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Managing decision fatigue: Evidence from analysts' earnings forecasts[☆]

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ABSTRACT

Prior literature shows decision fatigue reduces analysts' forecast accuracy. We study whether analysts strategically manage their decision fatigue. Firms within an analyst's research portfolio can differentially affect the analyst's reputation and career, with larger firms with greater trading volumes and institutional ownership being more important. We find that analysts choose to issue forecasts for more important firms when they are less decision fatigued, i.e., when the number of prior forecasts the analyst has issued in the day is lower. Young analysts, analysts in low-status brokerage houses, and analysts who become decision fatigued more easily manage fatigue more, and analysts experience more favorable career outcomes after strategically managing fatigue. Finally, fatigued analysts differentiate between more important and other firms in herding and self-herding.

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1. Introduction

Financial analysts' forecasting behavior is an important area in accounting, economics, and finance research, with prior literature emphasizing conflicts of interest and psychological bias.[1] An important recent study by Hirshleifer et al. (2019, HLLT hereafter) highlights the effects of decision fatigue, that is, a decline in decision quality after extensive decision-making, on the quality of analyst forecasts. They show the number of prior forecasts an analyst has issued in a day negatively affects the accuracy of her current forecast (on the same day).[2] Building upon their work, we argue that analysts should be aware of their decision fatigue and manage it, and we examine their fatigue management behavior.

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[1] See, among others, Ljungqvist et al. (2007), Ramnath et al. (2008), Mola and Guidolin (2009), Christophe et al. (2010), Kirk (2011), and Kothari et al. (2016).

[2] As noted by HLLT, the implicit assumptions here are 1) decision fatigue increases with the number of prior forecasts the analyst has issued in the day, and 2) forecasts are in general issued in the order they are performed. The first assumption is intuitive; the second assumption is supported by the evidence that analysts issue forecasts under strong time pressure (e.g., O'Brien and Bhushan, 1990; Altinkilic et al., 2013; Groysberg and Healy, 2013).

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Analysts should be aware of their decision fatigue for the following reasons. First, anecdotal evidence suggests that professionals understand the effects of decision fatigue. For example, Steve Jobs and Mark Zuckerberg have famously worn limited styles and colors of clothing to devote more brainpower to important decisions.[3] Some tech firms, hedge funds, and law firms encourage employees to take breaks or naps to prevent heuristic decision-making and/or improve productivity.[4] Second, analysts receive repeated and reliable feedback on the accuracy of their forecasts, which is likely to allow them to learn that they are less accurate when more decision fatigued.[5] Third, decision fatigue is an extensively studied cognitive constraint. Many studies provide evidence for it and discuss mitigation strategies (e.g., Levav et al., 2010; Danziger et al., 2011; Baumeister and Tierney, 2012; Augenblick and Nicholson, 2016).

Once aware of their decision fatigue, analysts have strong incentives to use strategies to manage it because, as shown by HLLT, it hurts the accuracy of earnings forecasts, which is known to affect analysts' reputations and career outcomes. Brokerage houses value analysts with strong influence on the buy side, and their influence is tied to forecasting expertise (Hong and Kubik, 2003; Groysberg et al., 2011). Hong and Kubik (2003) and Mikhail et al. (1999) show forecast accuracy affects analysts' career outcomes. These studies examine average forecast errors; seeking to reduce them for career concern considerations can motivate analysts to devote more mental resources to firms that are more difficult/complex to forecast because potential errors for these firms are large. Forecast difficulty/complexity may also make information acquisition more profitable, leading to career benefits for the analyst (e.g., Barth et al., 2001).[6] Recent research by Harford et al. (2019), on the other hand, highlights forecasting expertise for firms more important for an analyst's reputation and career, arguing that these firms bring greater career benefits, resulting in incentives for analysts to allocate greater mental resources to them.

Examining individual analysts' earnings forecasts from 2002 to 2019, we confirm HLLT's finding on decision fatigue among analysts: an analyst's one-year-ahead EPS forecast contains more errors when issued after she has issued forecasts for a greater number of other firms on the same day.[7] We also show decision fatigue persists at the individual level: analysts who become decision fatigued more easily in the past, reflected by a stronger relationship between forecast error and the number of prior forecasts in the day, also suffer from stronger decision fatigue in the future.

To manage decision fatigue, analysts need to strategically allocate mental resources within a workday; our focus is the strategy of placing firms that might have stronger career impacts, such as the more important or more difficult/complex ones in an analyst's research portfolio, earlier in the day's decision queue (i.e., when the analyst is less decision fatigued). Exogenous factors may influence a forecast's timing, but, net of their effects, an analyst should choose to work on the prioritized firms earlier in the workday than on other firms.[8] Positions in an analyst's decision queue within a workday specifically capture the decision fatigue effects, and the specific day-level forecast sequencing is relatively unlikely to arise from alternative explanations.

We first examine whether analysts prioritize the more important firms in their research portfolios in decision fatigue management. Larger firms have more trading and institutional following, making them more important for analysts (Hong and Kubik, 2003). Firms with larger trading volumes or institutional ownership are more lucrative sources of commission fees for brokerage houses (Frankel et al., 2006); institutional investors' evaluations of analysts are a key basis for trade allocation (Ljungqvist et al., 2007; Maber et al., 2014). The ability to generate commission revenue affects analysts' reputations and labor market mobility (Groysberg et al., 2011). Using a firm's market capitalization, trading volume, and institutional ownership to measure its relative importance for an analyst, we find that analysts tend to prioritize more important firms (e.g., the top quartile in an analyst's portfolio based on the focal firm importance proxy) by placing their forecasts earlier in the forecast queue of the day.[9]

Drawing on Barth et al. (2001), Ashbaugh-Skaife et al. (2007), Dichev and Tang (2009), Cohen and Lou (2012), and Donelson and Resutek (2015), among others, we measure a firm's level of difficulty/complexity for an analyst to forecast using its earnings volatility, amount of intangible assets, and number of segments. We find that analysts place more difficult/complex forecasts earlier in the forecast queue of the day as well, but forecast importance appears to matter more: analysts prioritize more important forecasts regardless of whether they are more difficult/complex or not, whereas less important but more difficult/complex forecasts tend to be either not prioritized or less prioritized than the more important ones.

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[3] President Barack Obama said in 2012: "*I don't want to make decisions about what I'm eating or wearing. Because I have too many other decisions to make* …" (See "Obama's way," by M. Lewis, *Vanity Fair*, September 5, 2012).

[4] See, for example, "A hedge fund wrote a letter to investors explaining why they should read a classic book about cognitive biases," by T. Wadhwa, *Business Insider*, November 2, 2016, and "Law firm gives nod to nodding off at work," by G. Cinquegrani, *Bloomberg*, May 30, 2017.

[5] We thank the referee for pointing this out.

[6] From this perspective, analysts may consider difficult/complex firms to be to some degree important. In identifying firms important for analysts, Harford et al. (2019) focus on factors more directly related to analysts' compensation and upward mobility in the labor market, such as generating trading for brokerage houses, which we follow.

[7] The number of prior forecasts allows us to capture the effect of decision fatigue (rather than that of the analyst being just fatigued) because, for the same analyst on the same day, a later forecast indicates more prior decisions, and, like HLLT, we control for the time of day for the forecast (as a proxy for physical fatigue) in relevant analyses.

[8] If the analyst is close to being fatigued but has not finished forecasting the prioritized firms, she should defer the remaining prioritized firms to early the next day and switch to tasks that matter less (if possible).

[9] Depending on the context, we sometimes refer to the forecasts for more important (difficult/complex) firms as more important (difficult/complex) forecasts.

We focus on forecast importance in the remaining analyses based on the above findings but need to note an important caveat—the finding that forecast difficulty/complexity is less relevant than forecast importance in decision fatigue management may stem from the difficulty/complexity proxies being noisier than the importance proxies. More research on measurement noise and its impacts on studies, including those on capital market participants' mental or other resource allocation strategies, can be fruitful.

We find that young analysts and analysts in low-status brokerage houses are more likely to issue more important forecasts earlier in the workday than more experienced analysts and analysts in high-status brokerage houses. While reputations and career outcomes matter for all analysts, young analysts and analysts in low-status brokerage houses tend to have stronger incentives to improve them; some of these analysts may also have fewer supporting resources or are less able to use them efficiently (e.g., young analysts). Our findings suggest that these factors can motivate analysts to manage decision fatigue more strategically. We also find that analysts who become decision fatigued more easily are more likely to issue more important forecasts earlier in the workday, consistent with these analysts being more affected by decision fatigue and consequently having a stronger need to manage it.[10]

Decision fatigue management has important career outcome implications for analysts: we find that analysts who manage decision fatigue more strategically, as indicated by a greater tendency to issue more important forecasts earlier in the workday, are more likely to move from a low-status brokerage house to a high-status one. This finding suggests that fatigue management can help analysts improve their career prospects.

We also examine other complementary strategies analysts may adopt to deal with decision fatigue. First, we show fatigued analysts herd more for more important firms than for other firms. Analysts may strategically herd more when they are less accurate so that their lower-quality forecasts do not stand out (e.g., Clement and Tse, 2005), and our finding suggests that important firms' strong career impacts enhance this tendency. Second, we show fatigued analysts reissue their own previous forecasts (i.e., self-herd) less for more important firms than for other firms, suggesting that they engage in heuristic decision-making less for more important tasks.[11]

This paper contributes to three strands of literature. The first is the literature on individuals' management of cognitive constraints, which we expand by providing evidence that information intermediaries strategically manage decision fatigue. Second, to the extent that decision fatigue limits analysts' cognitive abilities, by studying how they manage it, we contribute to the literature on factors affecting agents' acquisition and understanding of financial information.[12] Third, we contribute to the literature on analysts' forecasting behavior and career outcomes by showing that the management of decision fatigue is associated with differential treatment of firms by analysts and affects their career progression.

The remainder of the paper is organized as follows. Section 2 develops hypotheses. Section 3 describes data, sample, and measures. Section 4 presents empirical evidence. Section 5 concludes.

2. Hypotheses

The psychology literature has shown people tend to make judgments or decisions heuristically when under pressure, distraction, or fatigue.[13] Decision fatigue has been documented in both nonprofessional and professional settings (e.g., Vohs et al., 2008; Levav et al., 2010; Danziger et al., 2011; Augenblick and Nicholson, 2016; HLLT). Its adverse effects on performance raise the question of whether and how individuals, especially professionals motivated to perform well, manage this important cognitive constraint, linking our paper to the literature on cognitive constraint management. For example, some studies in the hyperbolic discounting literature have debated whether agents can or should engage in commitment strategies in advance of being tempted to consume too much; a number of studies examine individuals' allocation of attention.[14]

An individual's awareness of the effect a cognitive constraint has on her is important for its management. For example, projection bias can be challenging to self-manage because agents suffering from it do not understand that later they will feel differently (or at least the degree to which they will feel differently).[15] The analyst earnings forecast setting that we study, in

[10] Access to greater supporting resources and/or more efficient use of resources may help lessen the severity of an analyst's decision fatigue. Untabulated results show weaker fatigue, i.e., a weaker relation between an analyst's forecast error and the number of her prior forecasts in the day, for more experienced analysts than for young analysts, though fatigue still exists for both. The results relevant to analysts who become fatigued more versus less easily are not driven by the difference between young and more experienced analysts (untabulated).

[11] There is some evidence (untabulated) that young analysts and analysts in low-status brokerage houses adopt these strategies more and that analysts adopting them more are more likely to move from low-status brokerage houses to high-status ones, but the results are overall weaker than those discussed earlier for strategic forecast sequencing.

[12] See Blankespoor et al. (2020) for a review.

[13] Heuristic versus non heuristic decision-making can be understood using Kahneman's (2011) decision classification. In Stanovich and West (2000), decisions are from either System 1 or System 2 thinking: heuristic (non heuristic) decisions from the former (latter) use quick and automatic cognitive processes (slow and controlled reasoning processes). Individuals switch to System 1 thinking after extensive System 2 thinking. Baumeister et al. (1998) posit that mental resources can be temporarily depleted by use, leading to impaired decisions.

[14] See, e.g., Ashraf et al. (2006), Kaur et al. (2015), Laibson (2015, 2018), and Schilbach (2019) for the former and Sims (2003), Peng and Xiong (2006), Hirshleifer et al. (2011), Huang et al. (2019), and Li (2022) for the latter.

[15] See, e.g., Loewenstein et al. (2003), Conlin et al. (2007), Acland and Levy (2015), Busse et al. (2015), and Augenblick and Rabin (2019) for studies on the projection bias.

contrast, is characterized by a high likelihood of analysts becoming aware of their decision fatigue from the feedback they receive on forecast quality.

Analysts receive frequent and reliable feedback on decision quality. They forecast earnings frequently, with the quality of each forecast reliably measured ex post by comparing it with the actual result. The notion that feedback can help individuals understand what affects their performance has long been recognized (e.g., Judd, 1905; Wright, 1906), and accurate, frequent, and consistent feedback is more effective (e.g., DeNisi and Sonesh, 2011). Therefore, an analyst may learn from feedback that she is less accurate when she is more decision fatigued.

One may argue that analysts do not necessarily become self-aware about decision fatigue from feedback: for example, they may attribute (incorrectly) the decline in forecast quality to other factors such as firm characteristics. A helpful feature of the analyst setting is that analysts often have relatively long forecast histories for firms. Their portfolios are stable—Harford et al. (2019) report that 85% of firms covered by an analyst this year remain in her portfolio next year. Repeated feedback for the same firm can consistently show an analyst is less accurate when more fatigued, allowing her to identify decision fatigue as the cause of the deterioration in forecast quality.

After an analyst becomes self-aware about her decision fatigue, career concern considerations can drive her to strategically manage it by allocating more mental resources to firms that have stronger impacts on her career. A straightforward way of doing so is to work on the forecasts for these firms when more mental resources are available (i.e., before making other decisions). As discussed previously, analysts may prioritize forecasts for firms that are relatively more important, forecasts for firms that are relatively more difficult/complex, or both. This leads to our first two hypotheses:

H1: Analysts rank-order their forecasts within the workday, with forecasts for the relatively more important firms being earlier in the queue.

H2: Analysts rank-order their forecasts within the workday, with forecasts for the relatively more difficult/complex firms being earlier in the queue.

Some analysts may manage decision fatigue more than others. First, compared with more experienced analysts, young analysts may have stronger incentives to manage decision fatigue because of their stronger career concerns (e.g., Hong et al., 2000). Young analysts also often have fewer supporting resources or lack the experience to use them efficiently, which could result in them having stronger fatigue and thus managing it more. The countervailing factor is the shorter forecast histories of young analysts may make them less able to learn about their decision fatigue or even firms' career impacts. Second, analysts in low-status brokerage houses may be more motivated to manage decision fatigue than analysts in high-status brokerage houses in order to improve their career prospects.[16] Third, heterogeneity in the severity of decision fatigue across individuals (e.g., Baumeister and Tierney, 2012; Evans et al., 2016) implies that analysts who become decision fatigued more easily are more affected by decision fatigue, and they therefore may be more motivated to manage it. In sum, we hypothesize:

H3: The tendency to issue forecasts for firms with stronger career impacts earlier in the workday is stronger for analysts who are less experienced in forecasting.

H4: The tendency to issue forecasts for firms with stronger career impacts earlier in the workday is stronger for analysts in brokerage houses of lower status.

H5: The tendency to issue forecasts for firms with stronger career impacts earlier in the workday is stronger for analysts who become decision fatigued more easily.

Since career concern considerations are likely to drive analysts' decision fatigue management behavior, those who manage fatigue successfully should be able to improve their career prospects. Thus, we expect analysts who manage decision fatigue more strategically to be more likely to experience favorable career outcomes, such as moving from a low-status brokerage house to a high-status one. This leads to our next hypothesis:

H6: The likelihood of an analyst moving from a low-status brokerage house to a high-status one increases with the intensity of her decision fatigue management.

Decision fatigued analysts are more inclined to use heuristics because of their limited mental resources (HLLT). Career impacts of the focal firm may mitigate this tendency: individuals with limited mental resources may be more willing to use (rather than reserve) them for tasks that matter more (e.g., Evans et al., 2016). Herding forecasts have been found to be associated with both analysts' heuristic decision-making (e.g., HLLT) and strategic response to career concerns (e.g., Hong et al., 2000). In the former case, fatigued analysts should herd less for firms with stronger career impacts than for other firms. The opposite arises in the latter case because an analyst would strategically herd more when she is less able to make accurate decisions (e.g., Clement and Tse, 2005), and the need to do so increases with the firm's impact on her career.[17] Self-

[16] More experienced analysts manage teams of analysts more, so it is also possible that they manage their fatigue differently. High-status brokerage houses may have bigger teams to share the workload, whereas some analysts in smaller shops may have to handle tasks by themselves, which could potentially increase the need to manage fatigue. We do not detect a difference in decision fatigue (i.e., the relation between an analyst's forecast error and the number of her prior forecasts in the day) between analysts in high- and low-status brokerage houses empirically (untabulated), suggesting that this factor is not a key driver for our findings related to H4.

[17] In the latter case, being similar to others is better than standing out if the analyst turns out to be wrong. H7 is non-directional because of these conflicting predictions.

herding is a heuristic adopted by fatigued analysts (HLLT), and they should resort to it less for forecasts with stronger career impacts than for other forecasts. Thus, we hypothesize:

H7: The relation between the number of prior forecasts an analyst has issued in the day and her likelihood to herd differs between firms with stronger and weaker career impacts.

H8: The relation between the number of prior forecasts an analyst has issued in the day and her likelihood to reissue her own previous forecast decreases with the firm's career impact.

3. Data, sample, and measures

Data on analyst EPS forecasts are from the Institutional Brokers' Estimate System (I/B/E/S) database for the sample period from 2002 to 2019. We start with 2002 because it is the first year for the announcement time of the forecast to be verified (Hoechle et al., 2015). Following the previous literature (e.g., Gleason and Lee, 2003; Clement and Tse, 2005; Kumar, 2010), we 1) focus on one-year-ahead earnings forecasts, and 2) exclude utilities and financial services firms (SIC codes 4900−4999 and 6000−6999). Firm financials and security data are from Compustat and CRSP.

Our focus is forecasts issued during the workday, i.e., forecasts performed or at least partially performed during a specific day and released on that day. Specifically, we focus on days when the analyst issues forecasts only between the hours of 9:00 a.m. and 11:00 p.m.[18] For each analyst-day, each forecast is marked as a decision based on the order in which it is issued. Table 1 shows the number of decisions made by analysts in our sample, partitioned by the number of forecasts an analyst issues in a day. On days when forecasts are issued, analysts on average make 1.32 forecasts per day, and our sample consists of 605,835 forecasts in total. On the majority of analyst-days (384,084), an analyst would issue only one forecast. On 50,415 analyst-days, analysts issue two forecasts per day, resulting in 100,830 forecasts; the number of analyst-days with a greater number of forecasts issued continues to drop with the number of forecasts per day.

A key variable in our analysis is the degree of decision fatigue an analyst experiences when performing a specific forecast. Drawing on HLLT, we measure it by the logarithm of one plus the number of forecasts an analyst has issued in the day before the focal forecast, denoted by $Decision\ Rank_{i,j,t}$ for analyst i, firm j, and time t. An analyst is expected to become more decision fatigued when she has made forecast decisions for a greater number of other firms before the current forecast on the same day. Appendix A describes the main variables used in this study.

As discussed previously, we adopt three proxies for the relative importance of a firm to an analyst. The first is the firm's market capitalization (denoted by $Size_{j,t}$), computed as the product of the number of shares outstanding and share price at the last quarter-end. The second importance proxy is a firm's dollar trading volume (denoted by $Trading\ Volume_{j,t}$), computed as the product of share price and the monthly number of shares traded (measured at the last quarter-end).[19] Our last importance proxy is the firm's institutional ownership, denoted by $Institutional\ Ownership_{j,t}$, computed by multiplying the number of shares held by institutional investors in the Thomson/Refinitiv 13F Filings database with share price at the last quarter-end.

Table 1
Analyst forecast sample.

Number of Forecasts in the Day	Number of Days	Number of Forecasts
1	384,084	384,084
2	50,415	100,830
3	12,173	36,519
4	4636	18,544
5	2360	11,800
6	1436	8616
7	985	6895
8	724	5792
9	564	5076
≥10	2124	27,679
Average: 1.32	Total: 459,501	Total: 605,835

The number of forecasts in the day is the number of annual EPS forecasts the analyst makes in a specific day. The number of days is the number of analyst-days in which an analyst makes at least one forecast. The number of forecasts is the number of analyst-day-forecasts in the sample.

[18] HLLT focus on forecasts issued from 9:00 a.m. to 7:00 p.m. We extend the time range to 11:00 p.m. because analysts work in highly time-sensitive environments (O'Brien and Bhushan, 1990; Altinkilic et al., 2013; Groysberg and Healy, 2013) and anecdotes (e.g., Reingold and Reingold, 2007) suggest that they can continue to work into the night if needed. Bradley et al. (2014) show a rise in forecasts issued outside regular working hours over time. Our results are robust to alternative cutoffs.

[19] Prior studies have found mixed evidence of the extent to which share price and the number of shares traded affect commission fees (e.g., Keim and Madhavan, 1997, 1998; Goldstein et al., 2009). The results are consistent if using share trading volume.

Because a firm's importance for an analyst is determined by not only its own characteristics but also by characteristics of other firms in the analyst's portfolio, there are wide variations in a firm's relative importance across analysts. Similar to Harford et al. (2019), for each analyst *i* at each time *t*, we create a dummy indicating the top quartile of firms in her research portfolio based on each of the three firm importance proxies. For example, $TOP^{SZ}_{i,j,t}$, the dummy based on firm size, is equal to 1 if firm *j* is in the top quartile of analyst *i*'s portfolio in the quarter in terms of firm size (measured at the last quarter-end) and 0 otherwise. $TOP^{VOL}_{i,j,t}$ and $TOP^{IO}_{i,j,t}$, the dummies indicating important firms based on trading volume and institutional ownership, are constructed in the same manner.

Comparing the decision rank between more important and other forecasts, we find that the mean *Decision Rank* of the more important forecasts is 0.109 (0.108 and 0.109) when firm size (trading volume and institutional ownership) is the focal proxy, whereas that of other forecasts is 0.160 under all three proxies. The differences between the more important and other forecasts are significant at the 1% level for all three proxies, suggesting that analysts tend to issue more important forecasts when they are less decision fatigued. These patterns need to be interpreted with caution due to the lack of control of confounding factors such as analyst characteristics, which we address in the next section.

We also adopt three proxies to capture the level of difficulty or complexity a firm poses to an analyst in forecasting. The first proxy is a firm's earnings volatility, denoted by $Earnings\ Volatility_{j,t}$. It is measured as the standard deviation of the difference between a firm's quarterly earnings and its earnings for the same quarter of the previous year over the past eight quarters. Our second and third difficulty/complexity proxies are the amount of intangible assets a firm has (denoted by $Intangible\ Assets_{j,t}$), measured as intangible assets divided by total assets, and the number of business segments a firm has (denoted by $Number\ of\ Segments_{j,t}$). All three variables are measured at the last quarter-end.[20] We construct dummy variables capturing the quartile of firms of highest difficulty/complexity for an analyst, denoted by TOP^{EV}, TOP^{IA}, and $TOP^{SEG\#}$ for *Earnings Volatility*, *Intangible Assets*, and *Number of Segments*, respectively.

Comparing the decision rank between more difficult/complex and other forecasts, we find that more difficult/complex forecasts also often have lower decision ranks than other forecasts: the mean *Decision Rank* is 0.109 (0.121 and 0.136) for more difficult/complex forecasts when earnings volatility (intangible assets and the number of segments) is the focal proxy, and it is 0.157 (0.151 and 0.144) for other forecasts, and the differences between them are also all significant. Again, these patterns need to be interpreted with caution due to the lack of control of confounding factors.

We draw on HLLT and include the number of firms covered by the analyst, the size of the brokerage house, the analyst's experience with the firm, the age of the forecast, the forecast frequency, and the number of analysts who cover the firm as control variables in most of our regression analyses. As can be seen from Appendix A, all these variables except for the number of analysts covering the firm are adjusted relative to other analysts covering the same firm. Following HLLT, we also control for the forecast's time of day. Appendix B presents the summary statistics for the main control variables.

4. Results

4.1. Validation tests for decision fatigue and firm importance

For analysts to manage decision fatigue, we need to verify decision fatigue exists among them. HLLT establish this existence by showing analysts' forecast accuracy decreases with the forecast's decision rank. Following HLLT, we estimate the following regression model:

$$Relative\ Error_{i,j,t} = \alpha + \beta_1 Decision\ Rank_{i,j,t} + \beta_2 Controls + \varepsilon_{i,j,t} \tag{1}$$

Drawing on prior research (e.g., Jacob et al., 1999; Clement, 1999; Cowen et al., 2006; HLLT), we measure relative forecast error by comparing the error of an analyst's one-year-ahead EPS forecast for a specific firm at a specific time to the average error of all analysts making forecasts for the same firm and time period with the same forecast horizon (see Appendix A). The key independent variable is the forecast's decision rank, $Decision\ Rank_{i,j,t}$ (for analyst *i*, firm *j*, and time *t*), defined in Section 3. The control variables are those discussed in Section 3.

Following HLLT, we estimate Equation (1) with analyst-day fixed effects, which allows us to examine whether for a given analyst-day the forecast error deteriorates as a function of the number of forecasts the analyst has previously issued in that day. This method controls for the possibility that forecast errors may be greater on some days than on others. The results, reported in Panel A of Table 2, confirm the existence of strong decision fatigue among analysts, as shown by the positive and significant coefficients on *Decision Rank* in both columns.

Next, we examine the persistence of decision fatigue for individual analysts. The heterogeneity in endowments and accumulation of mental resources across individuals (Baumeister and Tierney, 2012; Evans et al., 2016) implies that decision fatigue should persist at the individual level—analysts who become decision fatigued more easily in the past should tend to remain so in the future. This persistence, if verified, highlights the importance of using strategies to manage decision fatigue, especially for analysts who become fatigued more easily.

[20] Since data on the number of segments are on an annual basis, we apply the value to the 12 months before the fiscal year-end. Firms with missing segment data are treated as single-segment firms, although dropping them does not affect our results. The results are consistent if firms with more than one or two segments are classified as the more difficult/complex ones (rather than cross-sectional partitions).

Table 2
Validation tests.

Panel A. Existence of Decision Fatigue		
Dependent variable:	(1)	(2)
	Relative Error	*Relative Error*
Decision Rank	0.017**	0.030***
	(2.25)	(3.26)
Controls	No	Yes
# of obs.	605,835	605,835
R^2	0.461	0.461
Fixed effects	Analyst-day	Analyst-day

Panel B. Persistence of Decision Fatigue	
Dependent variable:	(1)
	Relative Error
$Decision\ Rank \times D^{High\ Fatigue}$	0.024**
	(1.98)
$D^{High\ Fatigue}$	0.010
	(1.64)
Decision Rank	0.059***
	(8.76)
Controls	Yes
# of obs.	478,402
R^2	0.124
Fixed effects	Analyst, Day, Firm

Panel C. The Brokerage House's Trading Volume from Important versus Other Firms			
Importance proxy:	(1)	(2)	(3)
	Size	*Trading Volume*	*Institutional Ownership*
Important Firms	109.73***	110.23***	109.01***
	(35.41)	(35.42)	(35.28)
Other Firms	44.75***	44.44***	45.20***
	(37.21)	(37.42)	(37.27)
Difference (Important − Other)	64.98***	65.79***	63.81***
	(19.55)	(19.75)	(19.22)

In Panel C, the average dollar trading volume (in millions) generated by the important and other firms for the analyst's brokerage house in the quarter, as well as the difference between the two, are reported, with important firms being firms in the top quartile of the analyst's portfolio in terms of the relevant importance proxy. All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors, and those in Panels A and B are clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

To measure past fatigue severity, we first calculate the correlation between an analyst's forecast error and decision rank over the past two years. The top quartile of this correlation in the quarter is classified as cases of high past decision fatigue, indicated by a dummy variable $D^{High\ Fatigue}$. We add this dummy and an interaction term between it and *Decision Rank* to Equation (1). Since $D^{High\ Fatigue}$ is constructed for each analyst on each day, we cannot include analyst-day fixed effects in the regression and use analyst, day, and firm fixed effects instead. The results, presented in Panel B of Table 2, show decision fatigue indeed persists at the individual analyst level, as indicated by the positive and significant coefficient on $Decision\ Rank \times D^{High\ Fatigue}$.

Our final set of validation tests is for the relative importance proxies. As discussed previously, an analyst's ability to generate trading commissions for her brokerage house is critical for her career. Thus, she should view firms that can generate more trading volume for her brokerage house as more important. We compare the brokerage house's trading volume generated from important versus other firms for the analyst using the stock-brokerage house level trading volume data from the Bloomberg Terminal. Due to the laborious data collection process, we focus on 50 randomly selected brokerage houses. The Bloomberg Terminal only provides data for the past five years, limiting the sample to 2017–2019.[21]

We compute the average dollar trading volume generated by the more important (i.e., the top quartile of the corresponding importance proxy among firms in the analyst's portfolio) and other firms for the analyst's brokerage house in the quarter and compare the difference between the two. These results, reported in Panel C of Table 2, show larger firms and firms with higher trading volume and institutional ownership in the analyst's portfolio generate drastically higher trading volume for her brokerage house than other firms.

[21] We manually collect the names of I/B/E/S brokerage houses from the LinkedIn employment history, media coverage, and brokerage websites for analysts in the I/B/E/S recommendation file and then match them to the brokerage house names in the Bloomberg Terminal. Brokerage houses in the I/B/E/S recommendation file are matched to those in forecast data using the linking table of Law (2023).

Table 3
Decision rank of important firms.

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Decision Rank	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*
TOP^{SZ}	−0.020***			−0.020***		
	(−4.63)			(−4.53)		
BTM^{SZ}				−0.001		
				(−0.24)		
TOP^{VOL}		−0.020***			−0.020***	
		(−4.83)			(−4.71)	
BTM^{VOL}					0.000	
					(0.00)	
TOP^{IO}			−0.018***			−0.018***
			(−4.34)			(−4.18)
BTM^{IO}						0.004
						(1.10)
Time of Day	0.148***	0.148***	0.148***	0.148***	0.148***	0.148***
	(93.52)	(93.51)	(93.44)	(93.44)	(93.37)	(93.41)
Firm Experience	−0.010	−0.010*	−0.010	−0.010	−0.010	−0.010*
	(−1.63)	(−1.65)	(−1.63)	(−1.61)	(−1.64)	(−1.67)
Broker Size	−0.023	−0.023	−0.023	−0.023	−0.023	−0.025*
	(−1.61)	(−1.58)	(−1.60)	(−1.60)	(−1.59)	(−1.69)
Effort	0.001	0.001	0.001	0.001	0.001	0.001
	(0.17)	(0.18)	(0.20)	(0.18)	(0.18)	(0.19)
Firms Followed	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002
	(−0.24)	(−0.22)	(−0.23)	(−0.24)	(−0.22)	(−0.23)
Forecast Age	0.013	0.014	0.013	0.013	0.014	0.013
	(1.27)	(1.33)	(1.28)	(1.27)	(1.33)	(1.26)
NUMEST	−0.022***	−0.021***	−0.022***	−0.022***	−0.021***	−0.022***
	(−6.25)	(−6.07)	(−6.34)	(−5.88)	(−5.68)	(−5.87)
Constant	−0.516***	−0.517***	−0.515***	−0.515***	−0.517***	−0.517***
	(−31.53)	(−31.73)	(−31.46)	(−31.14)	(−31.74)	(−31.24)
# of obs.	605,835	605,835	605,835	605,835	605,835	605,835
R^2	0.640	0.640	0.640	0.640	0.640	0.640
Fixed effects	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day

All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.2. Decision rank of important firms

To assess whether analysts choose to issue forecasts for more important firms when they are less decision fatigued (H1), we estimate the following regression model:

$$Decision\ Rank_{i,j,t} = \alpha + \beta_1 TOP_{i,j,t} + \beta_2 Controls + \varepsilon_{i,j,t} \tag{2}$$

The dependent variable is analyst *i*'s decision rank for firm *j* on day *t*. *TOP* is the relative importance dummy indicating whether the firm is in the top quartile of the analyst's research portfolio in terms of the focal importance proxy; i.e., *TOP* is either TOP^{SZ}, TOP^{VOL}, or TOP^{IO} (see Section 3). The control variables are the same as those in Equation (1). We estimate Equation (2) with analyst-day fixed effects to control for day-to-day variations in analysts' decision rank choices.[22]

Table 3 reports the results. The first three columns show, consistent with our hypothesis, that analysts prioritize more important firms in decision rank choices (on a given workday). For example, the coefficient on TOP^{SZ} in column 1 is −0.020 and significant at the 1% level, translating into a forecast earlier for bigger firms than for other firms. The results for TOP^{VOL} and TOP^{IO} (in columns 2 and 3) are similar. Another way to understand this is to look at the frequency of more important forecasts among earlier versus later forecasts: for analyst-days when the analyst issues more than one forecast (i.e., when she potentially manages decision fatigue), more important forecasts account for 32% of the first forecast when firm size is the importance proxy, and the fraction declines monotonically to 25% for forecasts ranked fifth or more. The pattern is also similar for the other two importance proxies.

In columns 4–6 of Table 3, we add dummy variables indicating the least important firms in an analyst's research portfolio to Equation (2). Specifically, BTM^{SZ}, BTM^{VOL}, and BTM^{IO} are equal to 1 if the firm is in the lowest quartile of market capitalization, trading volume, or institutional ownership, respectively, among firms in an analyst's research portfolio and 0 otherwise. None of the coefficients on them is significant. While analysts have incentives to prioritize firms that are more

[22] The results are consistent when using analyst fixed effects, when firm fixed effects are added, and under alternative partitions of firms (e.g., quintiles or terciles). Requiring the analyst to cover at least four firms in the quarter (similar to Harford et al. (2019)) leads to even stronger results.

important for them, their incentives for other firms are vaguer in that more accurate forecasts for them may bring few career benefits. Our results are consistent with this idea and underscore a non-monotonic allocation of mental resources by analysts: More important firms are allocated the greatest amount of mental resources while other firms are treated more or less homogeneously.

4.3. Importance versus difficulty/complexity

To examine whether analysts issue forecasts for more difficult/complex firms when they are less decision fatigued (H2), we replace the relative importance dummy in Equation (2) with dummies constructed to indicate more difficult/complex firms, TOP^{EV}, TOP^{IA}, and $TOP^{SEG\#}$, and re-estimate this equation. Table 4 reports the results.

Columns 1 and 2 of Table 4 show that, when firms' earnings volatility and intangible assets are focal difficulty/complexity proxies, analysts tend to prioritize more difficult/complex firms in decision rank choices: the coefficients on TOP^{EV} and TOP^{IA} are negative and significant. The coefficient on $TOP^{SEG\#}$ in column 3 (when firms' number of segments is the focal proxy) is not significant. When dummies indicating the least difficult/complex firms (i.e., the bottom quartile of the focal proxy among firms in an analyst's portfolio) are added to the model in columns 4–6, none of the coefficients on them is significant, while the results related to TOP^{EV}, TOP^{IA}, and $TOP^{SEG\#}$ remain similar.

We further examine the roles played by forecast importance versus difficulty/complexity in the next set of tests. To this end, we divide forecasts into four groups: ones that are more important and more difficult/complex (indicated by $TOP^{Important} \times TOP^{Complex}$), more important but not more difficult/complex (indicated by $TOP^{Important} \times (1\text{-}TOP^{Complex})$), more difficult/complex but not more important (indicated by $TOP^{Complex} \times (1\text{-}TOP^{Important})$), and neither more important nor more difficult/complex (indicated by $(1\text{-}TOP^{Important}) \times (1\text{-}TOP^{Complex})$). $TOP^{Important}$ is TOP^{SZ}, TOP^{VOL}, or TOP^{IO}, and $TOP^{Complex}$ is TOP^{EV}, TOP^{IA}, or $TOP^{SEG\#}$. We then examine whether analysts treat these forecasts differently by replacing the relative importance dummy in Equation (2) with the first three interaction terms above (i.e., using the last group as the base group).

The results are reported in Table 5. They show analysts prioritize more important forecasts regardless of whether they are more difficult/complex or not, as indicated by the negative and significant coefficients for both types of forecasts across all nine columns. More difficult/complex but not more important forecasts are not prioritized in the majority of cases (see columns 1–3 and 6–9). When they are prioritized (columns 4–6), tests of differences between coefficients show they are less

Table 4
Decision rank of difficult/complex firms.

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Decision Rank	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*
TOP^{EV}	−0.015***			−0.015***		
	(−4.01)			(−4.12)		
BTM^{EV}				−0.001		
				(−0.24)		
TOP^{IA}		−0.013***			−0.013***	
		(−4.05)			(−3.87)	
BTM^{IA}					0.002	
					(0.51)	
$TOP^{SEG\#}$			−0.002			−0.002
			(−0.55)			(−0.63)
$BTM^{SEG\#}$						−0.005
						(−0.53)
Time of Day	0.148***	0.148***	0.148***	0.148***	0.148***	0.148***
	(91.02)	(91.07)	(90.95)	(90.99)	(91.06)	(90.94)
Firm Experience	−0.009	−0.008	−0.008	−0.009	−0.008	−0.008
	(−1.49)	(−1.28)	(−1.26)	(−1.49)	(−1.29)	(−1.25)
Broker Size	−0.025	−0.022	−0.021	−0.024	−0.023	−0.021
	(−1.63)	(−1.51)	(−1.40)	(−1.59)	(−1.52)	(−1.40)
Effort	0.000	0.001	0.001	0.000	0.001	0.001
	(0.07)	(0.17)	(0.21)	(0.07)	(0.17)	(0.20)
Firms Followed	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002
	(−0.24)	(−0.25)	(−0.25)	(−0.24)	(−0.26)	(−0.24)
Forecast Age	0.014	0.014	0.015	0.014	0.014	0.015
	(1.30)	(1.33)	(1.36)	(1.30)	(1.33)	(1.36)
NUMEST	−0.026***	−0.029***	−0.029***	−0.026***	−0.029***	−0.029***
	(−6.39)	(−6.69)	(−6.68)	(−6.50)	(−6.69)	(−6.68)
Constant	−0.507***	−0.501***	−0.505***	−0.507***	−0.501***	−0.505***
	(−30.27)	(−29.42)	(−29.73)	(−30.70)	(−29.38)	(−29.72)
# of obs.	585,778	585,778	585,778	585,778	585,778	585,778
R^2	0.640	0.640	0.640	0.640	0.640	0.640
Fixed effects	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day

All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Importance versus difficulty/complexity.

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Decision Rank	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*
	$TOP^{Important}$								
	TOP^{SZ}	TOP^{VOL}	TOP^{IO}	TOP^{SZ}	TOP^{VOL}	TOP^{IO}	TOP^{SZ}	TOP^{VOL}	TOP^{IO}
$TOP^{Important} \times TOP^{EV}$	−0.028***	−0.028***	−0.026***						
	(−4.95)	(−5.07)	(−4.67)						
$TOP^{Important} \times (1-TOP^{EV})$	−0.010**	−0.013***	−0.009**						
	(−2.13)	(−2.66)	(−1.97)						
$TOP^{EV} \times (1-TOP^{Important})$	−0.005	−0.005	−0.007						
	(−1.03)	(−1.19)	(−1.42)						
$TOP^{Important} \times TOP^{IA}$				−0.031***	−0.034***	−0.030***			
				(−5.15)	(−5.59)	(−5.02)			
$TOP^{Important} \times (1-TOP^{IA})$				−0.015***	−0.015***	−0.012**			
				(−2.88)	(−3.03)	(−2.39)			
$TOP^{IA} \times (1-TOP^{Important})$				−0.008**	−0.008**	−0.008**			
				(−2.35)	(−2.15)	(−2.27)			
$TOP^{Important} \times TOP^{SEG\#}$							−0.021***	−0.022***	−0.019***
							(−3.82)	(−4.08)	(−3.50)
$TOP^{Important} \times (1-TOP^{SEG\#})$							−0.012***	−0.014***	−0.011**
							(−2.64)	(−2.93)	(−2.34)
$TOP^{SEG\#} \times (1-TOP^{Important})$							0.004	0.003	0.003
							(1.08)	(0.83)	(0.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	585,639	585,639	585,639	585,639	585,639	585,639	585,639	585,639	585,639
R^2	0.640	0.640	0.640	0.640	0.640	0.640	0.640	0.640	0.640
Fixed effects	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day

All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

prioritized than more important and more difficult/complex forecasts in all three columns and more important but not more difficult/complex forecasts in column 5.[23]

Conditional on the forecast being important for the analyst, tests of differences between coefficients indicate that forecast difficulty/complexity can play a reinforcing role in analysts' decision rank choices—they prioritize more important and more difficult/complex forecasts to a significantly higher degree than more important but not more difficult/complex forecasts for six out of the nine regressions in Table 5. Overall, there appears to be an order of priority in analysts' decision fatigue management: mental resources are allocated based on forecast importance first and then by forecast difficulty/complexity.

As discussed previously, the results in Tables 4 and 5 need to be interpreted with caution due to the possibility that our difficulty/complexity measures can be noisier than our importance measures. Our remaining tests will focus on forecast importance given that we obtain clearer evidence for it.

4.4. Heterogeneity in decision fatigue management

4.4.1. Young analysts

We assess whether young analysts are more inclined to issue more important forecasts when they are less decision fatigued than more experienced analysts (H3) in this section. Drawing on Hong et al. (2000), we construct a dummy variable, denoted by *Young*, that is equal to 1 for analysts who have less than three years of forecast history and 0 otherwise. We then add this dummy and the interaction term between it and the firm's relative importance dummy (TOP^{SZ}, TOP^{VOL}, or TOP^{IO}) to Equation (2) and re-estimate this equation. Analyst-day fixed effects cannot be included for lack of variation in *Young* within an analyst-day, and we use analyst, day, and firm fixed effects instead.[24]

Table 6 reports the results. The coefficients on the interaction terms between *Young* and the relative importance dummies (TOP^{SZ}, TOP^{VOL}, and TOP^{IO}) are all negative and significant. For example, the coefficient on $TOP^{SZ} \times Young$ in column 1 is −0.009 and significant at the 5% level. Similar patterns can be observed for the other two relative importance proxies in columns 2 and 3 as well. These results are consistent with H3 and suggest that young analysts prioritize more important firms more in decision rank choices than more experienced analysts.

[23] The differences in columns 4 and 6 are insignificant.

[24] This applies to Table 8 as well for similar reasons.

Table 6
Decision fatigue management of young analysts.

Dependent variable:	(1)	(2)	(3)
	Decision Rank	*Decision Rank*	*Decision Rank*
$TOP^{SZ} \times Young$	−0.009**		
	(−2.51)		
TOP^{SZ}	−0.028***		
	(−15.01)		
$TOP^{VOL} \times Young$		−0.008**	
		(−2.25)	
TOP^{VOL}		−0.028***	
		(−16.65)	
$TOP^{IO} \times Young$			−0.009**
			(−2.38)
TOP^{IO}			−0.028***
			(−16.60)
Young	0.005	0.004	0.005
	(0.79)	(0.71)	(0.75)
Time of Day	0.014***	0.014***	0.014***
	(36.26)	(36.27)	(36.26)
Firm Experience	−0.012***	−0.012***	−0.012***
	(−5.24)	(−5.24)	(−5.24)
Broker Size	−0.031***	−0.031***	−0.031***
	(−4.38)	(−4.37)	(−4.40)
Effort	−0.031***	−0.031***	−0.031***
	(−12.22)	(−12.18)	(−12.22)
Firms Followed	0.050***	0.050***	0.050***
	(10.89)	(10.88)	(10.90)
Forecast Age	0.006	0.006	0.006
	(1.45)	(1.51)	(1.47)
NUMEST	0.007***	0.007***	0.007***
	(4.87)	(5.21)	(4.95)
Constant	0.058***	0.056***	0.058***
	(9.68)	(9.48)	(9.69)
# of obs.	605,835	605,835	605,835
R^2	0.208	0.208	0.208
Fixed effects	Analyst, Day, Firm	Analyst, Day, Firm	Analyst, Day, Firm

All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.4.2. *Analysts in low-status brokerage houses*

To examine whether analysts in low-status brokerage houses are more inclined to issue more important forecasts when less decision fatigued than other analysts (H4), we draw on Hong and Kubik (2003) and Harford et al. (2019) and create a dummy variable that is equal to 1 if the analyst works for a brokerage house ranked below 10 in terms of the number of analysts employed in the year and 0 otherwise (denoted by $Brokerage^{Low\text{-}status}$). We then interact this dummy with the firm's relative importance dummy (TOP^{SZ}, TOP^{VOL}, or TOP^{IO}) and add this interaction term, along with $Brokerage^{Low\text{-}status}$ itself, to the regression model in Equation (2).[25]

Table 7 reports the results. We find that the coefficients on the interaction terms between $Brokerage^{Low\text{-}status}$ and the three relative importance dummies (TOP^{SZ}, TOP^{VOL}, and TOP^{IO}) are all negative and significant. For example, the coefficient on $TOP^{SZ} \times Brokerage^{Low\text{-}status}$ in column 1 is −0.017 and significant at the 5% level. These results are consistent with H4 and suggest that analysts in low-status brokerage houses prioritize more important firms more in decision rank choices than analysts in more prestigious brokerage houses.

4.4.3. *Analysts who become decision fatigued more easily*

We now turn to examining whether analysts who become decision fatigued more easily are more inclined to issue more important forecasts when they are less decision fatigued (H5). Recall that we have constructed a dummy variable $D^{High\ Fatigue}$ to capture cases of strong past decision fatigue in Section 4.1. We interact $D^{High\ Fatigue}$ with the relative importance dummy, TOP^{SZ}, TOP^{VOL}, or TOP^{IO}, and add the interaction term (together with $D^{High\ Fatigue}$ itself) to the regression model in Equation (2).

The results are reported in Table 8. They are consistent with our hypothesis: For example, the coefficient on $TOP^{SZ} \times D^{High\ Fatigue}$ in column 1 is −0.007 and significant at the 5% level, suggesting that analysts who become decision fatigued more easily

[25] Analyst-day fixed effects can be included here because an analyst can issue forecasts for two brokerage houses on the same day (although very infrequently), for example, when the analyst is in the process of switching brokerage houses.

Table 7
Decision fatigue management of analysts in low-status brokerage houses.

Dependent variable:	(1)	(2)	(3)
	Decision Rank	*Decision Rank*	*Decision Rank*
$TOP^{SZ} \times Brokerage^{Low\text{-}status}$	−0.017**		
	(−2.05)		
TOP^{SZ}	−0.008		
	(−1.46)		
$TOP^{VOL} \times Brokerage^{Low\text{-}status}$		−0.018**	
		(−2.18)	
TOP^{VOL}		−0.007	
		(−1.32)	
$TOP^{IO} \times Brokerage^{Low\text{-}status}$			−0.018**
			(−2.30)
TOP^{IO}			−0.005
			(−0.96)
$Brokerage^{Low\text{-}status}$	−0.042	−0.041	−0.037
	(−0.32)	(−0.31)	(−0.28)
Time of Day	0.148***	0.148***	0.148***
	(93.52)	(93.52)	(93.44)
Firm Experience	−0.010	−0.010*	−0.009
	(−1.63)	(−1.65)	(−1.62)
Broker Size	−0.022	−0.022	−0.022
	(−1.55)	(−1.51)	(−1.53)
Effort	0.001	0.001	0.001
	(0.14)	(0.13)	(0.16)
Firms Followed	−0.002	−0.002	−0.002
	(−0.22)	(−0.19)	(−0.21)
Forecast Age	0.013	0.014	0.013
	(1.27)	(1.33)	(1.27)
NUMEST	−0.021***	−0.021***	−0.022***
	(−6.27)	(−6.08)	(−6.35)
Constant	−0.487***	−0.490***	−0.490***
	(−5.09)	(−5.11)	(−5.17)
# of obs.	605,835	605,835	605,835
R^2	0.640	0.640	0.640
Fixed effects	Analyst-day	Analyst-day	Analyst-day

All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

are more likely to issue forecasts for larger firms earlier in the forecast queue of the day. The results based on firms' trading volume and institutional ownership (in columns 2 and 3) are consistent as well.[26]

4.5. Decision fatigue management and analysts' career progression

We examine whether analysts who manage decision fatigue with greater intensity have more favorable career outcomes (H6) in this section. The results in Section 4.4 indicate that multiple factors can affect an analyst's fatigue management intensity; thus, we adopt an approach based on the analyst's observed tendency to prioritize more important forecasts in decision rank choices that can encompass multiple factors to capture her fatigue management intensity. Specifically, we first compute the correlations between *Decision Rank* and each of the relative importance dummies (TOP^{SZ}, TOP^{VOL}, and TOP^{IO}) over the past two years for each analyst on each day. A lower correlation indicates a stronger tendency for the analyst to issue more important forecasts earlier in the workday. Next, we classify the bottom quartile of each correlation in the quarter as cases where the analyst has high fatigue management intensity, denoted by indicator variables *Fatigue* $MGMT^{SZ}$, *Fatigue* $MGMT^{VOL}$, and *Fatigue* $MGMT^{IO}$, for variables based on firms' size, trading volume, and institutional ownership, respectively.

We relate *Fatigue* $MGMT^{SZ}$, *Fatigue* $MGMT^{VOL}$, and *Fatigue* $MGMT^{IO}$ to the probability for an analyst to move from a low-status brokerage house to a high-status one in the near future using conditional logit regressions.[27] Specifically, we estimate the following regression model:

[26] Untabulated analyses show decision fatigue management has little impact on an analyst's average forecast accuracy—analysts who are more likely to issue more important forecasts earlier in the workday have similar average forecast accuracy as other analysts. When average accuracy is not affected, accuracy for more important forecasts may become even more important, further motivating analysts with stronger career concerns and/or who are more affected by decision fatigue to prioritize these forecasts, as indicated by the results in Tables 6–8.

[27] The conditional form of the logit regression estimates the fixed effects model consistently (Chamberlain, 1980).

Table 8
Decision fatigue management of analysts who become fatigued more easily.

Dependent variable:	(1)	(2)	(3)
	Decision Rank	*Decision Rank*	*Decision Rank*
$TOP^{SZ} \times D^{High\ Fatigue}$	−0.007**		
	(−2.44)		
TOP^{SZ}	−0.023***		
	(−10.68)		
$TOP^{VOL} \times D^{High\ Fatigue}$		−0.006**	
		(−2.12)	
TOP^{VOL}		−0.022***	
		(−10.66)	
$TOP^{IO} \times D^{High\ Fatigue}$			−0.005*
			(−1.94)
TOP^{IO}			−0.023***
			(−11.36)
$D^{High\ Fatigue}$	0.001	0.001	0.000
	(0.20)	(0.21)	(0.10)
Time of Day	0.016***	0.016***	0.016***
	(34.18)	(34.17)	(34.18)
Firm Experience	−0.010***	−0.010***	−0.010***
	(−3.62)	(−3.63)	(−3.63)
Broker Size	−0.029***	−0.029***	−0.029***
	(−3.32)	(−3.32)	(−3.33)
Effort	−0.022***	−0.022***	−0.022***
	(−7.37)	(−7.35)	(−7.36)
Firms Followed	0.054***	0.054***	0.054***
	(10.21)	(10.18)	(10.21)
Forecast Age	0.004	0.004	0.004
	(0.83)	(0.83)	(0.81)
NUMEST	0.007***	0.008***	0.007***
	(4.54)	(4.73)	(4.60)
Constant	0.049***	0.049***	0.049***
	(6.71)	(6.71)	(6.78)
# of obs.	478,402	478,402	478,402
R^2	0.217	0.217	0.217
Fixed effects	Analyst, Day, Firm	Analyst, Day, Firm	Analyst, Day, Firm

All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

$$\Pr\left(Move\ Up_{i,t+1}\right) = f\left(\alpha + \beta_1 Fatigue\ MGMT_{i,t} + \beta_2 Controls + \varepsilon_{i,t+1}\right) \tag{3}$$

Move Up is a dummy that is equal to 1 if analyst *i* moves from a low-status (i.e., ranked below 10 in the number of analysts employed) brokerage house to a high-status (i.e., top 10) one within a year and 0 otherwise. *Fatigue MGMT* is either $Fatigue\ MGMT^{SZ}$, $Fatigue\ MGMT^{VOL}$, or $Fatigue\ MGMT^{IO}$. We control for the number of firms the analyst follows, the size of her brokerage house, her forecasting experience, and her average forecast error and forecasting effort in the past year in the regressions. Day fixed effects are also included.[28]

Table 9 presents the results. Consistent with our hypothesis, the coefficients on $Fatigue\ MGMT^{SZ}$, $Fatigue\ MGMT^{VOL}$, and $Fatigue\ MGMT^{IO}$ are all positive and highly significant. For example, the coefficient on $Fatigue\ MGMT^{IO}$ in column 3 is 0.224 and significant at the 1% level, with a marginal effect indicating that analysts with high fatigue management intensity are 4.32% more likely to move from a low-status brokerage house to a high-status one than other analysts. This effect is economically meaningful considering that all that is needed is to work on more important forecasts earlier in the workday if possible.

4.6. Herding and self-herding

We examine H7 and H8 in this section, starting with whether fatigued analysts' tendency to herd differs between more important and other firms. Following HLLT, we measure herding, denoted by *Herding*, by a dummy variable that is equal to 1 for forecasts between the analyst's own previous forecast and the consensus forecast and 0 otherwise. We interact *Decision*

[28] These regressions use analyst-day observations and include days when the analyst issues forecasts outside 9:00 a.m.–11:00 p.m. (i.e., an analyst-day is included if *Fatigue MGMT* can be constructed). The number of firms the analyst follows and brokerage house size are unadjusted for these regressions (whereas they are adjusted relative to other analysts covering the same firm for regressions in other tables, as discussed in Section 3) because of the analyst-day level observations. Analysts already in high-status brokerage houses are excluded. Additional control variables (e.g., the average size of the firms in the analyst's portfolio and the number of industries the analyst covers) do not change the results qualitatively.

Table 9
Labor market outcome of decision fatigue management.

Dependent variable:	(1)	(2)	(3)
	Move Up	*Move Up*	*Move Up*
Fatigue MGMT^{SZ}	0.088***		
	(2.60)		
Fatigue MGMT^{VOL}		0.169***	
		(5.04)	
Fatigue MGMT^{IO}			0.224***
			(6.78)
Firms Followed (Unadjusted)	0.015***	0.016***	0.016***
	(5.17)	(5.52)	(5.66)
Broker Size (Unadjusted)	0.024***	0.024***	0.024***
	(29.65)	(29.58)	(29.53)
Experience	−0.013***	−0.013***	−0.012***
	(−6.92)	(−6.84)	(−6.80)
Average Relative Error	−0.356***	−0.358***	−0.360***
	(−7.79)	(−7.82)	(−7.86)
Average Effort	0.203**	0.218**	0.219**
	(2.01)	(2.16)	(2.17)
# of obs.	338,691	338,691	338,691
Pseudo R^2	0.026	0.026	0.026
Fixed effects	Day	Day	Day

All variables are defined in Appendix A. Control variables (*Firms Followed (Unadjusted)*, *Broker Size (Unadjusted)*, *Experience*, *Average Relative Error*, and *Average Effort*) are measured in the last year. z-statistics (in parentheses) are from heteroskedastic-consistent standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Rank with the relative importance dummy (*TOP^{SZ}*, *TOP^{VOL}*, or *TOP^{IO}*) and relate the interaction term to an analyst's tendency to herd using the following regression model:

$$\Pr\left(Herding_{i,j,t}\right) = f\left(\alpha + \beta_1 TOP_{i,j,t} \times Decision\ Rank_{i,j,t} + \beta_2 Decision\ Rank_{i,j,t} + \beta_3 TOP_{i,j,t} + \beta_4 Controls + \varepsilon_{i,j,t}\right) \tag{4}$$

We use conditional logit regressions and control for analyst-day fixed effects. Control variables are the same as for Equation (1).

Panel A of Table 10 reports the results. Column 1 shows that, consistent with HLLT, an analyst's tendency to herd increases with the forecast's decision rank. Columns 2–4 show positive coefficients on the interaction terms: For example, the coefficient on *TOP^{SZ}* × *Decision Rank* is 0.094 and significant at the 5% level in column 2, and the results based on firms' trading volume and institutional ownership (in columns 3 and 4) are consistent with the firm-size-based result. These findings are consistent with the view that analysts herd more for more important firms than for other firms when they are less able to make accurate decisions.

Panel B of Table 10 focuses on analysts' reissuance activity (H8). We replace *Herding* in Equation (4) with *Reissue*, a dummy variable equal to 1 if the analyst reissues her own outstanding forecast and 0 otherwise, and re-estimate this equation. Consistent with our hypothesis, columns 2–4 of this panel show the coefficients on *TOP* × *Decision Rank* are all negative and significant. For example, the coefficient on *TOP^{SZ}* × *Decision Rank* is −0.288 and significant at the 1% level in column 2.[29] These findings suggest that fatigued analysts resort to heuristic decisions less for more important forecasts than for other forecasts.

4.7. Alternative explanations and robustness

While our results suggest that analysts manage decision fatigue by prioritizing forecasts more important for their reputations and careers in decision rank choices, it is important to consider other potential explanations for this finding. We make several attempts in this regard:

1. Trading Volume for the Day

One potential alternative explanation is analysts may place more important forecasts earlier in the forecast queue of the day so that investors have relatively more time to trade the stocks, which can lead to higher trading volume for that day. We explore this possibility in columns 1–3 of Panel A of Table 11 by relating a forecast's decision rank and importance to the stock's trading volume in the day. The positive coefficients on the relative importance dummies suggest that more important firms have higher daily trading volumes. However, placing a forecast earlier in the decision queue in itself does not lead to

[29] The positive coefficients on the importance dummies suggest that, controlling for decision fatigue related effects, analysts reissue more important forecasts more, which can possibly be strategic. HLLT are the first to examine reissued forecasts and call for more examinations.

Table 10
Herding and self-herding.

Panel A. Herding

Dependent variable:	(1)	(2)	(3)	(4)
	Herding	*Herding*	*Herding*	*Herding*
Decision Rank	0.064**	0.034	0.009	0.031
	(2.40)	(1.15)	(0.29)	(1.06)
$TOP^{SZ} \times$ *Decision Rank*		0.094**		
		(2.16)		
TOP^{SZ}		−0.011		
		(-0.65)		
$TOP^{VOL} \times$ *Decision Rank*			0.173***	
			(4.16)	
TOP^{VOL}			−0.051***	
			(−2.93)	
$TOP^{IO} \times$ *Decision Rank*				0.104**
				(2.51)
TOP^{IO}				−0.013
				(−0.77)
Controls	Yes	Yes	Yes	Yes
# of obs.	103,482	103,482	103,482	103,482
Pseudo R^2	0.001	0.001	0.001	0.001
Fixed effects	Anlst-day	Anlst-day	Anlst-day	Anlst-day

Panel B. Forecast Reissuance

Dependent variable:	(1)	(2)	(3)	(4)
	Reissue	*Reissue*	*Reissue*	*Reissue*
Decision Rank	1.077***	1.164***	1.154***	1.167***
	(18.51)	(19.70)	(19.47)	(19.72)
$TOP^{SZ} \times$ *Decision Rank*		−0.288***		
		(−11.60)		
TOP^{SZ}		0.161***		
		(7.37)		
$TOP^{VOL} \times$ *Decision Rank*			−0.255***	
			(−10.18)	
TOP^{VOL}			0.153***	
			(6.85)	
$TOP^{IO} \times$ *Decision Rank*				−0.297***
				(−11.94)
TOP^{IO}				0.162***
				(7.38)
Controls	Yes	Yes	Yes	Yes
# of obs.	144,356	144,356	144,356	144,356
Pseudo R^2	0.072	0.073	0.073	0.073
Fixed effects	Anlst-day	Anlst-day	Anlst-day	Anlst-day

All variables are defined in Appendix A. z-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

greater trading volume in the day, as shown by the insignificant coefficients on *Decision Rank*. The coefficients on *Time of Day* are all negative and significant (omitted from reporting), and untabulated analyses show this is driven by the afternoon rather than morning or evening forecasts; there is no evidence that analysts concentrate important or other forecasts in the afternoon. These results indicate that trading volume in the day is not the primary driver for analysts' choice of low decision rank for important forecasts.

Moreover, if trading volume in the day is the main driver for analysts' decision rank choices, their incentive to prioritize more important firms should be weak after trading hours. In contrast, we find in columns 4–6 of Panel A of Table 11 that analysts continue to prioritize more important forecasts after dropping forecasts issued before 6:00 p.m., casting doubt on this explanation.[30]

2. Information and Demand for Information

Another alternative explanation is analysts may place forecasts for more important firms earlier in the forecast queue of the day because they have better or more information for and face higher demand for information about these firms. Low decision rank for important firms can arise if 1) the information demand for these firms is higher than for other firms such

[30] The 6:00 p.m. cutoff is chosen because major markets close at 4:00 p.m. and Bradley et al. (2014) report an average delay of 2 h for I/B/E/S timestamps—the results are consistent under the 4:00 p.m. or 8:00 p.m. cutoffs.

Table 11
Alternative explanations.

Panel A. Trading Volume for the Day						
Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Vol of the Day	*Vol of the Day*	*Vol of the Day*	*Decision Rank*	*Decision Rank*	*Decision Rank*
Decision Rank	−0.002	−0.002	−0.002			
	(−1.31)	(−1.12)	(−1.56)			
TOP^{SZ}	0.159***			−0.018***		
	(47.52)			(−4.07)		
TOP^{VOL}		0.174***			−0.011**	
		(50.53)			(−2.16)	
TOP^{IO}			0.156***			−0.016***
			(46.67)			(−3.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	605,835	605,835	605,835	140,135	140,135	140,135
R^2	0.700	0.709	0.699	0.643	0.643	0.643
Fixed effects	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day

Panel B. Information/Demand for Information						
Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Decision Rank	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*
TOP^{SZ}	−0.019***			−0.024***		
	(−3.86)			(−4.37)		
TOP^{VOL}		−0.019***			−0.022***	
		(−3.97)			(−4.09)	
TOP^{IO}			−0.017***			−0.020***
			(−3.50)			(−3.47)
$TOP^{SZ} \times KMS^{DIST}$				0.027		
				(1.28)		
$TOP^{VOL} \times KMS^{DIST}$					0.012	
					(0.60)	
$TOP^{IO} \times KMS^{DIST}$						0.011
						(0.41)
KMS^{DIST}				0.007	0.009	0.007
				(0.63)	(0.85)	(0.73)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	547,993	547,993	547,993	605,835	605,835	605,835
R^2	0.643	0.643	0.643	0.640	0.640	0.640
Fixed effects	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day	Anlst-day

Panel C. Competition among Analysts			
Dependent variable:	(1)	(2)	(3)
	Decision Rank	*Decision Rank*	*Decision Rank*
TOP^{SZ}	−0.019***		
	(−3.91)		
TOP^{VOL}		−0.019***	
		(−4.04)	
TOP^{IO}			−0.017***
			(−3.62)
TOP^{SZ} × *Earlier Analyst #*	−0.002		
	(−1.25)		
TOP^{VOL} × *Earlier Analyst #*		−0.002	
		(−1.40)	
TOP^{IO} × *Earlier Analyst #*			−0.002
			(−1.39)
Earlier Analyst #	0.005***	0.005***	0.005***
	(3.16)	(3.31)	(3.22)
Controls	Yes	Yes	Yes
# of obs.	605,835	605,835	605,835
R^2	0.640	0.640	0.640
Fixed effects	Anlst-day	Anlst-day	Anlst-day

Columns 4–6 of Panel A omit forecasts issued before 6:00 p.m. Columns 1–3 of Panel B omit more important forecasts issued on the day after the firm's earnings announcement. All variables are defined in Appendix A. t-statistics (in parentheses) are from heteroskedastic-consistent standard errors clustered at the analyst level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

that analysts choose to release forecasts for them more quickly, and 2) on average information arrives evenly throughout the day.[31] To address this explanation, we consider two sets of tests on whether temporary fluctuations in information demand alone (i.e., when their correlations with the analyst's career concerns are low) drive analysts' tendency to prioritize more important firms in decision rank choices.

First, drawing on HLLT, we exclude important forecasts following an earnings announcement to address the possibility that our results are driven by analysts having more information and facing higher demand for forecasts after the earnings announcements of important firms. Specifically, we rerun our tests omitting important forecasts (under any importance proxy) with an earnings announcement on the preceding day. The results, presented in columns 1–3 of Panel B of Table 11, are similar to the results from the full sample (Table 3), suggesting that our findings are unlikely to be driven by the information and demand for information explanation.

Our second set of tests makes use of fluctuations in investors' attention to (and hence information demand for) specific firms identified by Kempf et al. (2017), whose method builds upon the idea that investors pay less attention to and demand less information about firms in an industry when they are distracted by attention-grabbing events in other industries. We interact the shareholder distraction measure of Kempf et al. (2017), denoted by KMS^{DIST}, with the relative importance dummies (TOP^{SZ}, TOP^{VOL}, and TOP^{IO}) and relate these interaction terms to a forecast's decision rank. If information demand is the primary reason for an analyst to prioritize important firms in decision rank choices, one would expect her to prioritize the firm less (more) when investor attention is lower (higher). The results, presented in columns 4–6 of Panel B of Table 11, however, show insignificant coefficients on the interaction terms.

In sum, although greater information/demand for information may coincide with greater firm importance, they are unlikely to be the primary drivers for analysts' choice of low decision rank for important firms.

3. Competition with Other Analysts

Another alternative explanation for our findings is that competition with other analysts may motivate an analyst to issue forecast earlier than others in the day. To verify robustness, we conduct tests taking into account the number of prior forecasts made by other analysts for the firm on the same day. If analysts compete on forecasting speed in the day for forecasts that are more important for them, the sense of urgency should be stronger when a greater number of other analysts have already issued forecasts for the firm in the day. In the tests presented in Panel C of Table 11, the relative importance dummies (TOP^{SZ}, TOP^{VOL}, and TOP^{IO}) are interacted with the number of other analysts who have issued forecasts for the firm earlier in the day, denoted by *Earlier Analyst #*. None of the coefficients on the interaction terms is significant, suggesting that analysts do not alter decision rank choices for more important firms based on the number of prior forecasts issued by other analysts on the same day.

A few additional points are worth noting. First, for lack of exogenous shocks, our tests should be interpreted as descriptive in nature, and we cannot fully rule out all alternative explanations. Our results appear most consistent with analysts' strategic management of decision fatigue. Second, analysts work in highly time-sensitive environments and work on each forecast tends to be closely followed by its issuance. Time lags (if any) between analysts' work and forecast issuance add noise to our tests and therefore bias against finding any evidence for strategic decision rank choices. Third, untabulated results show decision fatigue management persists at the individual analyst level—analysts with higher fatigue management intensity (see Section 4.5) in the past continue to manage decision fatigue more in the future. This persistence highlights the strategic (rather than incidental) nature of analysts' fatigue management behavior.

5. Conclusion

We study analysts' strategic management of decision fatigue. Our analyses show analysts strategically issue forecasts for firms more important for their reputations and careers when they are less decision fatigued, and the tendency to do so is stronger among young analysts, analysts in low-status brokerage houses, and analysts who become fatigued more easily. Analysts with greater fatigue management intensity are more likely to move up to more prestigious brokerage houses. Fatigued analysts herd (self-herd) more (less) for more important forecasts than for other forecasts.

Our paper can help motivate further research on fatigue management. For example, it would be interesting to examine capital market participants' reactions to their decision fatigue setting in, such as deferring the remaining important decisions and switching to less important tasks. Our work also highlights the importance of further research on individuals' cognitive constraint management behavior and its effects on individuals, firms, and society at large. Moreover, our paper can be useful for researchers exploring strategies that agents use in acquiring and understanding financial information in other contexts.

Our evidence suggests that employee relationship management practices targeting decision fatigue, such as those discussed previously for tech firms, hedge funds, and law firms, might benefit more individuals and firms. Research and practices

[31] 1) might be true. More investors may seek to trade larger firms and firms with higher trading volume or institutional ownership, which might be associated with higher information demand. Regarding 2), it seems difficult to verify the distribution of information arrival for analysts because some of it might be unobservable, but it is known that the arrival of some important information is not evenly distributed throughout the day. For example, since 2000, about 95% of firms announce earnings outside regular trading hours (e.g., Lyle et al., 2021).

refining them can be useful. Employees are a highlighted stakeholder group in the corporate stakeholder and ESG literature (e.g., Bae et al., 2011; Edmans, 2011; Chen et al., 2016; Serfling, 2016; Bai et al., 2020); improving their decision-making may create important value for companies.

Appendix A. Variable Definitions

Average Effort	Analyst *i*'s average *Effort* of the year.
Average Relative Error	Analyst *i*'s average *Relative Error* of the year.
Broker Size	The number of analysts employed by the brokerage house that employs analyst *i* following firm *j* in year *t* minus the minimum number of analysts employed by brokerage houses for analysts who follow firm *j* in year *t*, and this difference is then scaled by the range of brokerage house sizes for analysts who follow firm *j* in year *t*.
Broker Size (Unadjusted)	The number of analysts employed by the brokerage house that employs analyst *i* in the year.
$Brokerage^{Low\text{-}status}$	A dummy variable equal to 1 if analyst *i* works for a brokerage house ranked below 10 in the number of analysts employed in the year and 0 otherwise.
BTM^{EV}	A dummy variable equal to 1 if firm *j* is in the bottom quartile of analyst *i*'s portfolio in terms of *Earnings Volatility* at the last quarter-end and 0 otherwise.
BTM^{IA}	A dummy variable equal to 1 if firm *j* is in the bottom quartile of analyst *i*'s portfolio in terms of *Intangible Assets* at the last quarter-end and 0 otherwise.
BTM^{IO}	A dummy variable equal to 1 if firm *j* is in the bottom quartile of analyst *i*'s portfolio in terms of *Institutional Ownership* at the last quarter-end and 0 otherwise.
$BTM^{SEG\#}$	A dummy variable equal to 1 if firm *j* is in the bottom quartile of analyst *i*'s portfolio in terms of *Number of Segments* at the last quarter-end and 0 otherwise.
BTM^{SZ}	A dummy variable equal to 1 if firm *j* is in the bottom quartile of analyst *i*'s portfolio in terms of *Size* at the last quarter-end and 0 otherwise.
BTM^{VOL}	A dummy variable equal to 1 if firm *j* is in the bottom quartile of analyst *i*'s portfolio in terms of *Trading Volume* at the last quarter-end and 0 otherwise.
$D^{High\ Fatigue}$	A dummy variable equal to 1 if the correlation between analyst *i*'s *Relative Error* and *Decision Rank* during the past two years is in the top quartile of the quarter and 0 otherwise.
Decision Rank	The log value of 1 plus the number of prior forecasts analyst *i* has issued in the day before the current forecast.
Earlier Analyst #	The number of other analysts who have issued forecasts for firm *j* earlier in the day.
Earnings Volatility	The standard deviation of the difference between firm *j*'s quarterly earnings and its earnings for the same quarter of the previous year over the past eight quarters, measured at the last quarter-end.
Effort	The number of forecasts issued by analyst *i* who follow firm *j* in year *t* minus the minimum number of forecasts issued by analysts who follow firm *j* in year *t*, and this difference is then scaled by the range of numbers of forecasts issued by analysts who follow firm *j* in year *t*.
Experience	The number of years in analyst *i*'s forecast history.
$Fatigue\ MGMT^{IO}$	A dummy variable equal to 1 if analyst *i* is in the bottom quartile of the quarter of the correlation between an analyst's *Decision Rank* and TOP^{IO} during the past two years and 0 otherwise.
$Fatigue\ MGMT^{SZ}$	A dummy variable equal to 1 if analyst *i* is in the bottom quartile of the quarter of the correlation between an analyst's *Decision Rank* and TOP^{SZ} during the past two years and 0 otherwise.
$Fatigue\ MGMT^{VOL}$	A dummy variable equal to 1 if analyst *i* is in the bottom quartile of the quarter of the correlation between an analyst's *Decision Rank* and TOP^{VOL} during the past two years and 0 otherwise.
Firm Experience	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*, and this difference is then scaled by the range of years of firm-specific experience for analysts who follow firm *j* in year *t*.
Firms Followed	The number of firms followed by analyst *i* following firm *j* in year *t* minus the minimum number of firms followed by analysts who follow firm *j* in year *t*, and this difference is then scaled by the range of numbers of firms followed by analysts who follow firm *j* in year *t*.
Firms Followed (Unadjusted)	The number of firms analyst *i* follows in the year.
Forecast Age	The number of days from analyst *i*'s forecast date in year *t* to the date of the earnings announcement minus the minimum number of days from the forecast date to the date of the earnings announcement among analysts who follow firm *j* in year *t*, and this difference is then 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*.
Herding	A dummy variable equal to 1 if the forecast is between analyst *i*'s own previous forecast and the consensus forecast and 0 otherwise. The consensus forecast is the median among analysts who cover the firm within the same 90 days.
Institutional Ownership	Firm *j*'s share price multiplied by the number of shares held by all institutional investors, measured at the last quarter-end.
Intangible Assets	Firm *j*'s intangible assets deflated by total assets, measured at the last quarter-end.
KMS^{DIST}	The shareholder distraction measure for firm *j*, constructed following the method of Kempf et al. (2017).
Move Up	A dummy variable equal to 1 if analyst *i* moves from a brokerage house ranked below 10 in the number of analysts employed to a top 10 brokerage house within a year and 0 otherwise.
Number of Segments	The number of firm *j*'s business segments, measured at the last quarter-end.
NUMEST	The log value of the number of analysts who cover firm *j* at time *t*.
Reissue	A dummy variable equal to 1 if analyst *i* reissues her own outstanding forecast and 0 otherwise.
Relative Error	Analyst *i*'s forecast error for firm *j* at time *t* subtracting the median forecast error for all analysts who cover firm *j* within the same 90 days, and this difference is standardized across firms by dividing it by the standard deviation of forecast errors across all analysts who cover firm *j* within the same 90 days. Forecast error is the absolute value of actual earnings minus the earnings forecast of analyst *i* for firm *j* at time *t*.
Size	Firm *j*'s share price multiplied by the number of shares outstanding, measured at the last quarter-end.

(*continued*)

Time of Day	A measure taking 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.
TOP^{EV}	A dummy variable equal to 1 if firm *j* is in the top quartile of analyst *i*'s portfolio in terms of *Earnings Volatility* at the last quarter-end and 0 otherwise.
TOP^{IA}	A dummy variable equal to 1 if firm *j* is in the top quartile of analyst *i*'s portfolio in terms of *Intangible Assets* at the last quarter-end and 0 otherwise.
TOP^{IO}	A dummy variable equal to 1 if firm *j* is in the top quartile of analyst *i*'s portfolio in terms of *Institutional Ownership* at the last quarter-end and 0 otherwise.
$TOP^{SEG\#}$	A dummy variable equal to 1 if firm *j* is in the top quartile of analyst *i*'s portfolio in terms of *Number of Segments* at the last quarter-end and 0 otherwise.
TOP^{SZ}	A dummy variable equal to 1 if firm *j* is in the top quartile of analyst *i*'s portfolio in terms of *Size* at the last quarter-end and 0 otherwise.
TOP^{VOL}	A dummy variable equal to 1 if firm *j* is in the top quartile of analyst *i*'s portfolio in terms of *Trading Volume* at the last quarter-end and 0 otherwise.
Trading Volume	Firm *j*'s share price multiplied by the monthly number of shares traded, measured at the last quarter-end.
Vol of the Day	Firm *j*'s share price multiplied by the number of shares traded in the day.
Young	A dummy variable equal to 1 if analyst *i* has less than three years of forecast history and 0 otherwise.

Appendix B. Summary Statistics for Control Variables

Variable	Mean	STD	10th percentile	Median	90th percentile
Time of Day	6.30	3.96	1	6	12
Firm Experience	0.37	0.35	0.00	0.26	1.00
Broker Size	0.41	0.34	0.00	0.33	0.95
Effort	0.57	0.32	0.10	0.57	1.00
Firms Followed	0.43	0.30	0.02	0.38	0.91
Forecast Age	0.47	0.30	0.06	0.46	0.88
NUMEST	2.34	0.75	1.39	2.40	3.26

All variables are defined in Appendix A.

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