NBER WORKING PAPER SERIES

DECISION FATIGUE AND HEURISTIC ANALYST FORECASTS

David Hirshleifer
Yaron Levi
Ben Lourie
Siew Hong Teoh

Working Paper 24293
http://www.nber.org/papers/w24293

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2018

Decision Fatigue and Heuristic Analyst Forecasts
David Hirshleifer, Yaron Levi, Ben Lourie, and Siew Hong Teoh
NBER Working Paper No. 24293
February 2018
JEL No. D91,G02,G2,G24,G4,G41

ABSTRACT

Psychological evidence indicates that decision quality declines after an extensive session of decision-making, a phenomenon known as decision fatigue. We study whether decision fatigue affects analysts' judgments. Analysts cover multiple firms and often issue several forecasts in a single day. We find that forecast accuracy declines over the course of a day as the number of forecasts the analyst has already issued increases. Also consistent with decision fatigue, we find that the more forecasts an analyst issues, the higher the likelihood the analyst resorts to more heuristic decisions by herding more closely with the consensus forecast and also by self-herding (i.e., reissuing their own previous outstanding forecasts). Finally, we find that the stock market understands these effects and discounts for analyst decision fatigue.

David Hirshleifer
The Paul Merage School of Business
University of California, Irvine
4291 Pereira Drive
Irvine, CA 92697
and NBER
david.h@uci.edu

Yaron Levi
University of Southern California
3670 Trousdale Parkway, Suite 308
Bridge Hall 308, MC-0804
Los Angeles, CA 90089
yaronlevi1@gmail.com

Ben Lourie
Merage School of Business
University of California, Irvine
Irvine, CA 92697
blourie@exchange.uci.edu

Siew Hong Teoh
Merage School of Business
University of California, Irvine
Irvine, CA 92697
Steoh@uci.edu

1. Introduction

The literature on the determinants of analyst forecasting behavior (e.g., Clement, 1999; Bradshaw 2011) emphasizes the errors that derive from conflicts of interest (e.g. Kothari, So, & Verdi, 2016; Mola, & Guidolin 2009; Ljungqvist et al. 2007; Kirk, M. 2011; Christophe, S., Ferri, M., & Hsieh 2010), and psychological bias (see Ramnath, Rock, & Shane 2008 for a review of the literature). We test here whether analyst *decision fatigue* (i.e., a decline in decision quality after an extensive session of decision-making) affects forecasting behavior. Specifically, we investigate whether the number of forecasts an analyst has already made during a given day affects the accuracy of the next forecast the analyst makes on that same day. We also test whether analysts who have issued more forecasts during a given day behave more heuristically, in the form of herding in their forecasts toward the consensus forecast, or *self-herding* (i.e., reissuing their own outstanding forecasts).

A large body of evidence in psychology suggests that judgments and decisions made under greater pressure, distraction, or fatigue tend to be made more heuristically. The distinction between heuristic and non-heuristic decision-making can be understood using the classification of judgments and decisions emphasized by Kahneman (2011) and initially introduced by Stanovich and West (2000). In this model, decisions arise either from System 1, in which the decision is made using quick and easy intuitive cognitive processes, or from System 2, in which decisions are the result of slow, rigorous reasoning processes. System 2 thinking (i.e., non-heuristic decision-making) requires more mental resources, so individuals tend to switch to System 1 thinking (i.e., heuristic decision-making) after an extended period of System 2 thinking.

We expect that analysts who use System 2 thinking will produce higher quality forecasts than System 1 thinking. We also predict that when analysts become mentally fatigued, they will exhibit a reduced ability to issue an accurate forecast and are more likely to use heuristics (System 1 thinking) when issuing a forecast. These heuristics include techniques such as conforming to the consensus or reiterating a previous forecast.

Baumeister et al. (1998) describe decision fatigue as a consequence of "ego depletion,'' defined as a draining of mental resources. They argue that the self-control required for careful cognitive processing and systematic decision-making requires mental resources that are in limited supply. Self-control is typically impaired when the cognitive resources available for decision-making are low. Thus, when people devote effort to complex decisions over a given period of time, the resulting decision fatigue temporarily reduces the quality of their subsequent decisions. Many subsequent studies in psychology have provided further evidence in support of decision fatigue (Baumeister and Tierney 2012).

There is also anecdotal evidence that professionals are aware and concerned enough about the negative effects of decision fatigue that they take active steps to counteract it. For example, President Barack Obama has explained that he minimizes his food and clothing choices to improve his other decisions (Lewis 2012). Steve Jobs and Mark Zuckerberg famously wear only limited styles and color of clothing. Managers at hedge fund Voss Capital wrote to investors that they encourage their employees to take frequent breaks, even intraday naps or meditation, to prevent overuse of System 1 ("thinking fast") and to avoid making mistakes (Wadhwa 2016).

However, the recent controversy over the reproducibility of experimental studies in social psychology and other fields has also engulfed the large experimental literature on ego depletion. For example, a large scale multilab experimental study finds no discernible ego depletion effects (Hagger et al. 2016).[1] Nevertheless, even Hagger and Chatzisarantis (2016) in their rejoinder state that "For the record, we think that ego-depletion is a `real' phenomenon analogous to cognitive fatigue." They conclude with a call for further study of the topic. One of the contributions of our study is to evaluate decision fatigue using archival data on analyst forecasts instead of laboratory experiments.

[1] This triggered commentaries on the study by Baumeister and Vohs (2016) and Sripada et al. (2016) criticizing the strength of the treatments used to induce fatigue and raising other statistical issues in the Hagger et al. (2016) paper. See also the rejoinder by Hagger and Chatzisarantis (2016).

Our study is not the only one to use archival data to test for decision fatigue. The effects of decision fatigue on decision-making have also been documented in a wide variety of settings in other literatures such as political science (e.g., voting, in Augenblick & Nicholson 2015), and, more recently, in economics (e.g., purchasing a car, in Levav et al. 2010). Decision fatigue has also been shown to be important for major, life-changing decisions: For example, Danziger, Levav, and Avnaim-Pesso (2011) report that parole judges rule less favorably toward prisoners as the morning approaches lunchtime and as the afternoon approaches the end of the workday.

However, evidence as to whether decision fatigue affects professionals in the capital market setting is very limited. Hirshleifer, Lim, and Teoh (2009) provide evidence that on days when relatively more firms announce earnings, stronger post-earnings announcement drift can be interpreted as consistent with investor decision fatigue. However, the authors interpret this finding as a result of limited attention. Our goal is to test specifically for decision fatigue effects in a professional capital market setting.

For several reasons, analyst earnings forecasting provides an attractive context for studying decision fatigue. First, analysts' errors can be directly measured, allowing us to test for degradation of decision quality. Second, analysts often make forecasts of multiple firms in a single day, so it is feasible to test how the forecasting behavior of an analyst varies with the number of forecasts she has already issued that day. Therefore, the number of recently issued forecasts provides a proxy for analyst decision fatigue. Third, firms are often followed by several analysts. This allows us to measure forecast accuracy for the analyst relative to the consensus forecast. By using a measure of relative forecast accuracy, we can mitigate firm characteristic effects on forecast accuracy to isolate decision fatigue effects more successfully.

During the period for which data on the time issuance of individual analyst forecasts are verified (i.e., 2002–2015), we find strong evidence that is consistent with the negative effects of analyst decision fatigue on the accuracy of one-year-ahead EPS forecasts. Forecasts by analysts are less accurate when they are issued after the analysts have issued a greater number of forecasts of other firms that day.

We further investigate whether forecasts are made more heuristically as the analyst issues more forecasts that day. We find that forecasts of decision-fatigued analysts exhibit greater herding toward the prior consensus forecast. There is also greater self-herding, which means that the forecasts are also more likely to be reissuances of the analyst's own previous forecast of a firm. These results are consistent with fatigued analysts switching to System 1 thinking, i.e., decisions that are more non-reflective.

Finally, we study whether investors understand, and discount for, the lower accuracy of forecasts issued when analysts are more fatigued. We do this by testing how the sensitivity of cumulative abnormal returns to forecast revisions by the analyst varies with the number of forecasts of other firms the analyst has already issued the day. We find that the market understands the potential effect of decision fatigue on analyst forecasts: The market reacts less strongly to analysts' forecast revisions that are made when the analysts are decision fatigued.

In our tests of decision fatigue of analysts, we assume that fatigue increases with the number of forecasts the analysts have already issued that day, and that the forecasts are issued in the same order that they are being worked on during the day. The first assumption is highly intuitive. The second is consistent with past evidence that suggests that analysts work in a highly time-sensitive environment, which would pressure analysts to issue forecasts as soon as they are finalized (O'Brien & Bhushan 1990; Hansen 2009; Altinkilic, Balashov, & Hansen 2010; Groysberg & Healy 2013).

It is possible that a forecast issued after other forecasts have been issued that same day may actually have been developed earlier in the day (or week) before the analyst became fatigued, or by other non-fatigued analyst team members. Any such time lags between an analyst's work and the issuance of her forecast biases against obtaining non-null findings (i.e., that decision fatigue has no effect).

Another alternative to decision fatigue as an explanation for our results is that when analyzing firms that are more complex or more difficult to forecast, analysts defer making forecasts until after they issue other easier forecasts. If this were true, then firm characteristics (e.g., firm complexity) would also contribute to less accurate forecasts. Since the characteristics of any given firm are identical for all analysts who follow the firm, as discussed above, we eliminate the influence of firm characteristics on forecast accuracy in our test design by subtracting the consensus forecast accuracy from a specific analyst's forecast accuracy. This difference-in-difference design mitigates firm characteristic effects and focuses instead on the variation in the degree of decision fatigue across analysts in our tests.

Yet another alternative explanation—one that we cannot rule out entirely—is that analysts choose to structure their workday by first working on forecasts for which they have high-quality information relative to the consensus. This would explain both the higher accuracy of early forecasts and the lower tendency in such forecasts toward herding or self-herding. However, it is not obvious why analysts would follow such a work strategy. It may make sense for an analyst to prioritize making forecasts for firms about which the analyst has better information. However, this could just as easily entail making a well-informed forecast at the end of a workday, deferring the ill-informed forecast for the start of the next workday. Nevertheless, to mitigate this concern, in our robustness tests, we remove all forecasts that follow an earnings announcement, and we find that our results are similar, both qualitatively and quantitatively. This suggests that our results are not driven by new public information about firms that is not embedded in the consensus.

This paper draws from the literatures on decision fatigue (e.g., Levav et al. 2010) and analyst forecast accuracy and herding (e.g., Clement & Tse 2005) to examine whether and how decision fatigue affects analyst forecast behavior and to examine the resulting stock market implications (e.g., Givoly & Lakonishok 1979). Our study contributes to three strands of literature. The first strand is the scant literature on decision fatigue in professional settings, which we expand by showing that information intermediaries are affected by decision fatigue. Second, we contribute to the literature on analyst forecast accuracy and herding by showing that analyst forecasting behavior is influenced by the number of forecasts she issued during the same day. Third, we provide evidence about market efficiency by documenting that the market understands the effect of decision fatigue on analyst forecasts.

2. Hypothesis development

Extensive evidence from psychology indicates that judgments and decisions that are made under greater pressure, distraction, or fatigue tend to be made more heuristically. This can be described, in the terminology of Kahneman (2011), as greater use of System 1 thinking. Baumeister et al. (1998) propose that willpower is required to maintain attentional focus for decision-making, and, like muscle strength, willpower is temporarily depleted by use. Self-control and judgment are impaired when the available psychic resources are low.

Several papers have documented the effects of decision fatigue on decision-making. In four laboratory studies, Vohs et al. (2008) find that participants who made choices among consumer goods or college course options suffered from reduced self-control (i.e., less physical stamina, reduced persistence in the face of failure, more procrastination, and lower quality and quantity of arithmetic calculations). However, others who thought about these same options without making choices did not suffer this reduction in self-control. Augenblick and Nicholson (2015) conducted a field study and find that voters who face more decisions before a given vote are significantly more likely to abstain or to rely on decision shortcuts, such as voting for the status quo or voting for the candidates who are listed first on the ballot. Similarly, Levav et al. (2010) show in the field that consumers who are purchasing a car are more likely to choose default levels of attributes when they begin with attributes that offer a greater number of configuration options than when they begin with attributes that offer a smaller number of options.

To our knowledge, the only paper to examine the effect of decision fatigue in a professional setting is that of Danziger, Levav, and Avnaim-Pesso (2011). The authors studied the proportion of parole requests approved by eight parole judges in Israel in relation to the time since their last meal break. This proportion spikes after each meal, when about 65% of requests are granted (relative to an average of 35%). During the roughly two hours before the judges' next meal, their approval rate drops steadily to about zero just before the meal. It seems that tired and hungry judges tend to fall back on the easier default position of denying requests for parole. This evidence does not, however, distinguish between decision fatigue, physical fatigue, and hunger as the source of heuristic decision-making.

The equity analyst setting has some distinctive features that are especially well-suited for testing the effects of decision fatigue. Different analysts will issue different numbers of forecasts earlier in a given day; therefore, the presence of other analysts who cover the same firm at the same time offers a counterfactual benchmark to the forecast being evaluated. Unlike most professions, the outcome of an analyst's decision can be reliably measured: We can observe ex post how close the forecast was to the actual result. Finally, analysts work in a highly time-sensitive environment. As such, it is likely that most of their work is performed sequentially, forecast by forecast, with work on any given forecast closely followed by the issuance of the forecast.

Several findings provide support for this interpretation. O'Brien and Bhushan (1990) describe a customer–supplier relationship between financial institutions and brokerage houses. To the extent that institutional investors demand timely information to make trading decisions, financial analysts have incentives to provide prompt forecast revisions to financial institution clients. The evidence in Hansen (2009) and in Altinkilic, Balashov, and Hansen (2010) suggests that analysts release recommendations soon after the release of new information that has a material impact on the stock price. Groysberg and Healy (2013) report that analysts issue, on average, 12 notes to every one report, and each note only requires a few hours to write. It is important to note that even if the research is conducted by teams (i.e., associate analysts take part in the process of analyzing a company), a bottleneck is still created by the senior analyst who signs off on the report and is responsible for communicating the report to the public. When the senior analyst is fatigued and unable to invest the necessary mental resources to review the work done by the team, the senior analyst might resort to more heuristic behavior.

Clement (1999) shows that factors such as analysts' ability, available resources, and portfolio complexity significantly influence forecast accuracy. For example, the author shows that forecast accuracy increases with experience (a proxy for ability) and with employer size (a proxy for available resources), and accuracy decreases with the number of firms followed (a proxy for portfolio complexity). We contribute to this literature by testing how mental resources affect forecast accuracy, controlling for past known determinants wherever possible. We predict that, with each additional forecast in the sequence, the analyst becomes more fatigued. This fatigue causes the analyst to rely more on System 1 thinking than System 2 thinking when she makes a decision that reduces forecast accuracy. Accordingly, we hypothesize:

H1: An analyst's relative forecast accuracy decreases with the number of forecasts the analyst has made earlier in the same day.

An analyst who is fatigued can resort to some natural heuristic procedures for generating a forecast. One heuristic is to herd by issuing a forecast that is close to the consensus forecast. This is a reasonable shortcut to follow when the analyst lacks the cognitive resources to generate much incremental information relative to the consensus. This hypothesis is new to the herding literature, which has focused primarily on information transmission or agency problems.[2] We build on this literature by testing how analysts' mental resources are also a determinant to herding behavior. This leads to our second hypothesis:

H2: The likelihood that an analyst herds increases with the number of forecasts the analyst has made during the day.

Another possible heuristic is to stick closely to the analyst's previous outstanding forecast about the firm. When decision fatigue prevents an analyst from generating much useful new information, another reasonable shortcut is to rely more heavily on previous

[2] Welch (2000) documents herding behavior among analysts. Hong, Kubik, and Solomon (2000) show that herding is economically rational given analysts' career concerns: being wrong when everyone else is wrong is preferable to being wrong when others are correct. Clement and Tse (2005) find that analyst characteristics, especially those that reflect analyst forecast abilities, affect herding behavior.

analyses. In the extreme case, the analyst would self-herd by not updating the previous forecast at all. This leads to our third hypothesis:

H3: The likelihood that an analyst reissues an outstanding previous forecast increases with the number of forecasts the analyst has made during the day.

Past research indicates that sell-side analysts' forecast revisions are important for investor expectations about firms' earnings and for making investment decisions (e.g., Hodge 2003). This conclusion is supported by the substantial average stock market reaction to the release of forecast revisions (e.g., Brown, Foster, & Noreen 1985; Gonedes, Dopuch, & Penman 1976; Givoly & Lakonishok 1979). Furthermore, there is evidence that market reactions to forecast revisions take into account past forecast accuracy and other correlates of current forecast accuracy (e.g., Bonner, Walther, & Young 2003; Clement & Tse 2003; Gleason & Lee 2003; Michaely & Womack 1999).

This literature suggests that if the market is efficient, it will take into account the effects of decision fatigue on analyst forecast accuracy. For example, investors may directly take into account the number of previous forecasts the analyst has issued during the day. Alternatively, sophisticated investors understand that analyst herding occurs, and they take this into account when evaluating forecasts. Decision-fatigued analysts are more likely to offer forecasts that are similar to the consensus, and this may also lead to more discounting of their forecasts. This leads to our fourth and final hypothesis:

H4: The more forecasts an analyst has issued earlier in the same day, the weaker the reaction of investors when the analyst issues a forecast revision.

We discussed earlier the possibility that analysts intentionally issue their most well-informed forecasts early in the workday. To consider this in more depth, suppose that especially precise information signals arrive uniformly throughout the workday, and that the analyst tends to work on a firm forecast whenever a precise signal about that firm first arrives. If so, then precise forecasts will be distributed evenly throughout the workday. Now if we instead suppose that precise signals arrive only toward the end of the workday (perhaps because these signals are the product of analyst effort during the day), then the most precise forecasts will tend to be issued late in the day. This would bias against finding the results we document, and it strengthens our inference from our evidence that decision fatigue is a factor.

Another possible concern would be a scenario in which analysts generate their most precise signals overnight or over the weekend, and therefore they issue their most precise forecasts at the start of the workday. We cannot rule out this possibility, because it would generate results similar to the implications of decision fatigue. For example, firms often make voluntary disclosures outside of trading hours. This encourages the revision of forecasts, which may occur at the start of the next day. However, this is by no means always the case. Zhang (1998) documents that around half of analysts revise their forecasts in the three days following an earnings announcement, so it is clear that such revisions often occur later than the morning of the first day after the announcement. Nevertheless, we perform robustness checks to ensure that our results are not driven by morning revisions the day after earnings announcements.

Also, although morning forecast revisions are issued in response to news received overnight or during the previous weekend, forecasts issued during the rest of the day are also in response to the arrival of public information. So, although this news is informative, the fact that morning forecast revisions make use of new information does not imply that morning forecasts are more informative than forecasts made at other times of the day.

3. Data and descriptive statistics

Data on analysts' EPS forecasts were collected from the Institutional Brokers' Estimate System (I/B/E/S) database over the period 2002–2015. The starting year of 2002 was chosen since this is the first year that the announcement time of the forecast is verified (Hoechle, Schaub, & Schmid 2012). Similar to prior literature (e.g., Gleason & Lee 2003; Clement & Tse 2005; Kumar 2010), we focus on one-year-ahead earnings forecasts.

The focus of this paper is on timely forecasts that are issued during the workday. So, we focus on forecasts that were prepared, or at least partially prepared, during a single day and were released on that day in sequence. Accordingly, we limit our sample to days when the analyst only issued forecasts between the working hours of 9:00 a.m. and 7:00 p.m.[3] Each forecast issued during the day is marked as a decision by the order it was issued.

Table 1 shows the number of observations in our sample and the partition between the number of forecasts in a day. On average, analysts make 1.3 forecasts per day (on days when forecasts are issued), and our sample consists of 386,924 total observations. On most of the analyst–days in the sample (255,613), the analyst only made one forecast. On 27,975 analyst–days, the analyst made two forecasts, resulting in 55,950 observations; and the number of analyst–days that have a larger number of forecasts continues to decrease with the number of forecasts.

Our main dependent variables of interest are *ACCURACY*, *HERDING*, and *REISSUE*. Following prior research, we compare the accuracy of an analyst's one-year-ahead EPS forecasts for a particular company at a given time to the mean level of accuracy for all analysts who make forecasts for the same company and time period within a comparable forecast horizon (Jacob, Lys, & Neale 1999; Clement 1999; Hong & Kubik 2003; Cowen, Groysberg, & Healey 2006). This controls for any firm- or time-specific factors that affect forecast accuracy. We therefore define

[3] Changing the length of the workday provides qualitatively similar results.

$$RELATIVE\ ACCURACY_{i,j,t} = \frac{Average\ Forecast\ Error\ of\ All\ Analysts_{i,t} - Analyst's\ Forecast\ Error_{i,j,t}}{Standard\ Deviation\ (Forecast\ Error\ of\ All\ Analysts_{i,t})}$$

where $Analyst's\ Forecast\ Error_{i,j,t}$ is the absolute value of actual earnings minus the earnings forecast of analyst i at firm j at time t, and the subtracted term is the median EPS forecast error for all analysts who cover firm j within the same 90 days. The denominator standardizes across firms by dividing by the standard deviation of EPS forecast errors across all analysts who cover firm j at time t.

Following Clement and Tse (2005), we define $HERDING_{i,j,t}$ as a binary variable that receives the value of one if analyst i's forecast of company j at time t is between the consensus forecast at time t and the analyst's own previous forecast, and zero otherwise. (All other variables are defined in Appendix A.)

We also estimate a new measure, $REISSUE_{i,j,t}$, which is a dummy variable that takes the value of one if a forecast is reissued (self-herding) and zero otherwise. When an analyst reissues a forecast, I/B/E/S does not create a new record in its dataset. Instead, I/B/E/S collects information on the date (REVDATS) and time (REVTIMS) the analyst reissued the outstanding forecast.[4] We use this date and time to ascertain when a forecast was reissued.

[4] If an analyst's report does not contain a revision to the forecast, then I/B/E/S does not keep that forecast as a separate record. It retains the original record for that forecast but updates the review date (REVDATS) and time (REVTIME) for the forecast to make it current. If the forecast is changed, only then does I/B/E/S enter a new record in its database but with a new announcement date (ANNDATS).

Table 2 shows descriptive statistics by number of the forecast made by the analyst for the given day. As expected, *ACCURACY* declines and *HERDING* increases as the analyst makes more forecasts throughout the day. The size of the brokerage house and the forecast age (the number of firms the analyst follows) are decreasing (increasing) with each sequential decision. The analyst's experience with the firm and the level of effort invested in a firm do not seem to follow any specific pattern. The type of firm seems to be related to the decision order as well. It seems that smaller firms are forecasted earlier in the day if that firm has fewer analysts following, lower ROA, higher sales growth, higher R&D, and a higher fraction of intangible assets.

One possible reason for this phenomenon is that analysts try to first issue forecasts for firms for which the forecasting problem is more complex or for which the information environment is sparser. This may be valuable for investors who want to trade during the day and who will have the most trouble evaluating such firms until the analyst provides a new and timelier forecast. Alternatively, an analyst may recognize that she will be fatigued later in the day, and therefore try to complete the most challenging tasks much earlier in the day when she is not fatigued.[5]

[5] If this is occurring, and to the extent that our controls for determinants of decision accuracy are imperfect, it would tend to cause us to find that earlier forecasts are *less* accurate than later forecasts. It would therefore bias against the results that we actually find.

4. Results

4.1 Accuracy

To assess whether analysts' forecast accuracy decreases as a function of the number of earlier forecasts they have made during the day, we estimate the following regression model:

$$RELATIVE\ ACCURACY_{i,j,t} = \alpha + \beta_1 DECISION\ RANK_{i,j,t} + \beta_2 CONTROLS + \varepsilon_{i,j,t} \quad (1)$$

Where our key independent variable $DECISION\ RANK_{i,j,t}$ is the logarithm of the number of forecasts an analyst has issued before the focal forecast, plus one.[6] Our controls for other determinants of analysts' relative accuracy include the number of companies covered by the analyst, the brokerage house size, the analyst's firm-specific experience, the age of the forecast, the forecast frequency, and the number of analysts who cover the firm. Finally, we control for the time of day being a measure of physical fatigue rather than decision fatigue.

To test our hypotheses, we estimate Model 1 using three different specifications. The first specification excludes analyst fixed effects. It estimates whether the accuracy of a forecast deteriorates, on average, as a function of the number of forecasts an analyst has previously issued during the day under the implicit assumption that analyst accuracy is ex ante identical across analysts. The second model includes analyst fixed effects to

[6] We winsorize the variable at 5. Results are robust to not winsorizing.

control for analyst differences in accuracy. Thus, the model examines whether, on average, for a given analyst, the accuracy of the forecast deteriorates as a function of the number of forecasts the analyst has previously issued during the day. Finally, we include in the model analyst–day fixed effects, which compare whether, for a given analyst–day, the accuracy of the forecast deteriorates as a function of the number of forecasts the analyst has previously issued during that day, which controls for the fact that accuracy may be greater on some days than on others.

The results presented in Table 3, Columns 1 and 2, indicate that, on average, the accuracy of the forecast deteriorates as a function of the number of forecasts the analyst has previously issued during the day. In Column 2, the coefficient on our key independent variable, *DECISION RANK*, is −0.225 and is significant at the 1% level. This suggests that, on average, a one unit increase in DECISION RANK leads to a forecast that is 0.225 standard deviations less accurate relative to the consensus. This is an economically meaningful effect.

Columns 3 and 4 indicate that, for a given analyst, the accuracy of the forecast deteriorates as a function of the number of forecasts the analyst has previously issued during the day. In Column 4, the coefficient on our variable of interest, *DECISION RANK*, is −0.169 and is significant at the 1% level. This suggests that, on average, a one unit increase in DECISION RANK leads to a forecast that is 0.169 standard deviations less accurate relative to the consensus for the same analyst, regardless of what day or what type of firm the forecasts were issued.

H1 is formally tested in Columns 5 and 6. By adding analyst–day fixed effects to the regression specification, we test whether, for a given analyst–day, the accuracy of the forecast deteriorates as a function of the number of forecasts the analyst has previously issued during that day. In Column 6, the coefficient on our variable of interest, *DECISION RANK*, is −0.067, significant at the 5% level. This implies that, on average, a one-unit increase in *DECISION RANK* leads to a forecast that is 0.067 standard deviations less accurate relative to the consensus for the same analyst and the same day. A different way to interpret the economic magnitude is by examining Table 2. The average accuracy decreases from the first forecast to the second forecast by 0.089, which is equivalent to a decrease of 18.5%.

The results in this section suggest that forecast N is, on average, more accurate than forecast $N + 1$ and suggests that the quality of decisions deteriorates as a function of the number of previous decisions the analyst has made during that day. This is true for our three test specifications. First, analyst *i*'s forecast N is more accurate than analyst *j*'s forecast $N + 1$. Second, analyst *i*'s forecast N is more accurate than her forecast $N + 1$ on a different day. Third, and most importantly, analyst *i*'s forecast N is more accurate than forecast $N + 1$, which was issued on the same day. All of these comparisons hold constant the firm, and therefore the results are independent of firm characteristics.

4.2 Herding

We now turn to the question of whether analysts who are more decision fatigued resort more to heuristic decision-making. We therefore test whether analysts are more likely to issue a herding forecast as a function of the number of forecasts the analyst has previously issued during the day. We use the following logistic regression:

$$Pr\left(HERDING_{i,j,t}\right) = f\left(\alpha + \beta_1 DECISION\ RANK_{i,j,t} + \beta_2 CONTROLS + \varepsilon_{i,j,t}\right) \quad (2)$$

Table 4 summarizes the relationship between herding and decision fatigue. We present two regression specifications (logit and fixed effects logit). Both specifications include our set of controls from Model 1. Columns 1 to 6 indicate that an analyst's issuance of a herding forecast is positively associated with the number of earlier same-day forecasts by the analyst. This is true for all analysts on average (Columns 1 and 2), and for an analyst who covers a specific firm (Columns 3 and 4).

To formally test H2, we use the conditional form of the logit regression and control for analyst–day FE.[7] The results are presented in Columns 5 and 6. Consistent with the hypothesis, within a specific analyst–day, the analyst is more likely to herd with each

[7] We use conditional logit in order to estimate the fixed effects model consistently. By conditioning the likelihood on the number of successes in each panel, we avoid estimating the coefficients of the fixed effects themselves. As a result, this procedure produces consistent estimates of the remaining coefficients.

sequential decision. The coefficient is equal to 0.086, significant at the 5% level. The marginal effect at the mean is 0.02, meaning that a one standard deviation increase in *DECISION RANK* corresponds to a 0.7% increase in the probability of herding. A different way to interpret the economic magnitude is by examining Table 2. The probability of herding increases from the first forecast to the second forecast by 0.023, which is equivalent to an increase of 8.27%.

4.3 Reissued forecasts

Another possible heuristic is that the analyst would self-herd by not updating the previous forecast at all. We therefore test whether analysts are more likely to reissue an outstanding forecast as a function of the number of forecasts the analyst has previously issued during the day. We use the following logistic regression:

$$Pr\left(REISSUE_{i,j,t}\right) = f\left(\alpha + \beta_1 DECISION\ RANK_{i,j,t} + \beta_2 CONTROLS + \varepsilon_{i,j,t}\right) \quad (3)$$

The results are reported in Table 5. Consistent with the hypothesis, the coefficient of *DECISION RANK* is positive and significant across all specifications. H4 is formally tested in Columns 5 and 6. The results suggest that within a specific analyst–day, the more forecasts the analyst has issued previously during the same day, the more likely the analyst is to self-herd by reissuing an outstanding previous forecast. The marginal effect at the mean is 0.262, meaning that a one standard deviation increase in *DECISION_RANK* corresponds to 8.2% increase in probability of reissuing the same forecast within a given analyst day. Untabulated results show that the probability of reissuing the same forecast increases from the first forecast to the second forecast by 0.064, which is equivalent to an increase of 11.1%.

4.4 Market Reaction

To examine whether investors react differently to forecast revisions issued by analysts as a function of the number of earlier forecasts they have made during the day, we estimate the following regression:

$$
\begin{aligned}
CAR_{i,j,t} = {} & \alpha + \beta_1 DECISION\ RANK_{i,j,t} + \beta_2 FORECAST\ REVISION_{i,j,t} \\
& + \beta_3 DECISION\ RANK_{i,j,t} * FORECAST\ REVISION_{i,j,t} + \beta_4 CONTROLS \\
& + \varepsilon_{i,j,t} \qquad (4)
\end{aligned}
$$

where $CAR_{i,j,t}$ is the 3-day market-adjusted excess return for firm j centered on the forecast revision issued by analyst i at time t. The variable $FORECAST\ REVISION_{i,j,t}$ is a measure of the difference between the current annual earnings forecast for analyst i following firm j at time t and the annual earnings forecast issued immediately before the current annual earnings forecast, scaled by the standard deviation of forecasts of all analysts who cover firm j at time t.

To calculate the forecast revision, we require that the analyst issues both a current and a prior annual earnings forecast for the same firm and year. We choose the analyst's prior forecast to calculate the forecast revision, because it is more informative to the market than the consensus forecast (Gleason & Lee 2003; Stickel 1991).

Table 6 reports the results from estimating Equation (3). As expected, the estimated coefficient on *FORECAST REVISION* is positive and statistically significant regardless of the specification used, which indicates that the market reaction around the release of the revised forecast is associated with the signed magnitude of the forecast revision. Consistent with Hypothesis 3, the estimated coefficient on *FORECAST REVISION*DECISION RANK* is negative and statistically significant in all specifications. The coefficient on our variable of interest ranges from −0.007 without control variables and fixed effects to −0.001 when including all control variable and analyst–day fixed effects. The economic significance seems large. For example, in Column 5, the coefficient of *FORECAST REVISION*DECISION RANK* is −0.002, and it is equal to 20% of the coefficient of *FORECAST REVISION*.

This finding indicates that the market reacts less strongly the more prior forecasts the analyst has made during the day. This result is compatible with the results in Section 5.1 and 5.2 that analysts are less accurate and are more likely to herd the more prior forecasts they have made during the day. The market seems to understand these relationships and reacts accordingly.[8]

4.5 Robustness test of the effects of earnings announcement dates

To mitigate the concern that analysts choose to order their workday by first working on forecasts for which they have high-quality information, we re-conduct our main analysis omitting all forecasts in which firms announce earnings in the preceding day (possibly outside of trading hours). If analysts preferentially issue forecasts earlier in the day for firms that announced earnings on the preceding day, then the results might be driven by the increase in accuracy deriving from use of the new public signal that was not yet embedded in the consensus.

Hypotheses 1, 2 and 3 are reexamined in Table 7. The results suggest that omitting the forecasts that are made following the day, after an earnings announcement of a firm, do not qualitatively change the results, which are also quantitatively similar.[9] The inferences are identical, and the magnitude of the coefficients are very similar.

[8] There are rational settings in which herding or cascading is a rational means of exploiting the information possessed by earlier decision-makers (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). However, irrational herding, as induced, for example, by decision fatigue, will tend to reduce the quality of decisions.

[9] The results are also similar when removing forecasts that are made within three and five days after the earnings announcement.

5. Conclusion

We investigate whether decision fatigue is systematically associated with the forecasting behavior of sell-side security analysts' annual EPS forecasts. Our results suggest that analysts become decision fatigued during the day, which is consistent with views of cognitive processing developed by Baumeister (1998) and Kahneman (2011). When mental resources are high, analysts use System 2 thinking and make well-reasoned decisions. However, when mental resources are low, analysts begin to use System 1 thinking and make more intuitive, heuristic decisions. Our archival data test design helps address the potential irreproducibility problems that plague laboratory experiments that are most commonly employed to study the ego depletion phenomenon. We provide a distinct form of evidence about the negative consequences of decision fatigue as predicted in the psychology literature.

Specifically, we use the number of forecasts an analyst has issued earlier in the same day as a proxy for decision fatigue, and we find that analysts become less accurate as they become more decision fatigued. We also find that analysts become more heuristic in their forecasting strategies as they become more decision fatigued; they are more likely to herd toward the consensus forecast and are more likely to self-herd by reissuing their own previous outstanding forecast. Finally, we test how the market reacts to these forecasts in relation to the extent that decision fatigue affected the development of the forecast. We find that the stock market's reaction to a forecast revision is weaker when the issuing analyst is more decision fatigued.

We can rule out several alternative explanations. First, by controlling for the time of day, we can be confident that we are examining decision fatigue rather than physical fatigue. Second, our difference-in-difference design mitigates firm characteristic effects and focuses instead on the variation in the degree of decision fatigue across analysts in our tests. Third, by removing forecasts that follow earnings announcements, we mitigate the concern that our results are driven by new information.

Most behavioral accounting research focuses on cognitive constraints or illusions that are implicitly assumed to be constant for any given individual. For example, empirical findings are often interpreted in terms of some assumed traits of an investor, such as limited attention, overconfidence, or loss aversion. Often (though not uniformly) behavioral models assume that these investor traits are static. Our findings differ by focusing on how the judgment of economic decision-makers varies as a function of past actions. In our study, the past actions are the decisions made earlier in the day that result in decision fatigue. Our evidence suggests that there may be other important managerial and capital market contexts in which the decision-maker's performance varies over time in predictable ways that depend on the decision-maker's cognitive resources and past decisions.

References

Altinkiliç, O., Balashov, V. and Hansen, R., 2010. Evidence that analysts are not important information-intermediaries. Working paper, Freeman School of Business, Tulane University

Augenblick, N. and Nicholson, S., 2015. Ballot position, choice fatigue, and voter behaviour. *The Review of Economic Studies*, 83, 460-480.

Baumeister, R.F., Bratslavsky, E., Muraven, M. and Tice, D.M., 1998. Ego depletion: Is the active self a limited resource?. *Journal of Personality and Social Psychology*, 74, 1252-1265.

Baumeister, R.F., 2002. Ego depletion and self-control failure: An energy model of the self's executive function. *Self and Identity*, 1, 129-136.

Baumeister, R.F. and Tierney, J., 2012. *Willpower: Rediscovering the greatest human strength*. New York: Penguin Press.

Baumeister, R.F. and Vohs, K.D., 2016. Misguided effort with elusive implications. *Perspectives on Psychological Science*, 11, 574-575.

Bikhchandani, S., Hirshleifer, D. and Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100, 992-1026.

Bonner, S.E., Walther, B.R. and Young, S.M., 2003. Sophistication-related differences in investors' models of the relative accuracy of analysts' forecast revisions. *The Accounting Review*, 78, 679-706.

Bradshaw, M.T., 2011. Analysts' forecasts: what do we know after decades of work?. Working paper, Boston College.

Brown, L., Foster, G. and Noreen, E., 1985. Security analyst multi-year earnings forecasts and the capital market. *Studies in Accounting Research*, No. 23. American Accounting Association, Sarasota, FL.

Christophe, S., Ferri, M., and Hsieh, J., 2010. Informed trading before analyst downgrades: Evidence from short sellers. *Journal of Financial Economics*, 95, 85-106.

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

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

Cowen, A., Groysberg, B. and Healy, P., 2006. Which types of analyst firms are more optimistic?. *Journal of Accounting and Economics*, 41, 119-146.

Danziger, S., Levav, J., and Avnaim-Pesso, L., 2011. Extraneous factors in judicial decisions. *Proceedings of the National Academy of Sciences*, 108, 6889-6892.

Gailliot, M.T., Baumeister, R.F., DeWall, C.N., Maner, J.K., Plant, E.A., Tice, D.M., Brewer, L.E. and Schmeichel, B.J., 2007. Self-control relies on glucose as a limited energy source: Willpower is more than a metaphor. *Journal of Personality and Social Psychology*, 92, 325-336.

Givoly, D. and Lakonishok, J., 1979. The information content of financial analysts' forecasts of earnings: Some evidence on semi-strong inefficiency. *Journal of Accounting and Economics*, 1, 165-185.

Gleason, C.A. and Lee, C.M., 2003. Analyst forecast revisions and market price discovery. *The Accounting Review*, 78, 193-225.

Gonedes, N.J., Dopuch, N. and Penman, S.H., 1976. Disclosure rules, information-production, and capital market equilibrium: The case of forecast disclosure rules. *Journal of Accounting Research*, 14, 89-137.

Groysberg, B. and P. Healy., 2013. *Wall street research: Past, present and future*. Stanford, CA: Stanford University Press.

Hagger, M.S. and Chatzisarantis, N.L., 2016. Commentary: Misguided effort with elusive implications, and sifting signal from noise with replication science. *Frontiers in Psychology*, 7, 621.

Hagger, M.S., Chatzisarantis, N.L., Alberts, H., Anggono, C.O., Batailler, C., Birt, A.R., Brand, R., Brandt, M.J., Brewer, G., Bruyneel, S. and Calvillo, D.P., 2016. A multilab preregistered replication of the ego-depletion effect. *Perspectives on Psychological Science*, 11, 546-573.

Hirshleifer, D., Lim, S.S. and Teoh, S.H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, 64, 2289-2325.

Hodge, F.D., 2003. Investors' perceptions of earnings quality, auditor independence, and the usefulness of audited financial information. *Accounting Horizons*, 17, 37-48.

Hoechle, D., Schaub, N. and Schmid, M., 2015. Time stamp errors and the stock price reaction to analyst recommendation and forecast revisions. Working paper.

Hong, H., Kubik, J.D. and Solomon, A., 2000. Security analysts' career concerns and herding of earnings forecasts. *The Rand Journal of Economics*, 31, 121-144.

Jacob, J., Lys, T.Z. and Neale, M.A., 1999. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics*, 28, 51-82.

Kahneman, D., 2011. *Thinking, fast and slow*. New York: Farrar Straus and Giroux.

Kirk, M., 2011. Research for sale: Determinants and consequences of paid-for analyst research. *Journal of Financial Economics*, 100, 182-200.

Kothari, S.P., So, E.C. and Verdi, R.S., 2016. Analysts' forecasts and asset pricing: A survey. *Annual Review of Financial Economics*, 8, 197-219

Kumar, A., 2010. Self-selection and the forecasting abilities of female equity analysts. *Journal of Accounting Research*, 48, 393-435.

Levav, J., Heitmann, M., Herrmann, A. and Iyengar, S.S., 2010. Order in product customization decisions: Evidence from field experiments. *Journal of Political Economy*, 118, 274-299.

Lewis, M. "Obama's Way." The Hive. *Vanity Fair*, 2012. Available at: http://www.vanityfair.com/news/2012/10/michael-lewis-profile-barack-obama.

Ljungqvist, A., Marston, F., Starks, L. T., Wei, K. D., and Yan, H., 2007. Conflicts of interest in sell-side research and the moderating role of institutional investors. *Journal of Financial Economics*, 85, 420-456.

Michaely, R. and Womack, K.L., 1999. Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies*, 12, 653-686.

Mola, S., and Guidolin, M., 2009. Affiliated mutual funds and analyst optimism. Journal of Financial Economics, 93, 108-137.

O'Brien, P.C. and Bhushan, R., 1990. Analyst following and institutional ownership. *Journal of Accounting Research*, 28, 55-76.

Ramnath, S., Rock, S. and Shane, P., 2008. The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24, 34-75.

Sripada, C., Kessler, D. and Jonides, J., 2016. Sifting signal from noise with replication science. *Perspectives on Psychological Science*, 11, 576-578.

Stanovich, K. E., and West, R. F., 2000. Individual differences in reasoning: Implications for the rationality debate? *Behavioral and Brain Sciences*, 23, 645–665

Stickel, S.E., 1991. Common stock returns surrounding earnings forecast revisions: More puzzling evidence. *The Accounting Review*, 66, 402-416.

Vohs, K.D., Baumeister, R.F., Schmeichel, B.J., Twenge, J.M., Nelson, N.M. and Tice, D.M., 2008. Making choices impairs subsequent self-control: A limited-resource account of decision-making, self-regulation, and active initiative. *Journal of Personality and Social Psychology*, 94, 883-898.

Wadhwa, T. 2016 A Hedge Fund Wrote a Letter to Investors Explaining Why They Should Read a Classic Book about Cognitive Biases. *Business Insider*. Available at: http://www.businessinsider.com/voss-capital-investor-letter-on-daniel-kahnemans-thinking-fast-and-slow-2016-11.

Welch, I. 2000. Herding among security analysts. *Journal of Financial economics*, 58, 369-396.

Table 1

Sample Description

Number of observations and number of days used in the sample

Number of Forecasts [a]	Number of Days [b]	Number of Observations [c]
1	255,613	255,613
2	27,975	55,950
3	6,536	19,608
4	2,796	11,184
5	1,559	7,795
6	1,020	6,120
7	766	5,362
8	534	4,272
9	405	3,645
>=10	1,326	17,375
1.3	298,530	386,924

[a] The number of forecasts represents the number of annual EPS forecasts the analyst has made during day t.

[b] The number of days represents the distinct number of analyst–days in which an analyst has made at least one forecast.

[c] Number of Observations is the number of distinct analyst–days times the number of decisions (forecasts) during those days in the sample.

Table 2
Descriptive Statistics by Decision Order

	(1) Forecast 1	(2) Forecast 2	(3) Forecast 3	(4) Forecast 4	(5) Forecast >= 5
<u>Mean</u>					
ACCURACY	0.481	0.392	0.244	0.19	0.107
HERDING	27.80%	30.10%	32.20%	35.30%	37.70%
TIME OF DAY	3.41	4.32	4.58	4.59	4.58
FIRM EXPERIENCE	0.357	0.36	0.343	0.332	0.363
BROKER SIZE	0.27	0.249	0.234	0.221	0.182
EFFORT	0.575	0.57	0.555	0.56	0.589
FIRMS FOLLOWED	0.415	0.453	0.45	0.439	0.484
FORECAST AGE	0.503	0.505	0.504	0.494	0.491
LOG NUMEST	2.35	2.44	2.55	2.62	2.69
LOG MVE	7.95	8.03	8.13	8.26	8.19
ROA	2.69%	3.39%	4.28%	4.46%	4.46%
SALES GROWTH	0.26%	0.22%	0.18%	0.17%	0.21%
R&D	62.60%	60.50%	57.00%	52.30%	37.70%
INTANGIBLES ASSETS	17.60%	15.40%	13.20%	11.50%	7.82%
LOG ADVERTISING	3.76	3.90	4.10	4.33	4.26
<u>Median</u>					
ACCURACY	0.314	0.274	0.2	0.152	0.139
HERDING	0.00%	0.00%	0.00%	0.00%	0.00%
TIME OF DAY	3.00	5.00	5.00	5.00	5.00
FIRM EXPERIENCE	0.25	0.263	0.25	0.238	0.273
BROKER SIZE	0.149	0.131	0.111	0.0975	0.0504
EFFORT	0.571	0.571	0.556	0.556	0.6
FIRMS FOLLOWED	0.375	0.412	0.405	0.391	0.44
FORECAST AGE	0.513	0.515	0.514	0.507	0.491
LOG NUMEST	2.40	2.49	2.64	2.74	2.77
LOG MVE	7.87	7.96	8.05	8.24	8.14
ROA	5.13%	5.35%	5.63%	5.78%	5.91%
SALES GROWTH	0.03%	0.03%	0.02%	0.02%	0.03%
R&D	100.00%	100.00%	100.00%	100.00%	0.00%
INTANGIBLES ASSETS	10.80%	7.65%	5.11%	4.04%	1.41%
LOG ADVERTISING	3.78	3.94	4.15	4.26	4.25

The table presents mean and median of our variable of interest by number of the forecast made by the analyst for the given day. The sample includes all annual EPS forecasts on days when the analyst only issued forecasts between the working hours of 9:00 a.m. and 7:00 p.m between the years 2002-2015. Variable definitions are in appendix A.

Table 3

Relative Accuracy and Decision Fatigue

	(1)	(2)	(3)	(4)	(5)	(6)
DECISION RANK	-0.303***	-0.225***	-0.181***	-0.169***	-0.042**	-0.067***
	(-22.90)	(-16.71)	(-9.60)	(-9.11)	(-2.08)	(-2.85)
TIME OF DAY		-0.007***		-0.006***		0.006
		(-6.12)		(-4.65)		(1.17)
FIRM EXPERIENCE		0.137***		0.046***		0.041*
		(14.08)		(3.17)		(1.74)
BROKER SIZE		0.038***		0.033		0.006
		(3.26)		(1.18)		(0.11)
EFFORT		0.024**		-0.088***		-0.101***
		(2.22)		(-6.00)		(-3.71)
FIRMS FOLLOWED		0.004		0.016		0.022
		(0.32)		(0.80)		(0.54)
FORECAST AGE		-0.183***		-0.170***		0.044
		(-15.93)		(-12.40)		(1.16)
NUMEST		-0.232***		-0.184***		-0.088***
		(-46.10)		(-25.51)		(-6.65)
Constant	0.693***	1.224***	0.599***	1.151***	0.491***	0.706***
	(64.10)	(61.68)	(41.20)	(39.23)	(31.76)	(12.85)
Observations	386,924	386,924	386,924	386,924	386,924	386,924
Adjusted R-squared	0.001	0.010	0.045	0.049	0.398	0.398
Fixed Effects	N	N	Analyst	Analyst	Analyst–day	Analyst–day

The dependent variable is as follows: $RELATIVE\ ACCURACY_{i,j,t}$ is analyst *i*'s EPS forecast error of company *j* at day *t*. This EPS forecast error is compared to the median EPS forecast error for all analysts issuing EPS forecast error for company *j* up until day *t* (consensus). The relative accuracy is standardized across firms by deflating the standard deviation of EPS forecasts error across all analysts who cover the firm. The independent variables are as follows: *DECISION RANK* is the log value of the number of forecasts an analyst has made before the forecast being evaluated, plus 1. Definitions of the control variables are provided in Appendix A. *t*-statistics are provided in parentheses with heteroskedastic-consistent standard errors clustered at the analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4

Herding and Decision Fatigue

	(1) logit	(2) logit	(3) Conditional logit	(4) Conditional logit	(5) Conditional logit	(6) Conditional logit
DECISION RANK	0.348***	0.267***	0.167***	0.162***	0.082**	0.086**
	(13.03)	(10.05)	(7.49)	(7.18)	(2.40)	(2.04)
TIME OF DAY		0.008***		0.003*		0.003
		(3.87)		(1.73)		(0.33)
FIRM EXPERIENCE		-0.008		0.170***		0.009
		(-0.37)		(5.39)		(0.25)
BROKER SIZE		-0.058**		0.093**		0.216**
		(-2.18)		(2.18)		(2.48)
EFFORT		0.006		0.141***		0.074
		(0.23)		(6.09)		(1.60)
FIRMS FOLLOWED		0.064*		-0.006		0.060
		(1.83)		(-0.19)		(0.93)
FORECAST AGE		-0.170***		-0.137***		-0.243***
		(-8.76)		(-7.96)		(-3.45)
NUMEST		0.217***		0.182***		0.145***
		(21.30)		(14.13)		(6.89)
Constant	-1.199***	-1.620***				
	(-53.41)	(-41.47)				
Observations	324,456	324,456	263,839	263,839	61,276	61,276
Fixed Effects	N	N	Analyst-Firm	Analyst-Firm	Analyst–day	Analyst–day
Pseudo R-squared	0.000939	0.00478	0.000237	0.00164	0.000117	0.00132

The dependent variable, $HERDING_{i,j,t}$, is a binary variable with a value of 1 if analyst *i* forecast of company *j* at time *t* is between the consensus forecast at time *t* and his own previous forecast, and 0 otherwise. The independent variables are as follows: *DECISION RANK* is the log value of the number of forecasts an analyst has made before the forecast being evaluated, plus 1. Definitions of the control variables are provided in Appendix A. *t*-statistics are provided in parentheses with heteroskedastic-consistent standard errors clustered at the analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Reissuance of a Previous Outstanding Forecast and Decision Fatigue

	(1) logit	(2) logit	(3) Conditional logit	(4) Conditional logit	(5) Conditional logit	(6) Conditional logit
DECISION RANK	1.230***	1.151***	1.419***	1.349***	1.845***	1.927***
	(28.98)	(27.90)	(117.95)	(110.68)	(57.79)	(39.00)
TIME OF DAY		0.022***		0.027***		-0.014**
		(6.20)		(26.48)		(-2.30)
FIRM EXPERIENCE		0.089***		0.230***		0.052
		(3.92)		(12.57)		(1.35)
BROKER SIZE		0.558***		0.434***		-0.048
		(19.74)		(17.81)		(-0.59)
EFFORT		0.088***		0.105***		-0.017
		(3.30)		(8.19)		(-0.40)
FIRMS FOLLOWED		-0.080***		-0.045**		-0.053
		(-2.99)		(-2.48)		(-0.85)
FORECAST AGE		-0.798***		-0.893***		-0.972***
		(-61.24)		(-84.97)		(-17.75)
NUMEST		0.106***		0.183***		0.113***
		(8.39)		(21.87)		(5.60)
Constant	-0.571***	-0.673***				
	(-17.30)	(-11.16)				
Observations	696,884	696,884	653,156	653,156	52,252	52,252
Fixed Effects	N	N	Analyst-Firm	Analyst-Firm	Analyst–day	Analyst–day
Pseudo R-squared	0.0166	0.0315	0.0232	0.0373	0.0977	0.108

The dependent variable, $REISSUE_{i,j,t}$, is a binary variable with a value of 1 if analyst *i* forecast of company *j* at time *t* is the reissuance of her own previous forecast, and 0 otherwise. The independent variables are as follows: *DECISION RANK* is the log value of the number of forecasts an analyst has made before the forecast being evaluated, plus 1. Definitions of the control variables are provided in Appendix A. z-statistics are provided in parentheses with heteroskedastic-consistent standard errors clustered at the analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Stock Market Reaction to Analyst Forecast Revision and Decision Fatigue

	(1)	(2)	(3)	(4)	(5)	(6)
DECISION RANK	0.002***	0.001**	0.001	0.001	-0.000	-0.001
	(2.68)	(2.24)	(1.06)	(0.94)	(-0.01)	(-1.40)
FORECAST REVISION	0.017***	0.014***	0.017***	0.014***	0.011***	0.010***
	(48.77)	(24.28)	(44.07)	(21.67)	(21.00)	(10.05)
*DECISION RANK**	-0.007***	-0.006***	-0.007***	-0.005***	-0.002***	-0.001**
FORECAST REVISION	(-15.02)	(-12.57)	(-13.20)	(-11.02)	(-4.63)	(-2.27)
Controls	N	Y	N	Y	N	Y
Controls**FORECAST REVISION*	N	Y	N	Y	N	Y
Fixed Effects	N	N	Analyst-Firm	Analyst-Firm	Analyst–day	Analyst–day
Adjusted R-squared	0.117	0.122	0.168	0.172	0.565	0.568
Observations	324,456	324,456	324,456	324,456	324,456	324,456

The dependent variable $CAR_{i,j,t}$ is the 3-day market-adjusted excess return for firm j centered on the forecast revision issued by analyst i at time t. The independent variables are as follows: *DECISION RANK* is the log value of the number of forecasts an analyst has made before the forecast being evaluated, plus 1. *FORECAST REVISION* is a measure of the difference between the current annual earnings forecast for analyst i who follows firm j in time t and the annual earnings forecast issued immediately before current annual earnings forecast, scaled by the standard deviation of forecasts of all analysts who cover firm j in time t. Definitions of the control variables are provided in Appendix A. t-statistics are provided in parentheses with heteroskedastic-consistent standard errors clustered at the analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7

Forecasting Behavior and Decision Fatigue:

Omitting Forecasts Following an Earnings Announcement

	(1) Accuracy	(2) Accuracy	(3) Herding	(4) Herding	(5) Reissue	(6) Reissue
DECISION RANK	-0.055***	-0.058**	0.097**	0.111**	1.867***	2.298***
	(-2.65)	(-2.42)	(2.54)	(2.42)	(49.65)	(39.72)
TIME OF DAY		-0.001		-0.001		-0.076***
		(-0.13)		(-0.11)		(-10.36)
FIRM EXPERIENCE		0.051**		0.042		0.103**
		(2.13)		(1.02)		(2.23)
BROKER SIZE		0.055		0.275***		0.116
		(0.95)		(2.84)		(1.16)
EFFORT		-0.076***		0.013		-0.085
		(-2.72)		(0.27)		(-1.64)
FIRMS FOLLOWED		0.029		0.033		-0.096
		(0.70)		(0.47)		(-1.28)
FORECAST AGE		0.084**		-0.193**		-0.987***
		(2.13)		(-2.47)		(-15.83)
NUMEST		-0.050***		0.137***		0.062**
		(-3.66)		(5.79)		(2.55)
Constant	0.414***	0.497***	0.097**	0.111**		
	(25.79)	(8.52)	(2.54)	(2.42)		
Observations	313,841	313,841	53,393	53,393	37,707	37,707
Adj. (Pseudo) R-squared	0.441	0.049	0.000149	0.00110	0.101	0.115
Fixed Effects	Analyst–day	Analyst–day	Analyst–day	Analyst–day	Analyst–day	Analyst–day

The sample used in this table does not include forecasts that are made following the day after an earnings announcement of a firm. The dependent variables are as follows: $RELATIVE\ ACCURACY_{i,j,t}$ is analyst *i*'s EPS forecast error of company *j* at day *t*. This EPS forecast error is compared to the median EPS forecast error for all analysts issuing EPS forecast error for company *j* up until day *t* (consensus). The relative accuracy is standardized across firms by deflating the standard deviation of EPS forecasts error across all analysts who cover the firm. $HERDING_{i,j,t}$ is a binary variable with a value of 1 if analyst *i*'s forecast of company *j* at time *t* is between the consensus forecast at time *t* and her own previous forecast, and 0 otherwise. $REISSUE_{i,j,t}$, is a binary variable with a value of 1 if analyst *i*'s forecast of company *j* at time *t* is the reissuance of her own previous forecast, and 0 otherwise. The independent variables are as follows: *DECISION RANK* is the log value of the number of forecasts an analyst has made before the forecast being evaluated, plus 1. Definitions of the control variables are provided in Appendix A. *t*-statistics (*z*-statistics) are provided in parentheses with heteroskedastic-consistent standard errors clustered at the analyst level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix A

Variable Name	Description
FIRMS FOLLOWED	A measure of the number of companies analyst i follows in year t. It is calculated as the number of companies followed by analyst i following firm j in year t minus the minimum number of companies followed by analysts who follow firm j in year t, with this difference scaled by the range in the number of companies followed by the analysts who follow firm j in year t.
BROKER SIZE	A measure of the size of analyst i's brokerage house. It is calculated as the number of analysts employed by the brokerage that employs analyst i following firm j in year t minus the minimum number of analysts employed by brokerages for analysts who follow firm j in year t, with this difference scaled by the range of brokerage house sizes for analysts who follow firm j in year t.
FIRM EXPERIENCE	A measure of analyst i's firm-specific experience. It is calculated as the number of years of firm-specific experience for analyst i following firm j in year t minus the minimum number of years of firm-specific experience for analysts who follow firm j in year t, with this difference scaled by the range of years of firm-specific experience for analysts who follow firm j in year t.
EFFORT	A measure of analyst i's effort in forecasting firm j. It is calculated as the number of forecasts issued by analyst i following firm j in year t minus the minimum number of forecasts issued by analysts who follow firm j in year t, with this difference scaled by the range of forecasts issued by analysts who follow firm j in year t.
FORECAST AGE	A measure of the time from the forecast date to the earnings announcement. It is calculated as the number of days from the forecast date to the date of the earnings announcement for analyst i in year t minus the minimum number of days from the forecast date to the date of the earnings announcement for analysts who follow firm j in year t, with this difference scaled by the range of days from the forecast date to the date of the earnings announcement for analysts who follow firm j in year t.
RELATIVE ACCURACY	A measure of analyst i's EPS forecast error for company j at time t minus the median EPS forecast error for all analysts who cover firm j within the same 90 days (multiplied by -1). This difference is standardized across firms by dividing it by the standard deviation of EPS forecast errors across all analysts who cover firm j at time t.

DECISION RANK	The log value of the number of forecasts an analyst has made before the forecast being evaluated, plus 1.
TIME OF DAY	An ordinal measure that receives the value of 1 for the first hour of the workday (9:00 a.m.), the value of 2 for the second hour of the workday (10:00 a.m.), and so on.
HERDING	A dummy variable that receives the value of 1 for forecasts that are between the analyst's own prior forecast and the consensus forecast, and 0 otherwise.
FORECAST REVISION	A measure of the difference between the current annual earnings forecast for analyst i following firm j in time t and the annual earnings forecast issued immediately before the current annual earnings forecast, scaled by the standard deviation of forecasts of all analysts who cover firm j in time t.
CAR	The 3-day market-adjusted excess return for firm j centered on the forecast revision issued by analyst i at time t.
NUMEST	The number of analysts who cover firm j at time t.