22	−0.19	0.53	0.86	3.48	21

Table 1. Summary Statistics and Correlation-Continued

		Panel B: Pearson Correlation													
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
[1]	Absolute Forecast Errors	1.00													
[2]	Non-Negative Forecast Errors	—	1.00												
[3]	Negative Forecast Errors	—	—	1.00											
[4]	Have Depression	−0.01**	−0.03***	0.01	1.00										
[5]	Number of Firms Covered	−0.03***	0.01	−0.01	0.09***	1.00									
[6]	Number of Industries Covered	−0.07***	0.01	0.01	0.05***	0.56***	1.00								
[7]	Forecast Horizon	0.02***	−0.01	0.02***	0.09***	−0.19***	−0.27***	1.00							
[8]	Firm-specific Experience	−0.02***	0.05***	−0.01*	0.09***	0.11***	0.09***	0.03***	1.00						
[9]	Estimize Experience	−0.01*	0.05***	−0.02*	0.14***	0.12***	0.15***	−0.03***	0.50***	1.00					
[10]	Professional Status	−0.03***	−0.04***	0.02**	0.02***	0.06***	−0.01	0.07***	0.21***	0.03***	1.00				
[11]	Institutional Holdings	−0.03***	0.05***	−0.01*	−0.04***	0.04***	0.05***	−0.01	0.05***	0.02***	0.05***	1.00			
[12]	Firm Size	0.04***	0.01	0.02*	−0.01*	−0.31***	−0.24***	0.06***	0.09***	−0.05***	−0.06***	−0.16***	1.00		
[13]	Market-to-Book Ratio	−0.02***	−0.04***	0.01*	−0.06***	−0.17***	−0.14***	0.04***	0.03***	−0.01	0.00	0.26***	0.10***	1.00	
[14]	Income Per-Capita	0.08***	0.07***	−0.02*	0.50***	0.26***	0.15***	0.02***	0.07***	0.22***	−0.02***	−0.04***	−0.08***	−0.16***	1.00

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 policy-related 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)	-0.25^{***}	-0.19^{**}	-0.14^{*}	-0.21^{***}	-0.20^{***}	-0.17^{**}
	(0.08)	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)
Number of Covered Firms (t-1)	-0.14	-0.24^{**}	-0.24^{**}	-0.00	-0.22	-0.13
	(0.11)	(0.11)	(0.11)	(0.08)	(0.15)	(0.17)
Number of Covered Industries (t-1)	-0.95^{***}	-0.95^{***}	-0.96^{***}	-0.27^{***}	0.08	0.03
	(0.13)	(0.13)	(0.13)	(0.08)	(0.15)	(0.15)
Firm-Specific Experience (t-1)	-0.18	-0.14	-0.11	-0.19^{**}	-0.09	-0.10
	(0.16)	(0.16)	(0.16)	(0.08)	(0.07)	(0.06)
Estimize Experience (t-1)	-0.17	-0.29^{**}	-0.24^{*}	-0.00	4.29	4.47
	(0.14)	(0.14)	(0.14)	(0.11)	(4.05)	(4.05)
Forecast Horizon (t-1)	-0.01	-0.05	-0.03	0.14^{**}	0.01	0.04
	(0.11)	(0.11)	(0.11)	(0.06)	(0.06)	(0.06)
Professional Status	-0.50^{**}	-0.37	-0.41^{*}	0.07		
	(0.23)	(0.24)	(0.23)	(0.13)		
Institutional Ownership (t-1)	-0.19^{***}	-0.19^{***}	-0.20^{***}	0.36^{**}	0.25	0.26
	(0.07)	(0.07)	(0.07)	(0.16)	(0.16)	(0.16)
Firm Size (t-1)	0.46^{***}	0.46^{***}	0.43^{***}	6.42^{***}	5.81^{***}	5.74^{***}
	(0.11)	(0.11)	(0.11)	(0.98)	(1.00)	(0.99)
Market-to-Book Ratio (t-1)	-0.15	-0.13	-0.13	-2.22^{***}	-1.97^{***}	-1.98^{***}
	(0.10)	(0.10)	(0.10)	(0.25)	(0.23)	(0.23)
Income Per Capita (t-1)	1.52^{***}	-0.53^{**}	-0.06	0.50^{**}	0.51^{*}	1.46^{***}
	(0.11)	(0.22)	(0.25)	(0.25)	(0.26)	(0.33)
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. & Policy-related 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)	0.35***	0.49***	4.64***	4.48***	4.44***	4.38***
	(0.07)	(0.10)	(0.97)	(0.97)	(1.10)	(0.66)
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)	−0.15	−2.64***	−1.17***	−1.77***	−1.34***	−1.70***
	(0.58)	(0.67)	(0.39)	(0.44)	(0.34)	(0.33)
# of Obs.	45,627	45,627	45,627	45,584	44,934	44,934
Controls	✓	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓	✓
Quarter FEs			✓	✓	✓	✓
Firm FEs				✓	✓	✓
Analyst FEs					✓	✓
Macro. & Policy-related Controls						✓

Table 4. Reduced Optimism and Forecast Accuracy: Baseline Test

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 and time 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)	-0.47^{***}	-0.27^{***}	0.42^{***}	-0.31^{***}	-0.34^{***}	0.05
	(0.13)	(0.11)	(0.13)	(0.11)	(0.10)	(0.13)
Pessimism (t-1)						−0.19
						(0.24)
Have Depression × Pessimism (t-1)						-0.46^{***}
						(0.13)
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)	0.14	0.20^{**}	0.57^{***}	0.10	0.06	−0.09
	(0.09)	(0.08)	(0.11)	(0.08)	(0.08)	(0.13)
Pessimism (t-1)						−0.30
						(0.19)
Have Depression × Pessimism (t-1)						0.18
						(0.14)
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 5. Reduced Optimism and Forecast Accuracy: IV Test

The table repeats the instrumental variable analysis for the sub-samples of non-negative and negative forecast errors. We use the cumulative average of mild antidepressant prescriptions (i.e., *Mild Drugs*) as an instrument to examine the impact of depression on reducing optimism. Panel A (Panel B) reports the result of the second-stage regression for the sub-sample of non-negative (negative) forecast errors. 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 and time level and are shown in parentheses.

	Panel A: Non-Negative Forecast Error				
	Dependent Variable: Signed Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Have $\widehat{\text{Depression}}$ (t-1)	-1.73^{**}	-4.45^{***}	1.50^{***}	-0.14	-0.51
	(0.74)	(1.21)	(0.56)	(0.50)	(0.47)
# of Obs.	19,716	19,716	19,716	19,618	19,087
	Panel B: Negative Forecast Error				
	Dependent Variable: Signed Forecast Error (t)				
Have $\widehat{\text{Depression}}$ (t-1)	-1.46	1.01	3.26	3.05	1.97
	(2.71)	(1.69)	(2.48)	(2.62)	(1.40)
# of Obs.	25,911	25,911	25,911	25,818	25,261
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 6. Speed of Information Processing and Forecast Accuracy: Baseline Test
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. Panel A uses the full sample, while Panel B restricts forecasts to those issued in the ten days before announcements. 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: Full Sample				
	Dependent Variable: Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
Have Depression ×	-0.38^{***}	-0.34^{**}	-0.32^{**}	-0.21^{**}	-0.15
Slow Processor (t-1)	(0.14)	(0.15)	(0.14)	(0.10)	(0.10)
Have Depression (t-1)	-0.15^{*}	-0.10	-0.06	-0.16^{**}	-0.16^{**}
	(0.08)	(0.08)	(0.09)	(0.07)	(0.07)
Slow Processor (t-1)	-0.56^{***}	-0.58^{***}	-0.58^{***}	-0.25^{**}	-0.25^{**}
	(0.15)	(0.16)	(0.15)	(0.10)	(0.10)
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: Short-Horizon Forecast Sample				
	Dependent Variable: Absolute Forecast Error (t)				
Have Depression ×	-0.41^{**}	-0.37^{**}	-0.40^{**}	-0.36^{***}	-0.31^{**}
Slow Processor (t-1)	(0.17)	(0.18)	(0.18)	(0.14)	(0.14)
Have Depression (t-1)	-0.20^{**}	-0.13	0.02	-0.03	-0.03
	(0.09)	(0.09)	(0.10)	(0.07)	(0.08)
Slow Processor (t-1)	-0.20	-0.23	-0.25	-0.22^{**}	-0.28^{**}
	(0.19)	(0.20)	(0.20)	(0.11)	(0.11)
Adj. R^2	0.01	0.02	0.02	0.57	0.58
# of Obs.	31,236	31,236	31,236	31,165	30,683
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 7. Speed of Information Processing and Forecast Accuracy: IV Test

The table repeats the instrumental variable analysis but further includes *Slow Processor* and its interaction with instrumented *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. We use the cumulative average of mild antidepressant prescriptions (i.e., *Mild Drugs*) as an instrument to examine the impact of depression on speed of information processing. Panel A (Panel B) reports the result of the second-stage regression for the full (10-day-restricted) sample. Antidepressant data are 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: Full Sample				
	Dependent Variable: Absolute Forecast Error (t)				
	(1)	(2)	(3)	(4)	(5)
$\text{Have }\widehat{\text{Depression}}$ ×	−0.69**	−0.67**	−0.73***	−0.62***	−0.47**
Slow Processor (t-1)	(0.28)	(0.28)	(0.27)	(0.23)	(0.23)
$\text{Have }\widehat{\text{Depression}}$ (t-1)	0.21	−2.35***	−0.97**	−1.60***	−1.22***
	(0.54)	(0.64)	(0.39)	(0.43)	(0.34)
Slow Processor (t-1)	−0.56***	−0.62***	−0.60***	−0.26**	−0.25**
	(0.16)	(0.16)	(0.15)	(0.11)	(0.11)
# of Obs.	45,627	45,627	45,627	45,584	44,934
	Panel B: Short-Horizon Forecast Sample				
	Dependent Variable: Absolute Forecast Error (t)				
$\text{Have }\widehat{\text{Depression}}$ ×	−1.01***	−1.05***	−1.02***	−0.90***	−0.76**
Slow Processor (t-1)	(0.37)	(0.37)	(0.37)	(0.30)	(0.32)
$\text{Have }\widehat{\text{Depression}}$ (t-1)	0.04	−1.55***	−0.46	−1.15***	−1.26***
	(0.47)	(0.43)	(0.42)	(0.41)	(0.48)
Slow Processor (t-1)	−0.19	−0.23	−0.23	−0.20*	−0.23**
	(0.19)	(0.19)	(0.19)	(0.12)	(0.12)
# of Obs.	31,236	31,236	31,236	31,165	30,683
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table 8. Alternative Mechanisms: 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)	-0.20^{***}	-0.19^{**}	-0.21^{***}	
	(0.07)	(0.08)	(0.07)	
EPU Indicator (t-1)		-0.73^{***}		
		(0.15)		
Have Depression ×		0.00		
EPU Indicator (t-1)		(0.12)		
Recessionary States (t-1)			-0.94^{***}	
			(0.33)	
Have Depression ×			0.06	
Recessionary States (t-1)			(0.18)	
Residual Depression (t-1)				-0.20^{***}
				(0.07)
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 8 (*continued*)

	Panel B: Analyst Reliance			
	Dependent Variable: Absolute Forecast Error (t)			
Have Depression (t-1)	-0.22^{**}	-0.22^{***}	-0.16^{**}	-0.20^{***}
	(0.10)	(0.07)	(0.07)	(0.07)
No Guidance (t-1)	4.19^{***}			
	(0.55)			
Have Depression ×	0.05			
No Guidance (t-1)	(0.10)			
Low IO		-0.42		
		(0.27)		
Have Depression ×		0.10		
Low IO (t-1)		(0.14)		
High IVOL			-0.75^{***}	
			(0.20)	
Have Depression ×			-0.19	
High IVOL (t-1)			(0.14)	
Low Coverage				-0.84
				(2.12)
Have Depression ×				-0.17
Low Coverage (t-1)				(1.07)
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 8 (*continued*)

	Panel C: Analyst Career Concern			
	Dependent Variable: Absolute Forecast Error (t)			
	Non-Professional		Professional	
Have Depression (t-1)	-0.24^{*}	-0.19^{*}	-0.12	-0.22^{**}
	(0.12)	(0.10)	(0.11)	(0.10)
EPU Indicator (t-1)	-0.81^{***}		-0.56^{***}	
	(0.19)		(0.21)	
Have Depression $\times$	0.19		-0.22	
EPU Indicator (t-1)	(0.16)		(0.16)	
Recessionary States (t-1)		-1.61^{***}		-0.55
		(0.41)		(0.47)
Have Depression $\times$		0.04		0.23
Recessionary States (t-1)		(0.33)		(0.20)
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 8 (*continued*)

	Panel D: Analyst Effort			
	Dependent Variable: Log (1+ Number of Forecasts (t))			
EPU Indicator (t-1)	0.28***			
	(0.02)			
Recessionary States (t-1)		0.33***		
		(0.03)		
Have Depression (t-1)			0.02	
			(0.01)	
Mental Depressive Times (t-1)				0.02
				(0.02)
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
Non-Negative Forecast Error	The forecast error when forecast is greater than or equal to actual earnings per share	Estimize
Negative Forecast Error	The forecast error when forecast is less than 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)
Pessimism Dummy	An indicator of 1 if an analyst's forecast is below the management guidance, 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	
Mild Drugs	The national cumulative average of antidepressant prescription	Medical Expenditure Panel Survey
Depressive Times	An indicator of 1 if *Have Depression* is above the sample's median, and 0 otherwise	
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 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)
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
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	
SAD	An indicator of 1 if an analyst's forecast is created during the first and the fourth calendar quarters, and 0 otherwise	

Table A2. Temporal Dependencies in Depression

Panel A repeats the baseline analysis but demeans and detrends 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)	-0.28^{***}	-0.14^{**}	-0.11^{*}	-0.18^{***}	-0.17^{***}
	(0.07)	(0.06)	(0.07)	(0.06)	(0.06)
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)	-0.26^{***}	-0.21^{***}	-0.16^{**}	-0.24^{***}	-0.20^{***}
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)
Absolute Forecast Errors (t-1)	6.41^{***}	6.41^{***}	6.41^{***}	0.21	0.30
	(0.38)	(0.38)	(0.38)	(0.22)	(0.22)
Adj. R^2	0.20	0.20	0.21	0.53	0.55
# of Obs.	45,627	45,627	45,627	45,584	44,934
Controls	✓	✓	✓	✓	✓
Year FEs		✓	✓	✓	✓
Quarter FEs			✓	✓	✓
Firm FEs				✓	✓
Analyst FEs					✓

Table A3. 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. 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)	-0.19^{**}	-0.19^{**}		
	(0.08)	(0.09)		
Have Depression: MEPS (t-1)			-0.31^{*}	-0.36^{*}
			(0.18)	(0.19)
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)	-0.27^{**}	-0.24^{*}		
	(0.13)	(0.13)		
Google Index: Long List (t-1)			-0.36^{***}	-0.28^{***}
			(0.10)	(0.10)
Adj. R^2	0.53	0.55	0.53	0.55
# of Obs.	43,291	42,659	43,291	42,659
Controls	✓	✓	✓	✓
Year and Quarter FEs	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓
Analyst FEs		✓		✓

Table A4. 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)	-2.34^{***}					
	(0.87)					
Depressed State: Gallup (t-1)		-0.36				
		(0.42)				
Depressed State: CDC (t-1)			-0.22			
			(0.20)			
Depressed State: MEPS (t-1)				-0.36^{*}		
				(0.18)		
Depressed State: Google Trends (t-1)					-0.35^{***}	
					(0.12)	
Have $\widehat{\text{Depression}}$ (t-1)						-6.85^{***}
						(2.20)
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	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓				
Year and Quarter FEs			✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Analyst FEs	✓	✓	✓	✓	✓	✓

Table A5. 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 6 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)	-0.37^{***}	-0.35^{***}	-0.49^{***}	-0.63^{***}	-0.62^{***}
	(0.09)	(0.13)	(0.13)	(0.13)	(0.13)
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)	-0.25	-0.18	-0.50^{***}	-0.60^{***}	-0.48^{***}
	(0.21)	(0.19)	(0.19)	(0.19)	(0.15)
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)	0.25	-0.14	0.09	0.38^{*}	0.51^{**}
	(0.22)	(0.18)	(0.19)	(0.18)	(0.17)
Slow Processor × Have Depression (t-1)	-0.54^{***}	-0.25^{*}	-0.38^{**}	-0.44^{***}	-0.46^{***}
	(0.16)	(0.15)	(0.14)	(0.12)	(0.12)
Slow Processor × SAD (t-1)	0.90^{***}	0.43^{*}	-0.40	-0.34	-0.26
	(0.21)	(0.22)	(0.27)	(0.21)	(0.21)
Have Depression × SAD (t-1)	0.75^{***}	0.34	0.56^{**}	0.52^{***}	0.53^{***}
	(0.19)	(0.18)	(0.19)	(0.14)	(0.14)
Have Depression (t-1)	-0.15	-0.10	-0.06	-0.16^{*}	-0.16^{*}
	(0.08)	(0.08)	(0.09)	(0.07)	(0.07)
Slow Processor (t-1)	-0.52^{**}	-0.60^{***}	-0.57^{***}	-0.19^{*}	-0.17
	(0.16)	(0.16)	(0.15)	(0.10)	(0.11)
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 A6. Non-Severe vs. Severe Depression

Panel A repeats the same analysis of Tables 2 and A3 but replaces the main independent variable with measures of severe depression. Columns (1) and (2) use Gallup data to measure the proportion of individuals who have declared having little to no interest in activities. Columns (3) and (4) use CDC-BRFSS data to measure the proportion of individuals who responded to survey questions with chronic depression. Columns (5) and (6) use MEPS data to measure the proportion of individuals who responded to survey questions with major depressive disorder. Panel B shows the results using the interaction of these variables and *Have Depression*, which is defined for corresponding data from Gallup, CDC-BRFSS and MEPS as in Tables 2 and A3. 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 for the Gallup sample and from 2011 to 2016 for CDC-BRFSS and MEPS samples. 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)					
	Gallup		CDC		MEPS	
	(1)	(2)	(3)	(4)	(5)	(6)
Severe Depression (t-1)	−0.22	−0.15	−0.02	0.02	0.34***	0.20*
	(0.44)	(0.41)	(0.07)	(0.09)	(0.12)	(0.11)
Adj. R^2	0.55	0.56	0.52	0.54	0.52	0.54
# of Obs.	41,648	41,069	45,584	44,934	45,584	44,934
	Panel B: Non-Severe vs. Severe Depression					
	Dependent Variable: Absolute Forecast Error (t)					
	Gallup		CDC		MEPS	
Have Depression × Severe Depression (t-1)	0.55***	0.53***	0.03	0.03	0.65**	0.65**
	(0.12)	(0.13)	(0.05)	(0.06)	(0.27)	(0.27)
Have Depression (t-1)	−0.26***	−0.20**	−0.21**	−0.22**	−0.40*	−0.33
	(0.12)	(0.13)	(0.09)	(0.10)	(0.21)	(0.23)
Severe Depression (t-1)	0.97*	0.88	0.04	0.07	0.82***	0.67***
	(0.58)	(0.56)	(0.08)	(0.10)	(0.19)	(0.18)
Adj. R^2	0.55	0.56	0.52	0.54	0.53	0.54
# of Obs.	41,648	41,069	45,584	44,934	45,584	44,934
Controls	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Quarter FEs	✓	✓	✓	✓	✓	✓
Firm FEs	✓	✓	✓	✓	✓	✓
Analyst FEs		✓		✓		✓

B Additional Robustness Tests

In this section, we conduct several robustness tests to reinforce our main findings. While we do not present the full tables, we summarize the results and report the estimated coefficients and corresponding t-statistics from our most stringent specifications for reference.

We address concerns about including time fixed effects, given the limited time variation in our main independent variable. Excluding them yields consistent results (coefficient = -0.32; t-statistic = -5.46). To account for heterogeneity in analysts' firm selection, we add analyst-by-firm fixed effects and still find a significant effect (coefficient = -0.20; t-statistic = -3.32).

To rule out the possibility that non-severe depression is a fixed trait of analysts, we re-estimate β_1 from Regression (1) using random effects and obtain similar results (coefficient = -0.26; t-statistic = -3.59). We also perform a cluster bootstrapping test, resampling analyst-firm pairs 10,000 times. The average estimate of β_1 is -0.19 (standard error = 0.07), closely aligning with the result in 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).

We further address concerns about whether Gallup survey data accurately reflect the mental health of Estimize users. We rely on prior research about the demographics of stock market participants (e.g., Gallup Survey, 2016; and Bhagwat et al., 2023) and assume Estimize users are more likely to be non-Hispanic white males with higher education and income levels. Because Gallup data report depression rates by individual demographic categories only, we turn to CDC-BRFSS data to identify the subpopulation that jointly matches these characteristics. Subsequently, we conduct robustness tests by repeating our baseline analysis on various sub-samples. The results across all sub-samples consistently align with our main findings.

Specifically, the estimated coefficient for *Have Depression* is equal to -0.57 (t-statistic $= -6.61$) for the non-Hispanic white, -0.42 (t-statistic $= -3.78$) for the male, -0.23 (t-statistic $= -2.10$), for individuals with some college education, -0.69 (t-statistic $= -2.98$) for individuals with income greater than $\$3,000$, and -0.11 (t-statistic $= -2.32$) for the sub-sample from the CDC-BRFSS data with joint characteristics.

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 $= -3.01$; t-statistic $= -3.70$). We also note that the economic magnitude of this coefficient is larger, indicating a larger impact of depression when other public signals are muted.

We also estimate Regression (1) using alternative measures of forecast accuracy. Following Edmans (2011) and Malmendier and Shanthikumar (2014), we scale absolute forecast errors by either total assets or price per share. The results remain consistent: the coefficient is -0.01 (t-statistic $= -2.07$) when scaled by assets, and -0.02 (t-statistic $= -5.87$) when scaled by price.

To account for potential correlation in the residuals, we re-estimate our baseline model using double-clustered standard errors at the analyst-time and analyst-firm levels. The results remain consistent (coefficient $= -0.20$; t-statistics $= -3.17$ and -3.03, respectively). We also address potential bias from correlated forecast errors by weighting each observation by the inverse of the number of forecasters per firm-quarter, which accounts for the influence of earnings surprises in stocks with many contributors. The results remain robust (coefficient $= -0.17$; t-statistic $= -2.23$).

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 = −0.22; t-statistic = −3.10).

To account for the potential influence of anxiety, we include controls for it in our baseline regression using Gallup survey responses to "Experienced Stress Yesterday" and "Experienced Worry Yesterday," following prior studies that identify worry and stress as key indicators of anxiety disorders (Fichter et al., 2010). The results remain robust (coefficient = −0.19; t-statistic = −2.87). We also control for differences in firms' earnings quality, which can affect analyst forecasts by introducing information asymmetries. Specifically, we include discretionary accruals as a proxy for the information environment (Kothari et al., 2005). Our main findings continue to hold (coefficient = −0.22; t-statistic = −3.21).

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 = −0.23; t-statistic = −3.26). These findings suggest that the relationship between depression and forecast accuracy holds regardless of professional status.

Finally, we address concerns about skewed distributions in the number of firms covered by Estimize users, actual firm earnings, and stock prices. First, we winsorize the sample and find consistent results at both the 1% level (coefficient = −0.20; t-statistic = −3.01) and the 2% level (coefficient = −0.20; t-statistic = −2.93). Second, we trim the distribution of actual earnings before constructing the absolute forecast error measures. The results remain robust for both the unscaled error (coefficient = −0.22; t-statistic = −3.60) and the standardized error (coefficient = −0.01; t-statistic = −4.57). Third, we trim the distribution of stock prices used as the scalar and continue to find consistent results (coefficient = −0.02; t-statistic = −5.33).