Managing Decision Fatigue: Evidence from Analysts' Earnings Forecasts

Yawen Jiao*

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Abstract

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JEL Classification: G24; G41

Keywords: fatigue management, decision fatigue, analysts' earnings forecasts

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* University of California, Riverside, 900 University Ave., Riverside, CA 92521. Email: yawenj@ucr.edu. Phone: 951.827.3653. I thank Mingming Ao, Ben Lourie, Liang Ma, and participants at the 2021 Asian Finance Association (AsianFA) annual meeting and the 2021 Academy of Behavioral Finance & Economics (ABF&E) annual meeting for helpful comments and discussions. All remaining errors are my own.

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Abstract

Prior literature shows decision fatigue (the decline of decision quality after extensive decision-making) reduces analysts' forecast accuracy. We study whether analysts strategically manage 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, and the tendency to do so is further enhanced if the firm is also more difficult/complex to forecast. Analysts with stronger career concerns (e.g., young analysts or analysts in low-status brokerage houses) manage decision fatigue more, and so do analysts who are affected by decision fatigue more (e.g., analysts who become decision fatigued more easily or perform a greater number of forecasts in the day). Finally, analysts experience more favorable career outcomes after strategically managing decision fatigue.

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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 (e.g., Ljungqvist et al., 2007; Mola and Guidolin, 2009; Christophe, Ferri, and Hsieh, 2010; Kirk, 2011; Kothari, So, and Verdi, 2016) and psychological bias (e.g., Ramnath, Rock, and Shane, 2008).[1] An important recent study by Hirshleifer, Levi, Lourie, and Teoh (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. Specifically, 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] We build upon HLLT to examine analysts' fatigue management behavior. We argue that analysts are expected to recognize the information processing costs (e.g., Blankespoor, deHaan, and Marinovic, 2020) and performance implications of decision fatigue and are motivated to proactively manage it, as reflected by their adoption of certain ranking rules in forecasting decisions (detailed below).

We expect analysts to recognize the existence of decision fatigue among themselves and its costs for the following reasons. First, ample anecdotal evidence suggests that professionals understand the existence and effects of decision fatigue. For example, Mark Zuckerberg and Steve Jobs have famously worn only limited styles and colors of clothing to devote greater brainpower to important decisions.[3] During a *Vanity Fair* interview in 2012, President Barack Obama quoted research showing the act of making decisions degrades one's ability to make further decisions and

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[1] Clement (1999) shows analyst characteristics are important for forecasting behavior. See Bradshaw (2011) for a literature review.

[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 same order as 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 (see, e.g., O'Brien and Bhushan, 1990; Altinkilic et al., 2013; Groysberg and Healy, 2013).

[3] It has been reported that Albert Einstein wore several versions of the same grey suit because he did not want to waste brainpower on choosing an outfit (See "Steve Jobs always dressed exactly the same. Here's who else does," by J. Smith, *Forbes*, October 5, 2012).

went on to say, "*I'm trying to pare down decisions. I don't want to make decisions about what I'm eating or wearing. Because I have too many other decisions to make.*"[4] It has been reported that employees at some tech firms, hedge funds, and law firms are encouraged to take breaks or naps to prevent heuristic decision-making and/or improve productivity.[5] Second, analysts get repeated feedback on the accuracy of their forecasts, which is likely to allow them to learn that they are less accurate when more decision fatigued and consequently use strategies to manage decision fatigue.[6] Third, decision fatigue is a well-known cognitive constraint that has been studied extensively. A large body of psychology evidence shows heuristic decision-making is common when individuals are under pressure or fatigued.[7] Baumeister et al. (1998) describe decision fatigue as a result of "ego depletion" – the depletion of one's mental resources required for high-quality decision-making. Many studies provide evidence of decision fatigue and discuss strategies alleviating it (e.g., Levav et al., 2010; Danziger et al., 2011; Baumeister and Tierney, 2012; Augenblick and Nicholson, 2015).

We expect analysts to manage decision fatigue because, as shown by HLLT, it negatively affects the accuracy of earnings forecasts, which is known to affect analysts' reputations and career outcomes. Brokerage houses value analysts who are influential among the buy-side, and their influence is tied to forecasting expertise (Hong and Kubik, 2003; Groysberg et al., 2011). Hong and Kubik (2003) find greater forecast accuracy leads to favorable career outcomes, such as

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[4] See "Obama's way," by M. Lewis, *Vanity Fair*, September 5, 2012.

[5] 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.

[6] We thank an anonymous reviewer for pointing this out.

[7] Heuristic vs. non-heuristic decision-making can be understood using Kahneman's (2011) classification of decisions. In the seminal work of Stanovich and West (2000) where this idea is introduced, decisions are from either System 1 or System 2 thinking – (heuristic) decisions from the former use quick and easy intuitive cognitive processes, whereas (non-heuristic) decisions from the latter use slow and rigorous reasoning processes requiring greater mental resources. Therefore, individuals switch to System 1 thinking after extensive System 2 thinking.

moving up to a high-status brokerage house; Mikhail et al. (1999) find a similar link to analyst turnover. These studies examine average forecast errors; seeking to reduce them can motivate analysts to devote more mental resources to firms that are more difficult/complex to forecast because potential errors for such firms are large. Forecast difficulty/complexity may also make information acquisition more profitable, leading to some career benefits for the analyst (e.g., Barth et al., 2001).[8] On the other hand, recent research by Hartford et al. (2019) highlights forecasting expertise for firms more important to an analyst's reputation and career, showing lower errors for such firms bring greater career benefits, resulting in incentives for analysts to allocate greater mental resources to more important firms.[9]

Analysts' earnings forecasts represent an ideal setting for studying decision fatigue management. First, the earnings forecast setting is characterized by strong decision fatigue that adversely affects analysts' forecast quality (HLLT). Moreover, as noted by HLLT, analysts frequently issue forecasts for multiple firms in the same day and work in highly time-sensitive environments, with work on each forecast likely to be closely followed by its issuance. This makes it possible to identify decision rules analysts adopt in managing decision fatigue, such as the timing of issuing forecasts for more important or more difficult/complex firms.

Examining individual analysts' earnings forecasts from 2002 to 2019, we confirm HLLT's finding on strong 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

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[8] To the extent that information acquisition for more difficult/complex firms may be more profitable and bring career benefits, analysts may consider such firms to be to some degree important. In identifying firms important to analysts' reputations and careers, Hartford 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 and serving institutional investors. We follow the prior literature and choose proxies most closely linked to firms' importance and difficulty/complexity.

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

on the same day.[10] 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 that have been issued in the day, experience stronger decision fatigue in the future as well. The prevalence and persistence of decision fatigue for analysts lay the foundation for our tests – because more mental resources are available earlier in the decision queue (of the day) and decision fatigue hurts the quality of later forecasts, do analysts order forecasts strategically to prioritize certain firms, such as the more important or more difficult/complex ones? Is such behavior, if it exists, beneficial for the analyst's career?

We start by examining whether analysts prioritize the more important firms in their research portfolios by placing them earlier in the forecast queue during the workday. Hartford et al. (2019) note that firms within an analyst's portfolio can differentially affect the analyst's compensation, reputation, and career outcome. Larger firms have more trading and institutional following, making them more important to an analyst's compensation and reputation (Hong and Kubik, 2003). Firms with larger trading volumes are more lucrative sources of commission fees for brokerage houses (Frankel et al., 2006), and analysts' reputations and labor market mobility depend on the ability to generate commission revenue for their brokerage houses (Groysberg et al., 2011). Greater institutional ownership also means more lucrative sources of commission fees for brokerage houses (Frankel et al., 2006); institutional investors' evaluations of sell-side analysts are an important basis for trade allocation (Ljungqvist et al., 2007; Maber et al., 2014). Drawing on Hartford et al. (2019), we use a firm's market capitalization, trading volume, and institutional ownership to measure its importance to a specific analyst. Since a firm's importance to an analyst is determined by not only its own characteristics but also characteristics of other firms in the

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[10] The sample period starts from 2002 because it is the first time for the announcement time of analyst forecasts to be verified (Hoechle et al., 2015); HLLT also use this starting point.

analyst’s portfolio, a firm’s relative importance varies widely across analysts and changes for the same analyst depending on not only changes of its own characteristics but also changes of the characteristics of other firms in her portfolio.

We find strong evidence that analysts devote greater mental resources to more important firms in their portfolios by placing them earlier in the forecast queue during the workday. Specifically, compared to other firms, analysts tend to issue forecasts for firms with greater (e.g., the top quartile in an analyst’s portfolio) market capitalization, trading volume, or institutional ownership earlier in the workday. Interestingly, we also find analysts pay little attention to the timing of forecasts for the remaining (i.e., less important) firms: for example, no difference can be detected in the order of forecast issuance between the least (e.g., the bottom quartile in an analyst’s portfolio) important firms and other less important firms. These results show analysts allocate mental resources in a non-linear manner – the most important firms are allocated the greatest amount, whereas other firms are treated more or less homogeneously. Hartford et al. (2019) find lower forecast errors for more important firms in an analyst’s portfolio; our results suggest that managing decision fatigue can be an important way to improve the quality of these forecasts. By illustrating analysts’ decision fatigue management behavior, our results also suggest that analysts proactively try to counteract the adverse effects of decision fatigue on their reputations and careers.

Turning to a firm’s level of difficulty/complexity for an analyst to forecast, we draw 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, to measure difficulty/complexity using a firm’s earnings volatility, amount of intangible assets, and number of segments. We find that analysts place more difficult/complex forecasts earlier in the forecast queue during the workday as well, but the tendency to do so is weaker than for more important forecasts. Further tests show 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, suggesting that forecast importance is the critical factor analysts consider in decision fatigue management. Forecast difficulty/complexity appears to play a secondary role – although it alone is not a primary driver for the analyst's decision to prioritize a forecast, it can enhance the priority of an already important forecast.

Decision fatigue management can be more beneficial professionally if the analyst has stronger career concerns or if her forecast quality is more affected by decision fatigue, motivating such analysts to manage fatigue more. For example, young analysts may be more concerned about reputations and career outcomes than more experienced analysts (e.g., Hong et al., 2000) and therefore manage decision fatigue more. Analysts in low-status brokerage houses, in seeking to improve reputations and career outcomes, may also have stronger incentives to manage decision fatigue than analysts in high-status brokerage houses.[11] The persistence of decision fatigue for individual analysts discussed above may motivate analysts who become decision fatigued more easily to manage fatigue more. Analysts may be more inclined to work on more important forecasts earlier when performing a greater number of forecasts in the workday because of the concern that late forecasts on such days tend to be of particularly low quality.[12] Consistent with these predictions, we find that young analysts, analysts in low-status brokerage houses, analysts who become decision fatigued more easily, and analysts issuing a greater number of forecasts in the

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[11] Low-status brokerage houses provide considerably less support and resources to analysts than high-status ones (e.g., Clement, 1999; Hong and Kubik, 2003). To the extent that resources from the brokerage house might, to some degree, substitute for an analyst's own mental resources, the lack of resources from the employer can further motivate analysts in low-status brokerage houses to manage decision fatigue.

[12] For example, mental resource depletion may be of lesser concern for more important forecasts to the analyst when she performs only two or three forecasts in the day compared to when she performs more forecasts because a greater number of prior forecasts means a lower quality of the current forecast.

day practice fatigue management more, that is, they are more likely to issue forecasts for more important firms in their portfolios earlier in the workday.

Finally, we examine the career outcome implications of decision fatigue management for analysts. If analysts' fatigue management behavior is driven by career concern considerations, we expect more favorable career outcomes for analysts who manage decision fatigue more strategically. We measure the intensity of an analyst's decision fatigue management by the correlation between a firm's relative importance to the analyst and the position its forecast is in her forecast queue of the day – a greater tendency to issue more important forecasts earlier indicates a greater fatigue management intensity. Consistent with our prediction, we find that analysts with greater fatigue management intensity are more likely to move from a low-status brokerage house to a high-status one. This finding provides a logical explanation for analysts' decision fatigue management behavior that we observe.

This paper builds upon the literature on decision fatigue and analysts' forecasting behavior (e.g., Clement, 1999; Vohs et al., 2008; Hartford, et al., 2019; HLLT) to examine whether and how analysts use strategies to manage decision fatigue and the resulting career outcome implications. Our study contributes to three strands of literature. The first strand is the literature on individuals' management of cognitive constraints, which we expand by providing evidence that information intermediaries affected by decision fatigue strategically manage it. Relatedly, since decision fatigue increases agents' information processing costs, by illustrating information intermediaries' fatigue management behavior, we identify a successful strategy for managing these costs, thereby contributing to the information processing cost literature. Finally, we contribute to the literature on analysts' forecasting behavior and career outcomes by showing management of decision fatigue results in differential treatment of firms by the analyst and affects her career progression.

The remainder of the paper is organized as follows. Section 2 develops hypotheses. Section 3 describes measures, data, and sample. 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] Empirically, decision fatigue has been documented in settings such as choosing consumer goods or college courses, car-buying, and voting (Vohs et al., 2008; Levav et al., 2010; Augenblick and Nicholson, 2015). Compared to these nonprofessional settings, professional settings are characterized by a stronger motivation for individuals to perform well. Thus, professionals may exhibit lower levels of decision fatigue because the pressure to perform may lead them to develop greater mental resources (Muraven and Baumeister, 2000) or superior decision-making systems (Kahneman and Egan, 2011). Nevertheless, prior studies still find strong evidence of decision fatigue among professionals. Danziger et al. (2011) show judges' parole request approval rates drop before their next meal but spike after each meal.[14] HLLT show the number of prior forecasts an analyst has issued in a day is negatively related to the accuracy of her next forecast (on the same day).

The performance implication of decision fatigue raises the question of whether and how individuals manage this important cognitive constraint. Individuals' management of some of the other cognitive constraints has been extensively studied, underscoring the importance of this line of research. For example, there is a literature in the hyperbolic discounting literature debating whether agents can or should engage in commitment strategies in advance of being tempted to

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[13] Kahneman (2011) describes this phenomenon as a result of increased System 1 thinking. Baumeister et al. (1998) posit that mental resources can be temporarily depleted by use, leading to impaired decisions.
[14] See Evans et al. (2016) for a survey of the ego exhaustion literature.

consume too much (e.g., Ashraf et al., 2006; Kaur et al., 2015; Laibson, 2015, 2018; Schilbach, 2019). A number of studies examine individuals' allocation of attention (e.g., Sims 2003; Peng and Xiong, 2006; Hirshleifer et al., 2011; Huang et al., 2019; Li, 2021).

An individual's recognition and understanding of a cognitive constraint can be helpful for her in managing it. For example, the projection bias (e.g., Loewenstein et al., 2003; Conlin et al. 2007; Acland and Levy, 2015; Busse et al., 2015; Augenblicky and Rabin, 2019) 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). This applies to the management of decision fatigue as well – understanding the decline in decision quality (when fatigued) can help motivate the agent to manage fatigue. For this reason, professional settings with repeated performance (i.e., decision-quality) feedback allowing individuals to learn they perform worse when more fatigued, such as the equity analyst setting that we focus on, are especially suitable for studying decision fatigue management. However, to our knowledge, there is a lack of such studies.

Decision fatigue can impose significant information processing costs on individuals. In reviewing the information processing cost literature, Blankespoor et al. (2020) note that some cognitive constraints such as decision fatigue limit agents' cognitive capacities and therefore increase their information processing costs, which can affect information choices, trades, and market outcomes. Analysts are important information intermediaries whose information processing costs affect their own performance and careers as well as their clients' investments. Studying analysts' decision fatigue management not only enhances our understanding of whether and how agents manage this particular type of information processing cost but is also useful for exploring information processing cost strategies in other contexts.

As mentioned before, analysts are likely to learn that they are less accurate when more decision fatigued from the repeated feedback they get on the accuracy of their forecasts, allowing them to recognize the information processing costs and performance implications of decision fatigue. Decision fatigue can affect analysts' careers because it adversely affects forecast quality, which is known to affect analysts' reputations and career outcomes (e.g., Hong and Kubik, 2003; Mikhail et al., 1999; Hartford et al., 2019). Consequently, analysts have strong incentives to manage decision fatigue for career concern considerations.

In our context, the purpose of managing decision fatigue by adopting non-random ranking rules for mental resource allocation for decisions in a day is to improve the quality of certain forecasts (e.g., forecasts for firms more important to the analyst or more difficult/complex to forecast) rather than to prevent the analyst from becoming decision fatigued. Indeed, we still expect forecast quality to decline when the analyst is more fatigued.[15] We argue that because decision fatigue leads to lower quality for forecasts later in the forecast queue of the day, analysts are motivated to manage it by issuing forecasts for certain firms (e.g., more important or more difficult/complex firms) when they are less fatigued, thereby improving the quality of these forecasts and the analyst's reputation and career outcome.

Hartford et al. (2019) posit that firms within an analyst's research portfolio can differentially affect her compensation, reputation, and career outcome; consequently, they can be of different importance to the analyst. They show analysts issue more accurate forecasts for more important firms and interpret this finding as resulting from the greater effort exerted by analysts

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[15] There is a debate on whether decision fatigue stems from complete exhaustion of mental resources or the need to preserve partly depleted resources (e.g., Muraven et al., 2006; Baumeister and Vohs, 2007; Evans et al., 2016). The decision quality of a fatigued individual can improve in the latter case (by using preserved resources if motivated or incentivized) but not in the former case. We do not examine fatigue management tactics that specifically target mitigating declines in decision quality.

for these firms.[16] Since high-quality decision-making involves the consumption of limited mental resources (using System 2) and decision fatigue leads to lower quality for later decisions (HLLT), analysts should choose to work on forecasts for more important firms when more mental resources are available (i.e., before making other decisions). This leads to our first hypothesis:

> H1: The number of prior forecasts an analyst has issued in the day decreases with the relative importance of the firm to her.

Analysts may also attach greater value to better forecast quality for firms that are more difficult or complex to value, leading them to allocate more mental resources to such firms. Some prior studies (e.g., Barth et al., 2001) argue that information acquisition for more difficult/complex firms can generate more profitable trades and therefore is beneficial to analysts. Prioritizing more difficult/complex firms in mental resource allocation can also be a sensible strategy if the average forecast error (without greater weights on more important firms) is key to analysts' reputations and careers – they need to reduce the frequency of large errors that occur more often for more difficult/complex forecasts in this case, which leads them to work on more difficult/complex forecasts when they are less decision fatigued.[17] Thus, we hypothesize:

> H2: The number of prior forecasts an analyst has issued in the day decreases with the relative difficulty/complexity of the firm to her.

In the case that analysts prioritize both more important and more difficult/complex firms in mental resource allocation, the order of priority depends on how much benefit one factor brings in comparison to the other.

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[16] Hartford et al. (2019) do not define the term *effort*. The ego depletion literature argues that a person's mental resources, similar to energy or strength, are limited and are consumed by decision-making. In this context, effort can be interpreted as the consumption of limited resources while using System 2 for decision-making (HLLT). The term "effort" is often used in the literature but rarely defined. Many studies (e.g., HLLT) use the number of forecasts an analyst issues to proxy for the amount of effort she devotes to the focal firm, which we also control for in our analyses.

[17] Several studies of analysts' career outcomes, including Hong and Kubik (2003) and Mikhail et al. (1999), focus on average forecast error.

Since decision fatigue management can be more beneficial professionally if the analyst has stronger career concerns or if her forecast quality is more affected by decision fatigue, such analysts are expected to practice fatigue management more. First, young analysts may be more motivated to manage decision fatigue because they can be more concerned about reputations and career development than more experienced analysts (e.g., Hong et al., 2000). Second, analysts in low-status brokerage houses may be more motivated to manage decision fatigue to improve their reputations and career outcomes than analysts in high-status brokerage houses because low-status brokerage houses offer limited professional resources and career prospects (e.g., Clement, 1999; Hong and Kubik, 2003). Third, heterogeneity in the severity of decision fatigue across individuals (Baumeister and Tierney, 2012; Evans et al., 2016) implies that analysts who become decision fatigued more easily are more (adversely) affected by decision fatigue, and they therefore may be more motivated to manage it for reputations and careers. Fourth, analysts may be more inclined to work on more important forecasts earlier when performing a greater number of forecasts in the workday because mental resource depletion is a stronger concern for more important forecasts on such days, i.e., when decision fatigue leads to particularly low forecast quality for late forecasts, as implied by HLLT. Consequently, we hypothesize:

H3: Analysts who are less experienced in forecasting manage decision fatigue more.

H4: Analysts in brokerage houses of lower status manage decision fatigue more.

H5: Analysts who become decision fatigued more easily manage decision fatigue more.

H6: Analysts manage decision fatigue more when more forecasts are performed in the day.

Previous research (e.g., Mikhail et al., 1999; Hong and Kubik, 2003) shows analysts' forecasting behavior is motivated and/or affected by their reputation and career considerations – an analyst's compensation, reputation, and career prospects depend critically on her perceived forecasting expertise. If analysts strategically manage decision fatigue, that is, they prioritize more important or difficult/complex firms in mental resource allocation in a workday to improve the forecast quality for these firms, for the purpose of improving their career prospects, we expect an analyst to be more likely to experience favorable career outcomes, such as moving from a low-status brokerage house to a high-status one, if she manages decision fatigue more strategically. This leads to our seventh and final hypothesis:

> H7: The likelihood of an analyst moving from a low-status brokerage house to a high-status one increases in the intensity of her decision fatigue management.

3. Data, Sample, and Descriptive Statistics

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. The choice of 2002 as the starting year is driven by the fact that 2002 is the first year for the announcement time of the forecast to be verified (Hoechle, Schaub, and Schmid, 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).

(Insert Table 1 about here)

Our focus is forecasts issued during the workday. To this end, we focus on forecasts performed or at least partially performed during a specific day and released on that day. Specifically, we limit the sample to 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 issued in that day is marked as a

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[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 often continue to work into the night if needed. Moreover, Bradley et al. (2014) show a rise in forecasts issued outside regular working hours over time.

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. HLLT show *Decision Rank* captures decision fatigue well and forecast accuracy decreases with the forecast's decision rank, a result we confirm in Section 4 below. The main variables used in this study are described in Appendix A.

Our tests require proxies for the relative importance of a firm to an analyst. Hartford et al. (2019) argue firms within an analyst's research portfolio can differentially affect the analyst's compensation, reputation, and career outcome. Hong and Kubik (2003) note larger firms have more trading activities and institutional following and therefore greater impacts on an analyst's compensation and reputation. Thus, the first importance proxy we use is a firm's market capitalization (denoted by *Size*$_{j,t}$), computed as the product of the number of shares outstanding

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Earlier cutoffs, including 7:00 p.m., do not qualitatively change the results. Bradley et al. (2014) show an average delay of two hours for timestamps in I/B/E/S – our results are unchanged if the workday starts at 11:00 a.m.

and share price at the last quarter-end. Firm financials and security data used in this study are extracted from COMPUSTAT and CRSP.

The prior literature suggests that trading volume is another important factor determining a firm's importance to an analyst. Firms with large trading volumes are lucrative sources of commission fees for brokerage houses (Frankel, Kothari, and Weber, 2006), and an analyst's reputation and labor market mobility depend on her ability to generate commission revenue for her brokerage house (Groysberg, Healy, and Maber, 2011). The commission revenue for the brokerage house can depend on the number of shares traded as well as the share price (e.g., Keim and Madhavan, 1997, 1998). Consequently, we use a firm's dollar trading volume (denoted by $\textit{Trading Volume}_{j,t}$), computed as the product of share price and the monthly number of shares traded (measured at the last quarter-end), as our second importance proxy.[19]

Our third and last importance proxy is constructed based on the notion that institutional investors are critical to analysts' reputations and career outcomes. Firms with greater institutional ownership are more lucrative sources of commission fees for brokerage houses (Frankel, Kothari, and Weber, 2006); institutional investors' evaluations of sell-side analysts are also an important basis for trade allocation (Ljungqvist et al., 2007; Maber, Groysberg, and Healy, 2014). We compute each firm's institutional ownership, denoted by $\textit{Institutional Ownership}_{j,t}$, 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.[20]

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[19] Using the average daily dollar trading volume in the month or in the last quarter, or average monthly dollar trading volume in the last quarter leads to consistent results. 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). Consistent with its importance to trading cost, dollar trading volume is often used as a liquidity measure (e.g., Fang and Peress, 2009). The results are consistent if share trading volume is used.

[20] Other firm characteristics may also affect a firm's importance to an analyst. For example, Merkley et al. (2017) show the number of competing analysts can affect forecast quality. Hartford et al. (2019) suggest that firm size, trading volume, and institutional ownership are the most critical determinants of a firm's importance to an analyst.

Because a firm's importance to an analyst is determined by not only its own characteristics but also characteristics of other firms in the analyst's portfolio, there are wide variations in a firm's relative importance across analysts: For example, a firm highly important to analyst A may be of much lower importance to analyst B. Furthermore, a firm's importance to an analyst can change depending on not only changes of its own characteristics but also changes of the characteristics of other firms in her portfolio.[21] Similar to Hartford 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, $TOP_{i,j,t}^{SZ}$, the dummy variable constructed based on firm size, is equal to 1 if firm j is in the top 25% of analyst *i*'s portfolio in the quarter in terms of firm size (measured at the last quarter-end), and 0 otherwise. $TOP_{i,j,t}^{VOL}$ and $TOP_{i,j,t}^{IO}$, the dummies indicating important firms based on trading volume and institutional ownership, are constructed in the same manner based on *Trading Volume* and *Institutional Ownership*, respectively.

Next, we compare the decision rank between more important forecasts and other forecasts. 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. Note that these patterns need to be interpreted with caution due to lack of control of confounding factors, such as whether the analyst issues only one forecast in the day and analyst characteristics, which we address in the next section.

Untabulated analyses show using the number of analysts following a firm as an importance proxy leads to results consistent with those reported in the paper.

[21] See Hartford et al. (2019) for a more detailed discussion. In our sample, regardless of which importance proxy we use, if a firm is important to at least one analyst, it is also important for only 34% of the other analysts covering it, and about a quarter of firms important to an analyst in the current quarter become unimportant to her in the next quarter.

We also construct 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.[22] Barth et al. (2001), Ashbaugh-Skaife et al. (2007), Dichev and Tang (2009), Cohen and Lou (2012), and Donelson and Resutek (2015), among others, argue that firms with greater earnings volatility, intangible assets, and number of segments are harder to value and more difficult for analysts to forecast. Similar to the importance proxies, 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 forecasts 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 lack of control of other confounding factors, which we address in the next section.

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[22] Since data on the number of segments are on an annual basis, we apply the value to the twelve 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).

4. Results

4.1. The Existence of Decision Fatigue

For analysts to manage decision fatigue, we first 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:

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

The accuracy of a forecast is measured by its relative forecast error. 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. Specifically, $Relative\ Error_{i,j,t}$ is calculated as analyst i's forecast error for firm j at time t (the absolute value of actual earnings minus the forecast) minus the median forecast error for all analysts who cover firm j within the same 90 days, and the difference is then divided by the standard deviation of forecast errors across all analysts who cover firm j at time t.

The key independent variable in Equation (1) is the forecast's decision rank, $Decision\ Rank_{i,j,t}$, defined in Section 3 and Appendix A. 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. 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 to mitigate the effects of firm characteristics. Finally, following HLLT, we also control for the forecast's time of day. The summary statistics for the main control variables are presented in Appendix B.

(Insert Table 2 about here)

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 are reported in Panel A of Table 2. Consistent with HLLT, this panel illustrates the existence of strong decision fatigue among analysts, as shown by the positive and significant coefficients on *Decision Rank* in both columns. When all control variables are included in the regression, the coefficient on *Decision Rank* is 0.030 and significant at the 1% level, suggesting that on average a one-unit increase in *Decision Rank* leads to a forecast that is 0.03 standard deviations less accurate compared to the consensus for the same analyst and the same day.

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 tend to remain so in the future. The persistent nature of decision fatigue, if verified, highlights the importance of using strategies to manage it, especially for analysts who become fatigued more easily.

To measure the severity of an analyst's past decision fatigue, we first calculate the correlation between her forecast error and decision rank over the past two years, stopping on the day before *t* (i.e., day -730 to day -1). A higher correlation means a faster deterioration of forecast accuracy when decision rank increases, implying a stronger past decision fatigue. The top quartile of this correlation in the quarter are classified as cases of high past decision fatigue, indicated by a dummy variable $D^{High\ Fatigue}$.[23] We add this dummy and an interaction term between it and *Decision Rank* to Equation (1) – the coefficient on the interaction term measures the degree to which an analyst's past decision fatigue persists into the future. 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 the coefficient on *Decision Rank*×$D^{High\ Fatigue}$ is 0.024 and significant at the 5% level, suggesting that decision fatigue is persistent at the individual analyst level. Overall, the results in Table 2 suggest that decision fatigue is prevalent among analysts and persists at the individual analyst level, underscoring the importance for analysts seeking to demonstrate forecasting expertise for certain firms (e.g., more important or difficult/complex firms) for reputation and career purposes to strategically manage decision fatigue.

4.2. Decision Rank of Important Firms

We test H1 by examining whether individual analysts choose to issue forecasts for more important firms when they are less decision fatigued. Our proxies for firms' relative importance to an analyst, as discussed in Section 3, are a firm's market capitalization, trading volume, and institutional ownership. We examine whether the analyst places the more important firms in her portfolio, i.e., firms with greater market capitalization, trading volume, or institutional ownership, earlier in her decision queue of the day to take advantage of the availability of greater mental resources. More specifically, we test H1 by estimating the following regression model:

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[23] We adopt a relatively long time horizon (two years) to improve measurement accuracy (Hong and Kubik, 2003). Cases where correlations cannot be calculated (e.g., due to insufficient observations or lack of variation in *Decision Rank*) are dropped. All relevant results are consistent if using the top quartile of analysts' first or average correlation in the quarter to construct $D^{High\ Fatigue}$.

$$Decision\ Rank_{i,j,t} = \alpha + \beta_1 TOP_{i,j,t} + \beta_2 Controls + \varepsilon_{i,j,t}. \quad (2)$$

In Equation (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} (defined in Section 3 and Appendix A). 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.[24]

(Insert Table 3 about here)

The results are reported in Table 3. The first three columns of this table show, consistent with our hypothesis, analysts have a strong tendency to issue forecasts for more important firms in their portfolios earlier in the forecast queue of the day, i.e., when they are less decision fatigued. For example, the coefficient on TOP^{SZ} in column 1 is -0.020 and statistically 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 2-3) are similar. Since we control for analyst-day fixed effects in these regressions, the results show on a given workday, analysts tend to issue forecasts more important for their reputations and careers when less decision fatigued to improve the quality of these forecasts. Another way to understand the difference is to look at the frequency of more important forecasts among earlier vs. 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 using firm size as the importance proxy, and the fraction declines

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[24] The results (untabulated) 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 Hartford et al. (2019)) leads to even stronger results (untabulated).

monotonically to 25% for forecasts ranked fifth or more; the pattern is also similar for the other two importance proxies.

In the last three columns of Table 3, we add dummy variables indicating the least important firms in an analyst's research portfolio to our regression models in 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 (all measured at the last quarter-end), respectively, among firms in an analyst's research portfolio, and 0 otherwise. None of the coefficients on these dummies is statistically significant in these three columns. While analysts have incentives to prioritize firms more important to them, their incentives for other firms are vaguer in that more accurate forecasts for these firms may bring few benefits for their reputations and career outcomes. Our results are indeed 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 vs. Difficulty/Complexity

We test H2 by examining whether analysts issue forecasts for more difficult/complex firms when they are less decision fatigued. Our proxies for a firm's relative difficulty/complexity for an analyst, as discussed in Section 3, are the firm's earnings volatility, amount of intangible assets, and number of business segments. We replace the relative importance dummy in Equation (2) with dummies constructed to indicate more difficult/complex firms, TOP^{EV}, TOP^{IA}, and $TOP^{SEG\#}$ (based on earnings volatility, intangible assets, and the number of segments, respectively), and re-estimate this equation. The results are reported in Table 4.

(Insert Table 4 about here)

Columns 1-2 of Table 4 show when firms' earnings volatility and intangible assets are used as difficulty/complexity proxies, analysts tend to issue forecasts for more difficult/complex firms in their portfolios when they are less decision fatigued: the coefficients on TOP^{EV} and TOP^{IA} are negative and significant.[25] However, their magnitude is smaller than that of the coefficients on the relative importance dummies in Table 3. The coefficient on the relative difficulty/complexity dummy when firms' number of segments is the focal proxy ($TOP^{SEG\#}$ in column 3) is not significant. When dummies indicating the least difficult/complex firms (i.e., the bottom quartile of the focal difficulty/complexity proxy among firms in an analyst's portfolio) are added to the model in columns 4-6 of Table 4, denoted by BTM^{EV}, BTM^{IA}, and $BTM^{SEG\#}$ for dummies based on firms' earnings volatility, intangible assets, and number of segments, respectively, none of the coefficients on these dummies is significant, while the results related to TOP^{EV}, TOP^{IA}, and $TOP^{SEG\#}$ remain similar. Overall, although variations in results exist across difficulty/complexity proxies, the findings in Table 4 indicate a tendency for analysts to issue more difficult/complex forecasts when they are less decision fatigued.

(Insert Table 5 about here)

Since the results in Tables 3 and 4 indicate a tendency for analysts to prioritize both more important and more difficult/complex firms in their portfolios in decision fatigue management, we further examine the roles played by forecast importance (H1) vs. difficulty/complexity (H2) 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

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[25] The correlations between TOP^{EV} and relative importance dummies (TOP^{SZ}, TOP^{VOL}, and TOP^{IO}) range from 45% to 47%, while those between TOP^{IA} or $TOP^{SEG\#}$ and relative importance dummies are all below 20%. Thus, some firms with high earnings volatility might also be highly important to the analyst. Though interesting, this is beyond the scope of the current paper – we follow the prior literature and use earnings volatility as a complexity measure.

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 either TOP^{SZ}, TOP^{VOL}, or TOP^{IO}, and $TOP^{Complex}$ is either 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. As an example, in column 1, the relative importance dummy is TOP^{SZ} and the relative difficulty/complexity dummy is TOP^{EV} (i.e., $TOP^{Important}=TOP^{SZ}$ and $TOP^{Complex}=TOP^{EV}$). The coefficients in the first three rows of this column represent the degree to which analysts prioritize forecasts for larger firms with higher earnings volatility, larger firms with lower earnings volatility, and smaller firms with higher earnings volatility, respectively, in decision rank choices. The results in Table 5 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, as shown by the insignificant coefficients for them in columns 1-3 and 6-9. When they are prioritized (columns 4-6), tests of differences in coefficients show they are less prioritized than more important and more difficult/complex forecasts in all three columns. In addition, even more important but not more difficult/complex forecasts can be more prioritized than them (in column 5).[26]

Conditional on the forecast being important to the analyst, tests of differences in 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

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

out of the nine regressions in Table 5. In other words, forecast difficulty/complexity can further enhance the priority of an already important forecast. Overall, the findings in Table 5 point to an order of priority in analysts' decision fatigue management: mental resources tend to be allocated based on forecast importance first and then by forecast difficulty/complexity.

The results in Tables 3-5 suggest that although analysts prioritize both more important and more difficult/complex firms in decision rank choices, forecast importance is a far more critical consideration than forecast difficulty/complexity. Thus, the remaining tests in the paper will be based on analysts' decision fatigue management behavior that prioritizes more important forecasts.

4.4. Heterogeneity in Decision Fatigue Management

4.4.1. Young Analysts

To test H3, that is, young analysts manage decision fatigue more than more experienced analysts, we examine whether young analysts are more inclined to issue forecasts earlier in the workday (i.e., when they are less decision fatigued) for firms more important to them. To this end, we construct a dummy variable, denoted by *Young*, that is equal to 1 for analysts who have less than three years (1,095 days) of forecast history, and 0 otherwise.[27] 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. Similar to Panel B of Table 2, we cannot include analyst-day fixed effects for lack of variations in *Young* within an analyst-day, and use analyst, day, and firm fixed effects instead.[28] If young analysts manage decision fatigue more, the negative relation between a forecast's importance and decision rank should be stronger for them.

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[27] This approach is similar to that of Hong et al. (2000). The results are consistent if young analysts are defined as those with less than two or four years of forecast history.

[28] This applies to Tables 8 and 9 as well for similar reasons.

This means the coefficient on the interaction term between *Young* and the relative importance dummy (TOP^{SZ}, TOP^{VOL}, or TOP^{IO}) should be negative.

(Insert Table 6 about here)

The results for the above estimations are reported in Table 6. As can be seen, the coefficients on the interaction terms between *Young* and 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, suggesting that young analysts, being more driven by reputation and career concern considerations than their more experienced counterparts (e.g., Hong et al., 2000), manage decision fatigue more.

4.4.2. Analysts in Low-status Brokerage Houses

To test H4, that is, analysts in low-status brokerage houses manage decision fatigue more than other analysts, we examine whether analysts in low-status brokerage houses are more inclined to issue forecasts for firms more important to them when less decision fatigued. We 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 $Brokerage^{Low\text{-}status}$.[29] 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). If analysts in low-status brokerage houses manage decision fatigue more, the negative relation between a forecast's importance and decision rank should be stronger for

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[29] This approach is similar to that of Hong and Kubik (2003) and Hartford et al. (2019). Defining low-status brokerage houses using alternative cutoffs, such as those ranked below 20 in the number of analysts, leads to consistent results.

them. This means the coefficient on the interaction term between $Brokerage^{Low\text{-}status}$ and the relative importance dummy (TOP^{SZ}, TOP^{VOL}, or TOP^{IO}) should be negative.[30]

(Insert Table 7 about here)

The results are reported in Table 7. Consistent with H4, we find that analysts in low-status brokerage houses manage decision fatigue more than other analysts: 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. Similar patterns can be observed for the other two relative importance proxies in columns 2 and 3 as well. Interestingly, the coefficients on the relative importance dummies themselves are no longer significant once the interaction terms are included, suggesting that analysts in low-status brokerage houses are the main group managing decision fatigue.[31] Overall, the results in Table 7 are consistent with H4, suggesting that the reputation and career concern considerations of analysts in low-status brokerage houses lead them to manage decision fatigue more than other analysts.

4.4.3. Analysts Who Become Decision Fatigued More Easily

To test H5, that is, analysts who become decision fatigued more easily manage decision fatigue more, we examine whether such analysts are more inclined to issue forecasts for firms more important to them when less decision fatigued. Same as in Section 4.1, we compute the correlation between each analyst's forecast error and decision rank over the past two years,

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[30] 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. Note that this mainly affects whether the coefficient on $Brokerage^{Low\text{-}status}$ can be estimated or not.

[31] High-status brokerage houses offer much more resources than low-status ones (Clement, 1999; Hong and Kubik, 2003). The finding that analysts in low-status brokerage houses are the main group managing decision fatigue suggests that resources from the brokerage house may be a substitute for the analyst's mental resources.

stopping on the day before t (i.e., day -730 to day -1), and classify the top quartile of this correlation in the quarter as cases of high past decision fatigue, indicated by the dummy variable $D^{High\ Fatigue}$. Next, 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). A negative (positive) coefficient on the interaction term indicates that analysts who become decision fatigued more easily are more (less) likely to issue more important forecasts when less decision fatigued.

(Insert Table 8 about here)

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 are more likely to issue forecasts for larger firms in their portfolios 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 with the firm-size-based result. To summarize, the results in Table 8 are consistent with H5, suggesting that more severe decision fatigue leads analysts to manage fatigue more.

4.4.4. The Number of Forecasts the Analyst Issues in the Day

To test H6, that is, analysts manage decision fatigue more when performing a greater number of forecasts in the day, we examine whether analysts are more inclined to issue forecasts for firms more important to them when less decision fatigued on such days. Groysberg and Healy (2013) report that it usually takes a few hours for an analyst to prepare a note. To the extent that notes are the main vehicle analysts use to communicate timely information and can contain an analyst's current forecast (Franco and Hope, 2011), this can be helpful for estimating the amount of time the analyst spends in the day on a forecast. Thus, mental resource depletion might be a particularly strong concern for an important forecast performed after two or three other forecasts on the same day. We create a dummy variable, denoted by $D^{More\ Forecasts}$, that is equal to 1 if the analyst issues more than three forecasts in the day, and 0 otherwise.[32] $D^{More\ Forecasts}$ is then interacted with the relative importance dummy, TOP^{SZ}, TOP^{VOL}, or TOP^{IO}, and the interaction term (along with $D^{More\ Forecasts}$ itself) is added to the regression model in Equation (2).[33] A negative (positive) coefficient on the interaction term indicates that analysts are more (less) likely to issue more important forecasts when less decision fatigued on days of issuing more forecasts.

(Insert Table 9 about here)

The results are reported in Table 9. They are consistent with our hypothesis: For example, the coefficient on $TOP^{SZ} \times D^{More\ Forecasts}$ in column 1 is -0.037 and significant at the 1% level, suggesting that analysts are more likely to issue forecasts for larger firms in their portfolios earlier in the forecast queue of the day if they need to perform a greater number of forecasts on that day. The results based on firms' trading volume and institutional ownership (in columns 2 and 3) are consistent with the firm-size-based result. In sum, the results in Table 9 are consistent with H6, suggesting that analysts manage fatigue more when not placing important forecasts early in the forecast queue can cause the quality of these forecasts to be particularly low.

Finally, in untabulated analyses, we find that decision fatigue management has little impact on an analyst's average forecast accuracy. More specifically, we find that 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

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[32] Forecasts on these days account for 38% of forecasts issued on days when the analyst issues more than one forecast (i.e., when she potentially manages decision fatigue).

[33] The results are consistent when directly interacting the number of forecasts the analyst issues in the day with relative importance dummies.

forecasts may become even more important, further motivating analysts with stronger reputation and career concern considerations and/or who are more affected by decision fatigue to prioritize these forecasts in allocating mental resources, as indicated by the results in Tables 6-9.

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 (H7) 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 the intensity of her decision fatigue management. More 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 (i.e., day -730 to day -1) 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.[34]

(Insert Table 10 about here)

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. Specifically, we estimate the following regression model:

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[34] Using analysts' first or average correlation in the quarter to construct $Fatigue\ MGMT^{SZ}$, $Fatigue\ MGMT^{VOL}$, and $Fatigue\ MGMT^{IO}$ leads to consistent and slightly stronger results (untabulated).

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

In this equation, *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* $MGMT^{IO}$. If more strategic decision fatigue management results in more favorable career outcomes for analysts, we expect the coefficient on *Fatigue MGMT* to be positive. Drawing on prior work (e.g., Hartford et al., 2019), 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.[35]

The results are presented in Table 10. 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. Similar patterns can be observed for *Fatigue* $MGMT^{SZ}$ and *Fatigue* $MGMT^{VOL}$ (in columns 1 and 2) as well. Overall, the results in Table 10 suggest that analysts are likely to experience favorable career outcomes after managing decision fatigue strategically, thereby providing a logical explanation for their decision fatigue management behavior that we observe.

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[35] The conditional form of the logit regression estimates the fixed effects model consistently (Chamberlain, 1980). 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). Note that conditional logit regressions omit cases without variations in outcomes. 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.

4.6. Alternative Explanations and Robustness

(Insert Table 11 about here)

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

1. More Time to Generate Trading Volume

One potential alternative explanation is analysts may issue more important forecasts earlier in the day simply to allow more time to generate trading volume for that day. Note that a forecast early in the forecast queue of the day does not necessarily imply ample trading time: for example, an analyst may start to issue forecasts only after 4:00 p.m. (the end of trading hours for many stocks) on a day. If the trading time argument is true, analysts should try to issue more important forecasts at the start of or at least early in the trading hours of the day (so there is more time for trading).

Although decision fatigue management implies that fatigued analysts may postpone some important forecasts to the start of the next day to avoid heuristic decision-making, many important forecasts will still be issued (by non-fatigued analysts) late in time itself in the day (and they can still have low decision ranks). In our sample, the more important forecasts are issued after 2:00 p.m. more than half of the time and after 4:00 p.m. slightly less than 40% of the time under all three importance proxies, i.e., they are not concentrated early in the trading hours of the day.

We also directly test whether analysts time the issuance of important forecasts based on how much trading time is left for the day. To measure the amount of trading time left for a forecast, we divide the trading day (9:30 a.m.-4:00 p.m.) into 13 half-hour time blocks and compute the fraction of remaining blocks for each forecast, denoted by *Trading Time*. This variable is set to 0 for forecasts issued after 4:00 p.m. In columns 1-3 of Table 11, we relate the relative importance dummies (TOP^{SZ}, TOP^{VOL}, and TOP^{IO}) to *Trading Time*. *Time of Day* is omitted in control variables because it is highly correlated (-92%) with *Trading Time* and *Decision Rank* is added. As can be seen, none of the coefficients on the relative importance dummies is significant, suggesting that the amount of time left to generate trading volume for the day is not an important driver for analysts' decision rank choices for more important forecasts.

2. Information and Demand for Information

Another alternative explanation is analysts may issue forecasts for more important firms earlier in the forecast queue of the day because they have more information for and face higher demand for information about these firms. Although we cannot rule this explanation out entirely, it is not obvious why an analyst would choose to perform better-informed and/or more demanded forecasts earlier than other forecasts in the day. To see this, first consider a scenario without decision fatigue or fatigue management such that analysts do not strategically order decisions. In this case, while it seems possible for some analysts to start with better-informed and/or more demanded forecasts in a day, it seems equally possible for other analysts to start with less-informed and/or less demanded forecasts or to order forecasts in other ways (e.g., upon arrival of information), and overall there should be no significant link between a forecast's decision rank and whether it is better-informed and/or more demanded. Now consider the scenario in which the analyst strategically orders decisions to allocate more mental resources to certain forecasts for reputation and career concern considerations. In this case, a forecast's decision rank depends on its value to the analyst rather than whether it is a better-informed and/or more demanded forecast or not, and this scenario therefore does not counter our conclusion on decision fatigue management.

Moreover, our measure of a firm's importance to an analyst is based on its characteristics relative to those of other firms in the analyst's research portfolio. Thus, even without major changes in the firm's characteristics, its importance to the analyst can change with changes in the characteristics of other firms that she covers. In this case, it is unlikely for the analyst to start having more (less) information for or face higher (lower) demand for information about the firm simply because it has become more (less) important to her (without decision fatigue management).

HLLT conduct tests excluding forecasts following an earnings announcement to mitigate the concern that the arrival of more information or higher demand for forecasts after an earnings announcement simultaneously drive higher forecast quality and lower decision rank for such forecasts and therefore their results. We adopt a similar approach to address the possibility that our results are driven by analysts having more information or facing higher demand for forecasts after the earnings announcements of more important firms. Specifically, we rerun our tests omitting important forecasts (under any importance proxy) with an earnings announcement on the preceding day. The results are presented in columns 4-6 of Table 11 – as can be seen, they are similar to the results from the full sample (Table 3), suggesting that our findings are not driven by greater information and/or demand for forecasts after an earnings announcement for more important firms.[36]

3. Competition with Other Analysts

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[36] The results are also similar if dropping important forecasts made in three or five days after an earnings announcement or dropping all forecasts following earnings announcements (untabulated).

Another alternative explanation for our findings is competition with other analysts may motivate an analyst to issue forecast earlier than others in the day. Note that analysts issuing forecasts for firms that more other analysts are forecasting for on the same day earlier in time (than other analysts) does not mean such forecasts will have lower decision rank than other forecasts. For example, suppose analysts do not manage decision fatigue; instead, they perform each forecast upon arrival of new information but do so more quickly for more competitive forecasts. Then these forecasts will be issued earlier in the workday if information for them arrives early and late in the workday if information for them arrives late.

To further verify robustness, we conduct tests taking into account the number of prior forecasts made by other analysts on the same day. If analysts compete on forecasting speed in the day for forecasts that are more important to 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 columns 7-9 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 Anlst #*. *Earlier Anlst #* is also controlled for in the regressions. As can be seen, 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.

Although it is very difficult to rule out all alternative explanations, as discussed above, alternative explanations seem relatively implausible. Two other points related to the robustness of our results are also worth noting. First, analysts work in highly time-sensitive environments (O'Brien and Bhushan, 1990; Altinkilic et al., 2013; Groysberg and Healy, 2013) and work on each forecast tends to be closely followed by its issuance. However, as noted by HLLT, in some cases it is possible for a forecast to have been developed earlier in the day or before the current day when the analyst is not fatigued (or by non-fatigued analyst team members) but gets issued later in the day than other forecasts. Time lags between analysts' work and forecast issuance add noise to our tests and therefore bias against finding any evidence for decision fatigue management.

Second, untabulated results show decision fatigue management persists at the individual analyst level – analysts with higher fatigue management intensity in the past continue to manage decision fatigue more in the future. An individual's persistence in managing a cognitive constraint, for example, through developing a routine counteracting potential damages the constraint can cause, highlights the strategic (rather than incidental) nature of her constraint management behavior and can be important for realizing the benefits of such behavior. Thus, this finding suggests that the decision fatigue management behavior we observe for analysts reflects an important and long-term strategy they adopt to maintain high forecast quality for firms important for their reputations and careers.

5. Conclusion

HLLT find that decision fatigue can reduce analysts' forecast accuracy. Building upon their work, we study whether analysts strategically manage decision fatigue. Firms within an analyst's research portfolio can differentially affect her reputation and career outcome. Our analyses show analysts strategically choose to issue forecasts for firms more important for their reputations and careers when they are less decision fatigued, that is, when the number of prior forecasts the analyst has issued in the day is lower. This tendency is further enhanced if the firm is also more difficult/complex to forecast.

Analysts differ in the extent to which they manage decision fatigue: we observe stronger decision fatigue management among young analysts, analysts in low-status brokerage houses, and analysts who become decision fatigued more easily, as well as when the analyst issues a greater number of forecasts in the day. Consistent with decision fatigue management being driven by career concern considerations, we find that analysts with greater fatigue management intensity are more likely to move up to more prestigious brokerage houses. Several alternative explanations are discussed and addressed. Overall, our findings suggest that analysts understand the information processing costs and performance deterioration associated with decision fatigue and manage fatigue strategically.

Our paper contributes to the literature on individuals' management of cognitive constraints. By illustrating analysts' decision fatigue management behavior and its career progression implications, we highlight the importance of studying individuals' management of behavioral traits and the related effects on individuals, firms, and society at large. More studies on individuals' attempts and efforts to counteract the drivers of heuristic decision-making and their effects can be fruitful. Furthermore, cognitive constraints can increase agents' information processing costs by limiting their cognitive capacities; by identifying a successful strategy that analysts use to manage the information processing costs of decision fatigue, our analyses can be useful to other researchers exploring information processing cost strategies 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 refining them can be useful. For example, firms can implement measures to encourage employees to devote more mental resources to more important decisions, such as scheduling important tasks and meetings early in the workday.

Firms can also implement measures to limit the number of important decisions an employee has to make in a day and/or increase support and monitoring for later decisions when an employee has to make several important decisions in a day. 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.

Finally, an interesting question for researchers and practitioners alike is whether and what incentives can mitigate the performance deterioration driven by decision fatigue. Our findings show analysts' reputation and career concern considerations can lead to strategic decision sequencing, a strategy that manages decision fatigue without mitigating the decline in decision quality for fatigued individuals. More research on whether other decision fatigue management tactics can mitigate this decline, especially in professional settings, can be useful. Prior literature (e.g., Muraven et al., 2006; Baumeister and Vohs, 2007; Evans et al., 2016) debating whether decision fatigue stems from complete exhaustion of or the need to preserve mental resources suggests that incentives and motivations can improve the decision quality of a fatigued individual in the latter case. Thus, studying incentives has the potential to help develop new decision fatigue management strategies, improve employee compensation structures and employee relations, and enhance our understanding of the sources of decision fatigue.

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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	4,636	18,544
5	2,360	11,800
6	1,436	8,616
7	985	6,895
8	724	5,792
9	564	5,076
≥ 10	2,124	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.

Table 2. Decision Fatigue of Financial Analysts

Panel A. Existence of Decision Fatigue

Dependent variable:	(1)	(2)
	Relative Error	*Relative Error*
Decision Rank	0.017** (2.25)	0.030*** (3.26)
Time of Day		-0.004 (-1.59)
Firm Experience		-0.011 (-0.86)
Broker Size		0.008 (0.18)
Effort		0.092*** (5.94)
Firms Followed		0.006 (0.25)
Forecast Age		0.115*** (3.76)
NUMEST		0.051*** (6.34)
Constant	-0.389*** (-150.15)	-0.604*** (-16.29)
# 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×$D^{High\ Fatigue}$	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

$D^{High\ Fatigue}$ is a dummy variable equal to 1 if the correlation between an analyst's relative forecast error and decision rank during the past two years is in the top cross-sectional quartile of the quarter, and 0 otherwise. All other 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 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.

Table 4. Decision Rank of Difficult/Complex Firms

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	*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.

Table 6. Decision Fatigue Management of Young Analysts

Dependent variable:	(1) *Decision Rank*	(2) *Decision Rank*	(3) *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 (0.79)	0.004 (0.71)	0.005 (0.75)
Time of Day	0.014*** (36.26)	0.014*** (36.27)	0.014*** (36.26)
Firm Experience	-0.012*** (-5.24)	-0.012*** (-5.24)	-0.012*** (-5.24)
Broker Size	-0.031*** (-4.38)	-0.031*** (-4.37)	-0.031*** (-4.40)
Effort	-0.031*** (-12.22)	-0.031*** (-12.18)	-0.031*** (-12.22)
Firms Followed	0.050*** (10.89)	0.050*** (10.88)	0.050*** (10.90)
Forecast Age	0.006 (1.45)	0.006 (1.51)	0.006 (1.47)
NUMEST	0.007*** (4.87)	0.007*** (5.21)	0.007*** (4.95)
Constant	0.058*** (9.68)	0.056*** (9.48)	0.058*** (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

Young is a dummy variable equal to 1 if the analyst has less than three years (1,095 days) of forecast history, and 0 otherwise. All other 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 7. Decision Fatigue Management of Analysts in Low-status Brokerage Houses

Dependent variable:	(1) *Decision Rank*	(2) *Decision Rank*	(3) *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

$Brokerage^{Low\text{-}status}$ is a dummy variable equal to 1 if the analyst works for a brokerage house ranked below 10 in the number of analysts employed in the year, and 0 otherwise. All other 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 8. Decision Fatigue Management of Analysts Who Become Fatigued More Easily

Dependent variable:	(1) *Decision Rank*	(2) *Decision Rank*	(3) *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

$D^{High\ Fatigue}$ is a dummy variable equal to 1 if the correlation between an analyst's relative forecast error and decision rank during the past two years is in the top cross-sectional quartile of the quarter, and 0 otherwise. All other 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 9. Decision Fatigue Management on Days When the Analyst Issues More Forecasts

Dependent variable:	(1) *Decision Rank*	(2) *Decision Rank*	(3) *Decision Rank*
$TOP^{SZ} \times D^{More\ Forecasts}$	-0.037*** (-4.41)		
TOP^{SZ}	-0.015*** (-11.55)		
$TOP^{VOL} \times D^{More\ Forecasts}$		-0.038*** (-4.77)	
TOP^{VOL}		-0.015*** (-11.72)	
$TOP^{IO} \times D^{More\ Forecasts}$			-0.034*** (-4.38)
TOP^{IO}			-0.016*** (-12.35)
$D^{More\ Forecasts}$	0.452*** (36.01)	0.453*** (36.26)	0.452*** (36.29)
Time of Day	0.013*** (38.24)	0.013*** (38.25)	0.013*** (38.24)
Firm Experience	-0.009*** (-4.06)	-0.009*** (-4.11)	-0.009*** (-4.07)
Broker Size	-0.018** (-2.39)	-0.018** (-2.38)	-0.018** (-2.40)
Effort	-0.018*** (-7.73)	-0.018*** (-7.67)	-0.018*** (-7.72)
Firms Followed	0.034*** (7.62)	0.034*** (7.61)	0.034*** (7.63)
Forecast Age	0.005 (1.50)	0.005 (1.55)	0.005 (1.52)
NUMEST	0.001 (0.64)	0.001 (0.82)	0.001 (0.69)
Constant	0.003 (0.45)	0.002 (0.31)	0.003 (0.47)
# of obs.	605,835	605,835	605,835
R^2	0.303	0.303	0.303
Fixed Effects	Analyst, Day, Firm	Analyst, Day, Firm	Analyst, Day, Firm

$D^{More\ Forecasts}$ is a dummy variable equal to 1 if the analyst issues more than three forecasts in the day, and 0 otherwise. All other 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 10. Labor Market Outcome of Decision Fatigue Management

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

Move Up is a dummy variable equal to 1 if the analyst 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. *Fatigue MGMT*^{SZ} (*Fatigue MGMT*^{VOL}, *Fatigue MGMT*^{IO}) is a dummy variable equal to 1 if the analyst is in the top cross-sectional quartile of fatigue management intensity related to firm size (trading volume, institutional ownership), and 0 otherwise. Fatigue management intensity is measured by the correlation between the analyst's decision rank and each of the relative importance dummies in the past two years, with a lower correlation indicating a higher intensity. *# of Firms Followed* is the number of firms the analyst follows in the last year. *Size of the Brokerage House* is the number of analysts the analyst's brokerage house employs. *Experience* is the number of years in the analyst's forecast history. *Average Relative Error* is the analyst's average relative forecast error in the last year. *Average Effort* is the analyst's average forecasting effort 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.

Table 11. Alternative Explanations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	*Trading Time*	*Trading Time*	*Trading Time*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*	*Decision Rank*
TOP^{SZ}	0.000			-0.019***			-0.019***		
	(0.37)			(-3.86)			(-3.91)		
TOP^{VOL}		0.001			-0.019***			-0.019***	
		(0.69)			(-3.97)			(-4.04)	
TOP^{IO}			0.001			-0.017***			-0.017***
			(0.68)			(-3.50)			(-3.62)
TOP^{SZ} ×*Earlier Anlst #*							-0.002		
							(-1.25)		
TOP^{VOL} ×*Earlier Anlst #*								-0.002	
								(-1.40)	
TOP^{IO} ×*Earlier Anlst #*									-0.002
									(-1.39)
Earlier Anlst #							0.005***	0.005***	0.005***
							(3.16)	(3.31)	(3.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	605,835	605,835	605,835	547,993	547,993	547,993	605,835	605,835	605,835
R^2	0.892	0.892	0.892	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	Anlst-day	Anlst-day	Anlst-day

Trading Time (in columns 1-3) is the fraction of trading time left for the day. The trading day (9:30 a.m.-4:00 p.m.) is divided into 13 half-hour time blocks and the fraction of remaining blocks is computed for each forecast. *Trading Time* is set to 0 for forecasts issued after 4:00 p.m. Columns 4-6 omit more important forecasts issued on the day after the firm's earnings announcement. *Earlier Anlst #* (in columns 7-9) is the number of other analysts who have issued forecasts for the firm earlier in the day. All other variables are defined in Appendix A. *Time of Day* is excluded in control variables and *Decision Rank* is included in columns 1-3. 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.

Appendix A. Variable Definitions

Broker Size	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*.
BTM^{EV}	A dummy variable equal to 1 if firm *j* is in the bottom 25% of analyst *i*'s portfolio in terms of earnings volatility over the past eight quarters (measured at the last quarter-end), and 0 otherwise.
BTM^{IA}	A dummy variable equal to 1 if firm *j* is in the bottom 25% 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 25% 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 25% of analyst *i*'s portfolio in terms of the number of business segments at the last quarter-end, and 0 otherwise.
BTM^{SZ}	A dummy variable equal to 1 if firm *j* is in the bottom 25% of analyst *i*'s portfolio in terms of firm size at the last quarter-end, and 0 otherwise.
BTM^{VOL}	A dummy variable equal to 1 if firm *j* is in the bottom 25% of analyst *i*'s portfolio in terms of trading volume at the last quarter-end, and 0 otherwise.
Decision Rank	The log value of 1 plus the number of prior forecasts an analyst has issued in the day before the current forecast.
Earnings Volatility	The standard deviation of the difference between quarterly earnings (total assets divided by income before extraordinary items) and earnings for the same quarter of the previous year over the past eight quarters, measured at the prior quarter-end.
Effort	Analyst *i*'s effort in forecasting for firm *j*. It is calculated as 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*, with this difference scaled by the range of numbers of forecasts issued by analysts who follow firm *j* in year *t*.
Firm Experience	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*.
Firms Followed	The number of companies that 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 of numbers of companies followed by analysts who follow firm *j* in year *t*.

Forecast Age	The time period between the forecast date and the earnings announcement. It is calculated as 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*, 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*.
Intangible Assets	Intangible assets of firm *j*, calculated as firm *j*'s intangible assets at the last quarter-end deflated by total assets.
Institutional Ownership	The dollar amount of institutional investment in firm *j*, calculated as firm *j*'s share price at the prior quarter-end multiplied by the number of shares held by all institutional investors.
NUMEST	The log value of the number of analysts who cover firm *j* at time *t*.
Relative Error	Analyst *i*'s relative forecast error. It is calculated as 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. 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*.
Number of Segments	The number of firm *j*'s business segments, measured at the last quarter-end.
Size	The firm's share price at the last quarter-end multiplied by the number of shares outstanding at the last quarter-end.
Trading Volume	Monthly dollar trading volume of firm *j*, measured at the last quarter-end.
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 25% of analyst *i*'s portfolio in terms of earnings volatility over the past eight quarters (measured at the last quarter-end), and 0 otherwise.
TOP^{IA}	A dummy variable equal to 1 if firm *j* is in the top 25% 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 25% 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 25% of analyst *i*'s portfolio in terms of the number of business segments at the last quarter-end, and 0 otherwise.
TOP^{SZ}	A dummy variable equal to 1 if firm *j* is in the top 25% of analyst *i*'s portfolio in terms of firm size at the last quarter-end, and 0 otherwise.
TOP^{VOL}	A dummy variable equal to 1 if firm *j* is in the top 25% of analyst *i*'s portfolio in terms of trading volume at the last quarter-end, 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.