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EFFECTS OF INCREASED REPORTING FREQUENCY ON ACCURACY, DISPERSION AND CONFIDENCE INTERVALS OF NONPROFESSIONAL INVESTORS' EARNINGS PREDICTIONS

By

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ABSTRACT

Effects of Increased Reporting Frequency on the Accuracy, Dispersion and Confidence Intervals of Nonprofessional Investors' Earnings Predictions

By

Terence Jude Pitre

Using a between subjects experiment, I analyze how the frequency of reporting--weekly earnings, as opposed to quarterly earnings--affects the accuracy, dispersion and confidence intervals of earnings predictions by nonprofessional investors. I hypothesize and find that more frequent reporting results in less accurate predictions and larger dispersion of predictions for earnings with a strong seasonal pattern. I also hypothesize, but do not find support, that more frequent reporting significantly increases confidence interval widths among nonprofessional investors. Joint presentation of weekly and quarterly earnings reduces the prediction error generated by weekly reporting alone, but results in an increase in dispersion of predictions when compared to quarterly reporting alone.

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1.0 INTRODUCTION

The optimal frequency of earnings reporting has been much discussed. At one extreme, some European firms report semiannually and have resisted attempts by regulators to require quarterly reporting (Commission 2003). At the other extreme, firms such as Cisco, using in-house technology, have already adopted the concept of real-time internal reporting, and technologies such as XBRL (e**X**tensible **B**usiness **R**eporting **L**anguage) are expected to make more frequent external reporting a more realistic possibility for companies (Watson, McGuire and Cohen, 2000).

More frequent reporting of earnings is often seen as strictly advantageous to investors, while less frequent reporting is disadvantageous. A former Securities & Exchange Commission Chairman, Harvey Pitt, argues that "quarterly filings produce an out-of-date snap shot rather than a real-time window" (Levitt, 2002). Hunton, Wright, and Wright (2003) find that a sample of 215 financial mangers, analysts and investors believe that increasing the reporting frequency of earnings would increase the decision usefulness of financial statements and the quality of earnings.

Little is known about the consequences of more frequent reporting, however. One major benefit of more frequent reporting is increased timeliness of information provision to investors.[1] Offsetting this benefit, however, are potential negative effects on subjective judgment. More frequent evaluations made possible by more frequent reporting of securities returns increase nonprofessional investors' impressions of the uncertainty of the returns (Gneezy and Potters 1997), and more frequent evaluations of

[1] Other benefits have also been claimed for more frequent reporting. Hunton et al. (2003) argue that more frequent reporting of earnings would reduce the ability of managers to engage in earnings management and assist investors to detecting earnings management, because they would have more information to detect trends, patterns and fluctuations in earnings.

earnings could have similar effects. Moreover, larger data sets resulting from more frequent reporting could increase individuals' cognitive load, make pattern recognition more difficult, and make it more likely that nonprofessionals rely on simple heuristics. Human information processing theory (Schroder, Driver and Streufert 1967) suggests that there is an inverted U-shaped relationship between information load and decision quality. Larger data sets could increase a number of judgment errors that have been demonstrated in the psychology literature: failure to detect significant patterns in data series (Klayman 1988), incorrect identification of patterns in a non-random data series (Maines and Hand 1996), or a tendency to see nonexistent patterns in a random series (Andreassen 1987, 1990; Bloomfield et al. 2001; Lim and O'Connor 1996 and O'Connor et al. 1993).

Nonprofessional investors, who are unlikely to use sophisticated statistical models to predict earnings, could be particularly vulnerable to these subjective information-processing effects. As much as 42% of ownership in the top 1,000 U.S. companies is made up of nonprofessional investors (Editorial staff, 2000). As a result, recent research has focused on nonprofessional investors' use of earnings reports to make judgments about future earnings, risk and firm value (Maines and McDaniel 2000; Bartov, Radhakrishnan and Krinsky 2000; Maines and Hand 1996).

In this study, I experimentally examine how reporting frequency of earnings per share affects the accuracy, dispersion and confidence intervals of earnings predictions of nonprofessional investors.

I first test the effects of reporting frequency when participants are randomly assigned to *either* more frequent (weekly) *or* less frequent (quarterly) reporting. The weekly earnings series were constructed so that the weekly earnings provided no statistical advantage or disadvantage in estimating quarterly earnings. Consequently this study only measures judgment effects of more frequent reporting that are not due to differences in information content. Earnings predictions and confidence intervals were elicited from the participants. I also investigate the effects on subjective information processing when weekly *and* quarterly earnings per share data are jointly presented to nonprofessional investors.

The results indicate that more frequent reporting results in less accurate and more dispersed predictions of quarterly earnings when data are not presented jointly. More frequent reporting did not affect the confidence intervals of nonprofessional investors. Joint presentation, however reduces the prediction error generated by more frequent reporting. Finally, I find that the joint presentation of more and less frequent reporting results in an increase in dispersion of predictions when compared to the less frequent reporting condition.

This study contributes to the regulatory debate, both in the United States and abroad, about the usefulness of more frequent reporting of earnings. Regulators and researchers have tended to focus on the benefits of more frequent reporting. This study suggests that there are potential costs to investors' use of frequent reporting and these costs should be incorporated into the debate. This research also contributes to the time series forecasting literature. Previous research has examined the affects of periodicity,[2] trend, seasonality, noise and instability, but has not examined how the frequency of reporting can affect forecasting judgments.[3]

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[2] Periodicity refers to either, yearly, quarterly or monthly time series data.

[3] See Webby and O'Connor (1996) for a review of judgmental and statistical time series literature.

The remainder of this paper is organized as follows: Section 2 contains the literature review and hypotheses development; Section 3 contains the experimental design; Section 4 contains the empirical results and section 5 the conclusions.

2.0 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

"The annual and quarterly reporting regime is not only on its way to becoming less and less useful, it is on its way to becoming a dinosaur, an organism that has outlived its environment."

—ROBERT K. ELLIOTT, JULY 2000
U.S. Senate Banking Committee hearing on adapting a 1930's financial reporting model to the 21st century

The relative costs and benefits of increased reporting frequency have long been of interest both to managers and investors. Although the Securities and Exchange Act of 1934 specifically allowed the SEC to mandate both annual and quarterly financial statements for exchange-listed corporations, the SEC initially mandated only annual reports. In 1945, the SEC required quarterly revenue reporting but not net income, apparently acquiescing to public criticisms that quarterly income information would be unreliable and potentially misleading due to some businesses' seasonal nature. Mandatory quarterly reporting was not officially adopted until 1970 after the 1969 Wheat Commission. [4]

In 1995 a speech by SEC Commissioner Wallman called for consideration of more frequent reporting, stating, "Today, annual and even quarterly reports do not capture and communicate material developments in sufficient time to meet market informational needs" (Wallman 1995). In 2003, a proposal for more frequent reporting of earnings in Europe, motivated by the desire for more transparency, raised concerns that both short-termism and earnings management would increase as a result of more frequent reporting (Evans 2003).

[4] SEC, Securities and Exchange Act of 1934, Release No. 8683, October 15, 1969; and SEC, Securities and Exchange Act of 1934, Release No. 9004, October 28, 1970.

Results in the archival capital markets research literature suggest that nonprofessional investors are less successful at incorporating the time series properties of earnings into their forecast than are professional investors' (Abarbanell and Bernard 1992; Jacob and Lys 1996). Examining nonprofessional investors' judgments has the potential to add convergent validity to the results found in the capital markets literature as well as provide new insights into nonprofessional investors' use of time-series data.

More frequent reporting can affect the subjective judgment of nonprofessional investors, and examining some of the potentially negative effects on judgment is the main purpose of this research. First I summarize and review the literature related to the factors that affect confidence intervals and the accuracy of predictions. I then summarize the processes by which more frequent reporting can affect the judgment of nonprofessional investors. Next, I describe the time series model used to generate earnings data in this study. Finally, using this time series, I motivate my hypotheses about the specific effects of more frequent reporting on uncertainty, accuracy, and dispersions of predictions. These hypotheses begin by addressing the effects of nonprofessionals' using *either* more frequent *or* less frequent reporting. Because technology will make it possible for nonprofessional investors to use either form of reporting alone or both together, I then investigate and report the effects of presenting nonprofessionals with both forms of data.

Section 2.1 *Summary of the Literature Review*

The next 2 sections have described research that is important for understanding the judgments and decision making with time series data. Specifically the literature review addressed two major topics: (1) The effects of time series data on confidence intervals and (2) The effects of time series data on prediction accuracy. The dominant findings from the literature regarding confidence intervals can be summarized as follows (see following subsections for details):

(a) Individuals do not distinguish between positive and negative autocorrelated sequences when establishing their confidence intervals.

(b) Confidence intervals tend to be particularly narrow for flat series but close to that of a statistical model for both upward and downward series.

(c) Confidence intervals increase as the level of seasonality increases and are not found to be affected by the levels of noise in the series.

The dominant findings from the literature regarding prediction accuracy can be summarized as follows:

(a) Individuals are able to distinguish between positively autocorrelated sequences and random sequences, but sometimes see patterns in random data when they do not exist. Furthermore, individuals are not able to distinguish between negatively autocorrelated sequences and random sequences.

(b) Both trend and seasonality affect the ability of individuals to make accurate predictions.

(c) Prediction accuracy is enhanced when judgmental forecasts are combined with other judgmental forecasts or other quantitatively derived forecasts, extra causal information is used, a directive search strategy is employed and when decision aids are used to generate forecasts. Prediction accuracy is best when the forecast period is short.

(d) Prediction accuracy is worsened by the presence of discontinuities in the data series and also by the presence of incentives to bias the forecast (i.e., professional relationships with the firm being analyzed.)

(e) Individual forecasts are typically dampened slightly. That is, individuals tend to underforecast upward-trend series and overforecast down-trend series.

Section 2.2 *Factors that affect confidence intervals*

My research theorizes that more frequent reporting will affect the uncertainty (confidence intervals) of predictions generated from time series data. In this section, I review the key literature related to factors that affect confidence intervals.

Eggleton (1976, 1982) investigated and found that the width of the confidence intervals was affected by the nature of the statistical variation in the data. Results indicated that individuals did not distinguish between positively autorcorrelated, negatively autorcorrelated and random sequences when establishing confidence intervals. That is, individuals ignored the nature of the underlying sequence when setting their credible intervals.

Lawrence and Makridakis (1989) investigated the effects of the type of trend (upwards, flat or downwards), randomness and presentation on forecast accuracy and confidence intervals. They found that confidence intervals were particularly narrowed (overconfident) for the flat series, but were closer to confidence intervals generated by the statistical model for upward and downward trends.

Similarly, O'Connor and Lawrence (1989) used 33 real-life time series and found that confidence intervals surrounding predictions were excessively narrow, indicating overconfidence, but that these intervals increased over time with feedback. Because previous studies (Lichtenstein and Fischohoff, 1978) found that task difficulty in forecasting affected the width of confidence intervals, O'Connor and Lawrence (1989) also examined the effects of task difficulty (as defined by forecast error).[5] Specifically, they found that for medium to high difficulty tasks, confidence intervals were too narrow, indicating overconfidence. However, confidence intervals in the low task difficulty group were larger and significantly different from the medium and high difficulty task.[6]

In a subsequent study, O'Connor and Lawrence (1992) found a positive relationship between the level of seasonality and confidence intervals suggesting that as the level of seasonality increases, the size of the confidence interval will also increase. Surprisingly, the authors did not find support for an influence of noise on the width of confidence intervals. They also found that as the level of trend[7] increased, the width of the confidence interval increased.

Section 2.3 *<u>Factors That Affect Prediction Accuracy</u>*

My research also theorizes that more frequent reporting will affect the accuracy of predictions generated by nonprofessional investors. In this section I review key literature related to both the ability of individuals to make accurate predictions using time series data and the factors (i.e., seasonality and trend) that have been demonstrated to affect the accuracy of predictions.

Eggleton (1976, 1982) argued that the accuracy of individuals' estimates of future observations and their confidence intervals are a function of their ability to (1) correctly

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[5] Lichtenstein and Fischohoff, (1978) found that when the forecasting task is easy, underconfidence abounds, and when forecasting is difficult, overconfidence is prevalent.

[6] Analysis of the histograms of the magnitudes of the differences between the judgmental and statistical methods reveals that the judgmental confidence intervals for the low difficulty task was different from that of other groups, but the result did not occur for the high group.

[7] Trend was defined as the slope of the regression line fitting some interval of the deseasonalized data.

assess the nature of the underlying relationship in the data, (2) cognitively represent the characteristics of that relationship and (3) generate bias-free predictions from that cognitive representation. Based on ANOVA results and a post experiment questionnaire, Eggleton found that individuals were able to distinguish between positively autocorrelated (trend) sequences and random sequences, but were unable to distinguish between negatively autocorrelated (alternating) sequences and random sequences. Individuals' prediction performance can be summarized as follows: (A) for random sequences, predictions were accurate close to the mean of the sequence; (B) for positive autocorrelated (trend) sequences, they were below the statistical estimate, but above the mean of the sequence; and (C) for negatively autocorrelated (alternating) sequences, they were above the statistical estimate and close to the mean of the sequence. Eggleton concluded that the differences between individuals' predictions and that of the statistical model were due to the nature of the error and the characteristics of the time series. He also found that participants were more likely to read a systematic pattern into random series when the variability in the series increased.

Research from accounting literature examined the ability of individuals (investors) to recognize patterns. Maines and Hand (1996) examined whether individuals' earnings forecasts correctly reflect the positive autocorrelation in seasonal quarterly earnings and the negative fourth-order moving average term documented by Brown and Rozeff (1979). Their results indicated that participants' forecasts reflected the autoregressive and fourth-order moving average, but underweighted them. Additionally, the authors found that participants incorrectly identified an autoregressive component in data from a seasonal random walk series, illustrating that people sometimes see patterns where they do not exist.

Research has found that factors such as seasonality and trends also affect prediction accuracy. Lawrence, Edmundson and O'Connor (1985) documented the ability of individuals to generate accurate forecasts using time series data that contained a seasonal component. In a subsequent study Lawrence, Edmundson and O'Connor (1986) found that combining judgmental forecasts with either other judgmental forecasts or with quantitatively derived forecasts can improve the accuracy of the forecast. They documented the greatest benefit of combining forecasts arises when the forecast period is short and the task is easier.[8]

Lawrence and Makridakis (1989) investigated the effects of the type of trend (upwards, flat or downwards), randomness and presentation on forecast accuracy. They found that the deviations between participants' subjective forecasts and those generated by a regression model were influenced by the type of trend in time series data and that estimates were not influenced by noise (consistent with Mosteller et al. 1981). Similar to the results found in Eggleton (1976; 1982), individual forecasts tended to be dampened slightly. That is, individuals tended to underforecast upward-trend series and overforecast down-trend series.

Increasing the frequency of reporting has been shown to affect the saliency of the patterns or trends. Using a model of judgmental extrapolation based on exponential smoothing, Andreassen and Kraus (1990) presented support for the hypothesis that

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[8] In order to segment the ease of forecasting, the time series were stratified into three groups according to Mean Absolute Percentage Error (MAPE): those 25% with the highest MAPE were classified as more difficult, those 25% with the lowest average MAPE were considered less difficult and the remaining 50% that fell in between.

judgmental extrapolation forecasts vary as a function of salience of changes. They demonstrated that focusing participants' attention on price changes as opposed to price levels led to more accurate assessments of the trend.[9] They also demonstrated that changing the statistical properties (i.e., sample size) in the stock prices series so that the changes were more likely to be salient affected judgments.[10] They find that strong signals relative to noise levels affected the ability of participants to detect trends. This result was in direct contrast to the results of Mosteller et al. (1981) and Lawrence and Makridakis (1989). One major difference and possible explanation was that participants in the Andreassen and Kraus study were only given the latest value in the series and the change from the previous value, while participants in the other two studies were given graphs of series.

An implicit argument in the previous studies is that people expect past trends to continue. Using 38,000 forecasts of stock price data, De Bondt (1993), showed that non-experts expected continuation of past trends in prices. That is, they were optimistic in bull markets and pessimistic in bear markets. Interestingly, participants hedged their forecast. If they expected positive changes, participants' subjective probability distribution of future prices was left skewed, while the probability distribution was right skewed for negative changes.

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[9] Participants were required to choose one stock for 120 trials after the current price and the price change from the previous trial. Determination of the trend can be inferred from the pattern of trading. To measure the pattern of trading, authors computed a correlation between the price on a given trial and the number of shares the subject held at the end of the trial. The correlations were converted to z scores and referred to as a tracking measure. Detection of trend would result in participants holding more shares when average prices changes were positive and the price is relatively high and holding less shares when the average share changes have been negative and the price is relatively low.

[10] .Increasing sample size (holding the mean and variance constant) should increase the salience of the changes leading to positive shifts in the tracking measure.

Prior research has also studied how factors other than trend, saliency, and seasonality affect forecast accuracy. Lim and O'Connor (1996) found that people could distinguish between low causal cues and high causal cues. Low causal cues were those with low validity and high causal cues where those with high validity. They also found that participants could incorporate the extra-model causal information to make up for what the statistical time-series model lacked. In this study, extra-model causal information consisted of information beyond that of a statistical forecast. The authors found that people could use the extra-model information to generate forecasts that were superior to statistical models.

Whitecottton (1996) examined the effects of experience and use of a decision aid on forecast accuracy. The probability prediction[11] for a sample of 16 firms was used as a decision aid. Undergraduates, MBA students and professional analysts were used to proxy for three different levels of experience. She found that both experience and use of a decision aid had a positive effect on the accuracy as measured by the mean probability score. Interestingly, there was no significant difference in accuracy between MBA students and financial analysts. This was consistent with the contention of Yates, McDaniel and Brown (1991) that MBA students may be considered "semi-experts."

The type of search strategy an individual utilizes can affect the prediction accuracy as well. Hunton and McEwen (1997)[12] utilized an experiment to investigate the search strategy of financial analysts. They found that analysts generated more accurate forecasts

[11] The statistical probability that future earnings would be more than expected based on a sample of 385 firms including the sample firms used in the task. Participants were informed that the decision aid would be correct 75% of the time.

[12] It is important to note that the subjects in the Hunton and McEwen experiment had qualitative information in addition to the time series data. However, there findings are still likely to apply to pure time-series forecasting.

when they used a directive search strategy and less accurate forecast when they used a sequential forecast. Additionally, the authors examined if certain motivational incentives can influence analysts' forecast accuracy and lead to more optimistic estimates of earnings. Analysts were assigned to either a control group (no relationship with firm for which forecast is being made), firm following group (the analyst will be following the company in the future) or firm underwriting group (the brokerage firm will be underwriting a stock issue for the company. They found that analysts in both the firm following group and the firm underwriting group had higher forecast error than those in the control group.

Finally, increasing frequency of reporting will result in a larger number of breaks or discontinuities or changes in direction within a given time period. O'Connor, Remus and Griggs (1993) analyzed subjective predictions when using time series data that contained five discontinuities and two levels of randomness. They find that people performed significantly worse than statistical models in the presence of discontinuities. They also found that people responded to random fluctuations in data as if they were valid signals. It should be noted the participants were informed that the nature of the study was to investigate people's ability to recognize changes in time series data. This may have caused participants to be hypervigilant towards the changes.

The above review has identified factors that have been documented to affect the accuracy of predictions and confidence intervals surrounding those predictions. Some of the factors listed above that affect predictions will be controlled for in my study, while some will be varied independently of reporting frequency, and still some will explain the expected effects of more frequent reporting. The following sections will more specifically discuss and theorize how more frequent reporting will affect the accuracy of predictions and confidence intervals surrounding those predictions.

Section 2.4 <u>*Processing Effects of More Frequent Reporting*</u>

Analysis of the time series behavior of earnings for U.S. firms suggests that at least some seasonality is present in nearly every major industry (Palepu, Bernard and Healy, 1996). Seasonality is a pattern that could be more difficult for nonprofessional investors to detect, estimate, and use appropriately when more frequent reporting increases the volume of data available to them. I therefore use earnings data with a strong seasonal pattern, generated from the Foster model, which is commonly taught in financial statement analysis classes as a relatively simple and effective earnings-prediction model that captures these seasonal effects.[13]

$$E[Q_t] = Q_{t-4} + \delta + \varphi [Q_{t-1} - Q_{t-5}]$$

Where: Q_t = *Quarterly earnings in current period.*
Q_{t-1} = *Quarterly earnings one quarter prior*
Q_{t-4} = *Quarterly earnings 4 quarters prior* (1)
Q_{t-5} = *Quarterly earnings 5 quarters prior*
δ = *the long run trend in year-to-year quarterly earnings increases.*
φ = *year to year change in quarterly earnings experienced most recently* $[Q_{t-1} - Q_{t-5}]$.

Maines and Hand (1996) show that nonprofessionals can subjectively estimate and use seasonal and autoregressive components in quarterly earnings series. I therefore expect that nonprofessionals will be able to use quarterly earnings data based on the Foster model to predict future quarterly earnings, although it may be more difficult for them to do so when they have more frequently reported earnings.

[13] While the Brown and Rozeff model is believed to more accurately model earnings behavior, it requires iterative statistical techniques for parameter estimates that non-professional investors are not likely to be able to reproduce without the aid of sophisticated statistical software. On the other hand, the Foster model, which is a special case of the Brown and Rozeff model, can be easily estimated with a simple linear regression, which is more likely to be approximated by subjective judgment.

Section 2.5 *Model of Earnings Behavior*

More frequent reporting will result in larger data set for a given time period, which I expect will make pattern identification more difficult and lead to less accurate predictions. Larger data sets can increase the cognitive load imposed on nonprofessionals, thus increasing the use of simple heuristics such as representativeness and recency. More frequent reporting also affects perceived volatility of earnings. More frequent reporting can have the same effect as more frequent reviews of a portfolio, which have been linked to perceived higher risk because people judge risk by the frequency of negative returns (Gneezy and Potters, 1997). More frequently reported earnings are likely to have more reversals (switches between positive and negative earnings changes) within a given time period and so are likely to have more frequent negative changes which may have the same effect on risk perceptions as frequency of negative returns. Because nonprofessional investors have been shown to erroneously use the frequency of past earnings reversals as an indication of the likelihood of future reversals (Bloomfield and Hales 2002) a large number of reversals could lead to a perception of higher uncertainty.

Section 2.6 *Effects of Increased Frequency on Uncertainty*

Previous experimental studies have documented that investors' risk judgments increase with the variability of earnings (Maines and McDaniel 2000; Lipe 1998). More frequent earnings reporting can increase subjective uncertainty or perceived variability of earnings in nonprofessional investors, because they will not aggregate data temporally to the relevant time horizon and will use short-term fluctuations in earnings as a basis for judging uncertainty at a longer time horizon. If, as is often the case, nonprofessionals are buy-and-hold investors rather than frequent traders, their time horizons are relatively long, but if more frequent reporting is available to them, they may focus on shorter-term fluctuations, like investors who review their retirement portfolio quarterly or annually although their time horizon is twenty years (Benartzi and Thaler 1995). In the experiment, I ask individuals for predictions and confidence intervals for *quarterly* earnings, regardless of whether they have weekly or quarterly earnings reports. The relevant time horizon in this case is quarterly, and the volatility of quarterly earnings is more relevant to individuals' judgment than the volatility of weekly earnings. It is likely, however, that at least some individuals will not spontaneously aggregate weekly data into quarterly data, and will use weekly fluctuations to judge the uncertainty of quarterly earnings.

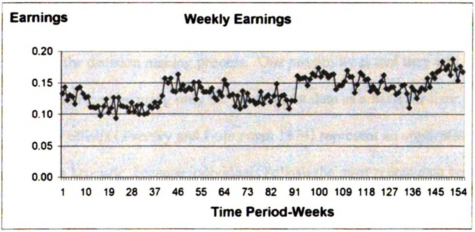
Using asset-return data, Gneezy and Potters (1997) demonstrate that more frequent evaluation of investments increases their perceived risk because people judge risk by the frequency of negative returns. (More frequent negative returns can be observed over a given period if people examine monthly returns, for example, rather than annual returns.) Similarly, Thaler, Tversky, Kahneman and Schwartz (1997) demonstrated that as the frequency of evaluation increases, investors chose to invest less in risky assets. Like returns, more frequently reported earnings will include more fluctuations (switches between negative and positive changes), and thus more negative earnings changes. The frequency of such changes could lead nonprofessional investors to perceive more frequently reported earnings as more volatile, leading to higher uncertainty about the future earnings. More frequent reporting is likely to have both frequent negative changes and more fluctuations in the data, which will lead nonprofessional investors to state wider confidence intervals around their quarterly earnings predictions.

Hypothesis 1: *Nonprofessional investors who receive more frequent earnings reports will exhibit wider confidence intervals around their quarterly earnings predictions than those who receive less frequent earnings reports.*

Section 2.7 *Effects of Increased Frequency on Accuracy*

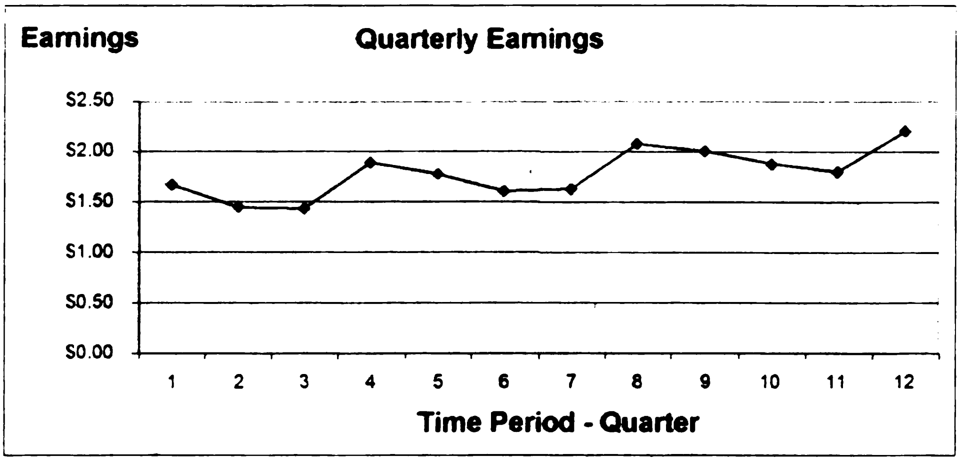
More frequent reporting can also affect the accuracy of nonprofessional investors' earnings predictions because of the increase in noise associated with more temporally disaggregated data. This can easily be illustrated visually. Consider, for example, the identical seasonal data presented in both weekly and quarterly format (Figure 1 and 2 respectively).

Figure 1 More Frequent Reporting-Seasonal Data



The weekly fluctuations in the data in Figure 1 can obscure the 4th quarter earnings increase that appears more clearly in Figure 2. If the seasonal (or other) pattern is obscured by weekly fluctuations, less accurate predictions can be expected.

Figure 2 Less Frequent Reporting-Seasonal Data



More frequent reporting (i.e., Figure 1) could also lead to large cognitive demands, resulting in the use of heuristics and predictable biases. Research suggests that information overload can occur with as little as seven plus or minus two items (Miller 1956). When nonprofessional investors process large quantities of data, they are not likely to focus consistently on the most relevant subset of the data (Bouwman 1982). Faced with high levels of information load, nonprofessional investors are likely to resort to heuristics to aid in the decision making process. One possibility is that they will reduce their information load by using only the most recent data as a basis for their predictions. Recency effects (Tversky and Kahneman 1974) represent an application of the representativeness heuristic, because individuals believe the most recent data best represents current characteristics of the earnings series. Hunton and McEwen (1997) find that recency can partially explain less accurate earnings forecasts by analysts.

The effects of recency will be different in each reporting frequency condition, however. Consider, for example, a scenario in which nonprofessional investors are given three years of reported earnings. Assume that nonprofessional investors can only cognitively process 12 data points. In the case of quarterly reporting, 12 data points provide three years of data, which gives nonprofessional investors an opportunity to identify and use the seasonal properties of earnings. In the weekly reporting condition, in contrast, the last 12 data points are insufficient as a basis for estimating seasonal properties of earnings. Consequently, recency effects will likely lead to less accurate predictions in the more frequent reporting condition than in the less frequent reporting condition.

> **Hypothesis 2:** *Nonprofessional investors' absolute prediction error will be greater in the more frequent reporting condition than in the less frequent reporting condition.*

Section 2.8 *Effects of Increased Frequency on Dispersions*

Dispersion of expectations about earnings is important in practice because it can lead to increased trading volume. The error predicted in H2 includes both dispersion and bias; H3 focuses on dispersion alone.

Earnings predictions are likely to be dispersed even when individuals' subjective predictions are based on the same data, because ability to manage increased cognitive load and strategies for doing so are likely to differ across individual nonprofessional investors. Individual differences are expected to have larger effects with more frequent reporting. When reporting is less frequent, fewer reports are generated over a given period of time. Most nonprofessional investors can then use a large enough data set (e.g. 12 quarterly reports over three years) to identify important patterns in the data, resulting in low dispersion of predictions. Three years of weekly data, however, include 156 earnings reports. Many nonprofessional investors will not use all of this data, and they will differ with respect to how much of it they use and what conclusions they draw from it.

People often tend to see trends or streaks in truly random data series (Andreassen, 1987, 1990; Bloomfield et al., 2001; Lim and O'Connor, 1996 and O'Connor et al., 1993). Nonprofessional investors have also been demonstrated to have difficulty in identifying patterns in nonrandom data series. For example, Maines and Hand (1996) find that nonprofessional investors incorrectly detected autoregressive components in quarterly seasonal random walk data. The larger number of data points and more frequent changes of direction in the more frequent reporting condition offer opportunities for individuals to see a greater variety of nonexistent patterns, as well as obscuring actual patterns in the data. Because of individual differences in cognitive processing, more dispersion in predictions is likely to result in the more frequent reporting condition.

> **Hypothesis 3:** Variance *of predictions will be larger in the more frequent reporting condition than in the less frequent reporting condition.*

Section 2.9 *Joint Effects of More and Less Frequent Reporting*

Hypotheses 1-3 predict that if nonprofessional investors examine only weekly earnings reports, their predictions will be less accurate, more uncertain and more dispersed than if they examine only quarterly reports. The question remains whether or not these judgment effects will persist when both weekly and quarterly reports are presented jointly. Online earnings reporting could offer investors their choice of reporting intervals (so that investors could choose to see only quarterly or only weekly earnings), or it could always present quarterly and weekly earnings together. In order to investigate the effects of these alternatives, I examine how joint presentation of weekly and quarterly reporting affects investor judgments.

Some prior research suggests reasons for believing that predictions based on joint presentation of weekly and quarterly earnings reports will be similar to predictions based on quarterly reports only. Other research, however, suggests reasons for believing that predictions based on joint presentation will be similar to predictions based on weekly reports only. It is not clear ex ante which of these sets of reasons will dominate in individuals' earnings-prediction behavior. I therefore summarize arguments on both sides and state research questions rather than directional hypotheses about the effects of joint presentation.

Nonprofessional investors' judgments in the joint reporting condition could resemble those of the less frequent reporting condition. Because of the large cognitive load presented by more frequently reported data, nonprofessional investors could voluntarily choose to ignore the larger data set and focus on the smaller data set when it appears to provide sufficient information for the earnings prediction task. In this case, nonprofessional investors in the joint reporting condition are likely to make judgments very similar to those in the less frequent condition.

On the other hand, judgments in the joint reporting condition could resemble those in the more frequent reporting condition. If nonprofessional investors believe that more frequent reporting is more informative and useful (Hunton et al. 2003), they will focus on it more strongly when making their judgments. Another possibility is that nonprofessional investors will have difficulty ignoring the more frequent earnings reports even if they focus primarily on the less frequent earnings reports (i.e., the curse of knowledge, Camerer 1989; Fischhoff 1977).

These arguments lead to the following set of research questions:

R1: *How will the provision of both more and less frequent earnings reports affect the confidence intervals around nonprofessional investors' quarterly earnings prediction, compared to the provision of either more or less frequent reports?*

R2: *How will the provision of both more and less frequent earnings reports affect the accuracy of quarterly earnings prediction of nonprofessional investors, compared to the provision of either more or less frequent reports?*

R3: *How will the provision of both more and less frequent earnings reports affect the dispersion around quarterly earnings prediction of nonprofessional investors, compared to the provision of either more or less frequent reports?*

3.0 RESEARCH DESIGN

Section 3.1 *Experimental Design and Dependent Variables*

The research design is a 2 (reporting frequency: quarterly or weekly) x 2 (earnings series created with two different random error draws) x 2 (direction of change: increases or decreases between actual earnings in the last reported period and expected earnings as predicted by the Foster model in the forecasted period) x 2 (tasks: in the first task, participants predicted quarterly earnings based on *either* quarterly or weekly data and in the second task, participants made decisions using *both* quarterly and weekly data). See Section 3.2 for an explanation of the random draw and direction variables. The first three variables are manipulated between subjects and the last variable is manipulated within subjects.

The dependent variables examined were 1) uncertainty, as measured by participants' confidence intervals, 2) accuracy of predictions of next quarter's earnings, measured by the absolute difference between the prediction and earnings forecasted by the model, and 3) dispersion of predictions, measured by the variance of participants' predictions.

Hypotheses 1-3 were tested by comparing judgment performance in the first task across frequency conditions. Research questions 1-3 were tested by comparing judgment performance in both tasks.

Section 3.2 *Independent Variables and Data Creation*

Participants' task was to predict quarterly earnings per share based on historical data. In the more frequent reporting condition, participants received weekly historical earnings per share data. In the less frequent reporting condition, participants received quarterly historical earnings per share data.

The Foster model was used to create earnings data with strong fourth quarter seasonality. Initial quarterly earnings were those of Compaq Computer Company for the year 1993, which a widely used textbook employs as an example of earnings that can be predicted with the Foster model (Palepu, Bernard & Healy, 1996). The expected earnings in the subsequent quarter were generated using Compaq's values for the phi (φ) parameter of .49 and the delta (δ) parameter of .09. In order to create weekly data the first 5 quarters generated from the initial process were selected. Each quarter was divided into 13 equal weeks and the original Foster model was adapted to create weekly data, resulting in the following equation:

$$E\,[W_i] = W_{it-4} + \delta + \varphi\,[W_{it-1} - W_{it-5}] \qquad (2)$$

Where: W_i = *Weekly earnings in current week.*
W_{it-1} = *The earnings in week i one quarter prior*
W_{it-4} = *The earnings in week i 4 quarters prior*
W_{it-5}= *The earnings in week i 5 quarters prior*
δ_w = *Year-to-year weekly earnings increases.*
φ_w = *A fraction of the year to year increase in weekly earnings experienced most recently*$[W_{it-1} - W_{it-5}]$

The Foster model adjusted for weekly calculations was then used to generate weekly earnings per share. A small amount of random error N(0, .01) was added to each weekly data point. The final weekly instrument consisted of 156 weeks presented in 13 week quarters. Quarterly data and instruments were created by summing each 13 weeks of data and presenting only quarterly totals.

The first earnings series was created as described above. The second was created by using a different 156-week period from data generated by the Foster model[14] with a different direction of change between the last reported quarter's earnings and the earnings predicted for the next quarter by the Foster model. In one series (forecast-period

[14] The parameters were identical in both data series.

increase), the next quarter's expected earnings were higher than the last reported quarter's earnings, while in the other series (forecasted period decrease), they were lower. Two versions of the increase series and two versions of the decrease series were created by adding two different sets of random error draws from the same N (0, .01) distribution to the weekly expected earnings generated from the weekly Foster model. The direction of prediction and the random error draw were manipulated to make sure that results were not unique to a single data series.

In the first and second task, individuals received earnings series that differed with respect to both direction and random error draw. For example, if they received an increase series with random error draw 1 in the first task, they received a decrease series with random error draw 2 in the second task. If they had received identical or very similar data sets in both tasks, demand effects might have driven them to make identical judgments in the two tasks.

The weekly data used in this experiment were constructed to ensure that real information content was constant across weekly and quarterly conditions and any difference between experimental conditions was due to differences in subjective processing. If actual weekly data had been less informative than quarterly data, this would add to the negative effects of weekly reporting. If, on the other hand, weekly data had been more informative than quarterly data, this would presumably offset, but not eliminate the negative effects shown in this study.[15]

[15] As a result of holding real information content constant, the weekly data have visible jumps at quarter end, potentially making the underlying quarterly seasonal pattern salient. However, this aspect of the data would bias against finding the predicted results.

Section 3.3 *<u>Experimental Materials and Procedures</u>*

Participants received a packet along with an instruction sheet. Each packet contained a consent form, case materials, and a post questionnaire. The case materials informed participants that the most recent quarter end for the target firm was December 31, 2003. Participants were asked to predict earnings for the first quarter of 2004. In the more frequent reporting condition, a special caution was added to ensure that subjects gave a quarterly and not a weekly prediction. Participants received earnings data in both tabular and graph form. In addition, a disk containing the tabular data was also given to the participants to aid in calculations if they desired. Experimental sessions took place in a computer lab, and all participants had access to spreadsheets. After making their predictions, participants were asked to generate the equivalent of 90% confidence intervals. See Appendix 1 for examples of instruments.

At the conclusion of the prediction task, a post-experiment questionnaire was administered. Questions were included on participants' (1) stock market experience, (2) finance and statistical knowledge, (3) risk attitude, (4) judgments about the perceived volatility of the data, and (5) reports of the level of importance and influence of recent time periods in their judgments. The latter allowed for the identification of recency effects. Questions targeted at assessing the participants' comprehension of range and variance was also included in the debriefing questionnaire. Finally participants were required to describe in detail how they generated their prediction. Participants earned class credit for participation in the experiment. In addition, participants with predictions within $.04 of the actual earnings per share earned an additional $10.

Section 3.4 *Participants*

Participants in the experiment were 84 first and second year MBA students as well as masters students from a large midwestern university. Results from 12 participants were excluded because they generated weekly earnings predictions instead of quarterly earnings predictions, resulting in 72 participants being used in the analysis. Participants were recruited from a MBA financial statement analysis classes. 22 (31%) of the participants indicated they had investing experience, which ranged from 1 month to 84 months. The average number of finance courses taken was three and the average number of statistics courses taken by participants was two. The experiment was administered in two sessions over the course of one day (morning and evening).

4.0 RESULTS: HYPOTHESES 1-3: EFFECTS OF MORE FREQUENT REPORTING

Hypotheses 1-3 test the between-subjects effects of more frequent reporting on uncertainty, absolute prediction error and dispersion of predictions. Therefore, only the data from the first task are used for analysis. Table 1 reports the correlations between reporting frequency, accuracy, and confidence intervals for the first task. The correlation between absolute prediction error and reporting frequency was marginally significant ($r = .21, p < .08$). In addition, there was a significant correlation between absolute prediction error and uncertainty ($r = .27, p < .02$). ANOVAs used to test H1and H2 include additional independent variables to test for the effects of different data sets participants received (random error draw and direction of prediction) as well as reporting frequency. I also tested for effects of prior investing experience and/or effects of session and include these variables in the reported ANOVAs when they had significant main or interaction effects ($p < .05$).

Analysis of H1

H1 predicts that uncertainty, measured by the width of the confidence interval, will be greater in the more frequent reporting condition. Cell means and standard deviations are shown in Table 2. Task two will be analyzed in section 4.1. The mean confidence intervals are .57 for both the less and more frequent reporting conditions. Results of the ANOVA for task one,[16] shown in Table 3, indicate no main effect of frequency ($F = .09$, $p < .76$). There were no other main effects or interactions present (all F's < 2.44, all p's > .13).

[16] Investing experience (in months) is used as a covariate.

Analysis of H2

H2 states that nonprofessional investors' earnings predictions will be less accurate, as measured by their absolute prediction errors, in the more frequent reporting condition than in the less frequent reporting condition. Table 4 reports the cell means and standard deviations. As expected, the absolute prediction error was larger (mean = .14) with more frequent reporting than with less frequent reporting (mean = .09). This difference was significant, as shown by the main effect of frequency in the ANOVA reported in Table 5. ($F = 4.04$, $p < .05$). There were also main effects of direction ($F = 15.83$, $p < .00$) and random error draw ($F = 22.16$, $p < .00$). However, there were no interactions involving these factors and frequency (all F's < 1.54, p's > .22). These results provide support for H2.

Although the main effects of experience and the frequency * experience interaction are not significant, I compared the prediction errors of the more and less experienced participants to allay concerns that the effect of frequency might be largely dependent on less experienced participants. Qualitatively, the analysis reveals that the difference between the frequency groups was greater for those participants who indicated they had investing experience. Here, experience is treated as a categorical, 0 – 1 variable where 1 represents previous investing experience and 0 otherwise. Previously, it was presented as a continuous variable (# of months). For experienced participants the mean was .08 in the less frequent reporting condition and .14 in the more frequent condition. For inexperienced participants the mean was .10 in the less frequent reporting condition and .14 in the more frequent condition. Thus the results cannot be explained a lack of investing experience

Absolute prediction error can include both random error and systematic error (signed error or bias). Mean signed error was .01 and not significantly different from zero ($t = .77, p < .44$). Analysis of signed prediction errors (Appendix –1 Table 10) revealed a main effect of random error draw ($F = 14.75, p < .00$) but no main effect of frequency ($F = .00, p < .95$) and no significant interaction between frequency and random error draw ($F = .38, p < .54$). Bias is significantly greater than from 0 ($t = 4.82, p < .00$) with one random error draw, though not significantly less than 0 with the other ($t = -.87, p < .39$).

Analysis of H3

H3 states that the dispersion of predictions will be larger in the more frequent reporting condition than in the less frequent reporting condition. Table 6 reports the variances of participants' earnings forecasts and results of the F-test for equal variances. The variance for the more frequent reporting condition was 0.016 and the variance for the less frequent reporting condition was 0.006 ($F = 2.56, p <.00$). These results support H3.

Discussion of Results from H1-3

Results of H1 were inconsistent with the theoretical discussion in section 2. The participants were not affected by the frequency of fluctuations (switches between negative and positive changes) brought on by more frequent reporting. One possible explanation for the lack of support of H1 is that participants' perception of volatility was not affected by more frequent reporting. In the more frequent reporting group, participants had a perceived volatility rating of 4.05 while those in the less frequent reporting condition had a rating of 4.54 ($F = 1.25, p < .27$). The results are inconsistent with the findings of Gneezy and Potters (1997) that suggest perceived risk should increase with more frequent reporting. Another possible explanation of the lack of support for H1 could be that participants did not perceive the task to be more difficult using more frequently reported data. In the more frequent reporting condition participants had a perceived difficulty rating of 3.73, while those in the less frequent reporting had a rating of 3.33 ($F = .57$, $p < .45$). If participants had perceived the volatility to be greater and perceived the task to be more difficult in the more frequent reporting condition, they would have generated wider confidence intervals indicating more uncertainty.

Results of a correlation analysis (Appendix 1 - Table 11) also confirm the results obtained from hypothesis testing. While there was a significant positive correlation between perceived difficulty and perceived volatility (.24, $p < .04$), there were no significant correlations between absolute prediction error and perceived volatility (-.04, $p < .72$) or absolute prediction error and perceived difficulty (-.04, $p < .73$). Similarly, there were no significant correlations between confidence intervals and perceived volatility (.07, $p < .54$) or confidence intervals and perceived difficulty (.03, $p < .82$).

Consistent with my predictions, more frequent reporting resulted in larger prediction errors and greater dispersion of predictions. Theoretical discussion in section 2 suggests that more frequent reporting could obscure the underlying data pattern leading to greater prediction errors and dispersion in predictions. Results of the post-experiment questionnaire revealed that an equal proportion (80%) of participants across both frequency reporting groups expected earnings per share data to be seasonal. However, 28 of 31 (90%) participants correctly identified the data pattern as seasonal in the less frequent reporting condition, while 31 of 41 (75%) of participants correctly identified the data pattern as seasonal in the more frequent reporting condition. Thus it appears, qualitatively, that more frequent reporting obscured the underlying data pattern making it more difficult for investors to make accurate predictions.

Although participants were less accurate in the more frequent reporting condition, they were not less confident, as measured by their confidence intervals. These results are counterintuitive since one would expect more uncertainty (wider confidence intervals) when earnings predictions were less accurate. One possible explanation could be the lack of difference in perceived difficulty across conditions.

Although I did not hypothesize effects of direction of prediction, ANOVAs revealed main effects of direction of prediction on prediction accuracy. Specifically, I find that when the prediction period is positive (negative), the mean of the less frequent reporting condition was .13 (.06) and the mean of the more frequent reporting condition was .18 (.10). This qualitatively suggests that participants performed worse when the prediction period was positive.

ANOVA results also indicated main effects of random error. For random error draw one (random error draw two), the mean of the less frequent reporting group was .14 (.05) and the mean for the more frequent reporting group was .19 (.08). This data qualitatively suggests that participants performed worse with one random error draw than with the other. These results are surprising since statistically, both random error draws had the same statistical properties. Future research should investigate these phenomena further.

Section 4.1 *Results: Research Questions 1-3: Effects of Joint Presentation*

Tests of the three research questions use the dependent variables from both tasks (i.e., prediction with single frequency and joint frequency reporting). Table 2 reports cell means and standard deviations of confidence intervals on the first and second tasks.

Table 7 shows the results of the repeated measure ANOVA with confidence interval as the dependent variable. Between-subject variables are the same as in previous ANOVAs. There were no significant main effect or interaction affects of session and experience, which are therefore omitted from the analysis shown in Table 7. Although the cell means in Table 2 show that adding weekly reporting (cell 2) to quarterly reporting (cell 1) appears to increase uncertainty, and adding quarterly (cell 4) to weekly reporting (cell 3) appears to decrease uncertainty, these effects are not significant, as shown by the task* frequency interaction ($F = .69$, $p < .41$). Additional analysis reveals no effects of reporting frequency on uncertainty.[17]

Tables 4 and 8 report the cell means and results of the repeated-measures ANOVA with prediction error as the dependent variable. Analysis revealed no main or interaction effects of session, thus session was omitted from the analysis. Examination of the task*frequency interaction in Table 8 allows me to determine if providing both quarterly and weekly data reduces or eliminates the differences in prediction errors shown in the first task. There is significantly less difference in accuracy between the two frequency groups in the second task than the first: (cell 1- cell 3) > (cell 2 – cell 4), ($F = 4.76$, $p < .03$). Simple effects tests reveal that the addition of weekly data to quarterly data (cell 2 – cell 1) increases the prediction error, but the increase is not significant ($F = 1.15$, $p < .30$). The addition of quarterly data to weekly data (cell 4 – cell 3) significantly reduces prediction error ($F = 4.51$, $p < .04$).

[17]Table 7 also shows a task*direction interaction and a task by random error interaction. Additional analysis (Appendix 1 – Tables 12-16 reveals that there was a marginally significant difference between task 1 (.60) and task 2 (.54) when the expected change in direction from the current period to the forecasted period was positive ($F = 2.92$, $p < .10$). Alternatively when the expected change in direction from the current period to the forecasted period was negative, the difference between task 1 (.53) and task 2 (.57) was not significant ($F = .90$, $p < .35$). Furthermore, for one random error draw, the difference between task 1 (.61) and task 2 (.44) was significant ($F = 15.84$, $p < .00$). For the other random draw, difference between task 1 (.52) and task 2 (.66) was significant ($F = 6.64$, $p < .01$).

I also compare the means of cell 1 and cell 4, to investigate whether adding quarterly to weekly data (cell 4) results in predictions that are as accurate as those based on quarterly data only (cell 1). The absolute mean prediction error was in cell 4 was .11, while the absolute mean prediction error in cell 1 was .09, (F = 1.30, p < .26). Finally, I examine means of cell 2 and cell 4 to investigate if participants weighted the most recently received data more heavily than the first data set. The mean absolute prediction error for those that received less frequent reporting data in the first task was .17 while the mean for those that received more frequent reporting data in the first task was .11. This difference was not significant (F = 1.22, p < .27).[18]

I also conducted a similar analysis (Appendix 1 - Tables 17-19) using signed prediction error as the dependent variable. There was no significant interaction between task and frequency of reporting (F = .09, p < .76). Additional analysis shows that the mean signed prediction error in the first task for those who received the less frequent reporting data was -.004 while for these participants in the second task (joint presentation), it was -.02 (F = .11, p < .74). The mean signed prediction error for those who received more frequent reporting data in the first task was .03 while for those in the second task (joint presentation), it was .01 (F = .78, p < .38).

[18] Table 8 reports a significant task * direction interaction. Additional analysis (Appendix 1 – Tables 20-29) reveals that there was a significant difference between task 1 (.16) and task 2 (.10) when the expected change in direction from the current period to the forecasted period was positive (F = 7.83, p < .01). Alternatively when the expected change in direction from the current period to the forecasted period was negative, the difference between task 1 (.08) and task 2 (.17) was significant (F = 12.38, p < .00). Table 8 also reports a significant task * error interaction. For one random error draw, the difference between task 1 (.17) and task 2 (.08) was significant (F = 18.29, p < .00). For the other random draw, difference between task 1 (.07) and task 2 (.19) was significant (F =17.25, p < .00). Finally, Table 8 reports a significant task*experience interaction. There is no significant difference between task 1 (.11) and task 2 (.13) when participants indicated they had prior investing experience (F = 1.89, p < .19). When participants indicated they had prior investing experience, the difference between task 1 (.12) and task 2 (.14) was not significant at the conventional level (F = 2.69, p < .11).

Analysis of the final dependent variable, prediction dispersion (Table 6), reveals that the addition of weekly data (cell 2) to quarterly data (cell 1) results in a significant increase in prediction dispersion ($F = 4.73$, $p < .00$). Referring to Table 6 it can be seen that the addition of quarterly data (cell 4) to weekly data (cell 3) results in a decrease in dispersion ($F = 1.87$, $p < .03$). I also compare cell 2 and cell 4. The variance for those participants that received less frequent reporting in the first task was .17 while the mean for those participants that received more frequent reporting in the first task was .09 ($F = 3.27$, $p < .00$). These results can suggest that participants weighted the most recently received data set more heavily. Comparison of means from cell 1 and cell 4 show that nonprofessional investors that use both weekly and quarterly data generate predictions with dispersion equal to those that only receive quarterly data ($F = 1.37$, $p < .19$).

5.0 CONCLUSIONS

This study investigates the effects of more frequent reporting on nonprofessional investors' earnings predictions. As hypothesized, I find that more frequent reporting of earnings per share results in less accurate and more dispersed predictions of quarterly earnings per share. I hypothesize but do not find that more frequent reporting significantly increases confidence interval widths among nonprofessional investors.

I find that the addition of weekly data to quarterly data increases prediction error by 89%, but the effect is not significant. Conversely, I find that the addition of quarterly data to weekly data significantly reduces prediction errors. Nonprofessional investors who receive both weekly and quarterly data generate predictions of quarterly earnings comparable to those who receive only quarterly data. The addition of weekly data to quarterly significantly increases dispersion of predictions. Additionally, I find that the addition of quarterly data to weekly data results in a significant decrease in the dispersion of prediction. I find no such effects on confidence intervals.

The results of this study have several implications for regulators to consider regarding the adoption of increased frequency of reporting. Should more frequent reporting be adopted, it appears that joint presentation could mitigate some but not all of the negative effects created by sole dependence on more frequently reported information.

This study is subject to several limitations. First, I limited the amount of information participants received. Typically, when investors are evaluating the financial performance of a firm, more information is available and the information environment is more complex. However, reducing the complexity allows me to make stronger inferences about the effects of more frequent reporting. Second, this experiment uses MBA students as surrogates for nonprofessional investors. It is likely that they have less investment experience than many nonprofessional investors and therefore their actions may not accurately reflect the opinions of actual investors. Finally, this experiment uses earnings data that contains fourth quarter seasonality which may not be applicable to all firms. Future research should investigate the effects of more frequent reporting when earnings data has different properties (i.e. random walk).

Table 1-Descriptive Data Correlations

	Frequency	*Absolute Prediction Error*	*Confidence Interval*
Frequency	1	-	-
Absolute Prediction Error	.21**	1	-
Confidence Interval	.00	.27*	1

*Correlation is significant at the 0.05 level (2-tailed)
*Correlation is significant at the 0.10 level (2-tailed)

Frequency = The frequency which the historical data is presented (high or low).
Accuracy = The absolute prediction error (difference between earnings predicted by the participant and that generated by the Foster model.
Confidence interval = The uncertainty surrounding the prediction generated by participants, measured by the difference between the upper and lower bounds.

Table 2-Cell Means and Standard Deviations for Confidence Intervals in Task 1 and 2

Reporting Frequency in 1st Task	Task 1 Single Frequency	Task 2 Joint Frequency
Less Frequent	Cell 1	Cell 2
Mean	.57	.61
(s.d.)	(.49)	(.44)
[n]	[31]	[31]
More Frequent	Cell 3	Cell 4
Mean	.57	.52
(s.d.)	(.32)	(.32)
[n]	[41]	[41]

Planned Pairwise Comparisons for Research Question 1
Dependent Variable = Confidence intervals

Less frequent reporting in task 1 = Less frequent reporting in task 2.
Cell 2 = Cell 1, ($F = .06$, $p < .81$)

More frequent reporting in task 1 = More frequent reporting in task 2.
Cell 3 = Cell 4, ($F = .87$, $p < .36$)

Less frequent reporting = both more and less frequent reporting.
Cell 1 = Cell 4, ($F = .25$, $p < .62$)

Less frequent reporting received 1st = more frequent reporting received 1st.
Cell 2 = Cell 4, ($F = 1.27$, $p < .26$)

Table 3-Analysis of Effects of Reporting Frequency on Confidence Intervals

Between-Subjects ANOVA with Confidence Interval as DV

Source	df	F-value	p-value
Corrected Model	25	1.51	.11
Intercept	1	33.04	.00
Frequency	1	.09	.76
Direction	1	.67	.42
Session	1	.02	.90
Rand.Error	1	1.02	.32
TimeInvesting	1	.37	.55
Frequency*Direction	1	1.69	.20
Frequency*Session	1	.00	.98
Frequency*Rand.Error	1	.16	.70
Frequency*TimeInvesting	1	.42	.52
Direction*Session	1	1.79	.19
Directin*Error	1	.68	.41
Direction*TimeInvesting	1	.35	.56
Session*Error	1	.22	.64
Session*TimeInvesting	1	2.44	.13
Rand.Error*TimeInvesting	1	.75	.39
Frequency*Direction*Session	1	.81	.38
Frequency*Direction*Rand.Error	1	.11	.75
Frequency*Direction*TimeInvesting	1	.40	.53
Frequency*Session*Rand.Error	1	.12	.73
Frequency*Session*TimeInvesting	1	2.11	.15
Frequency*Error*TimeInvesting	1	.01	.93
Direction*Session*Rand.Error	1	1.09	.30
Direction*Session*TimeInvesting	1	2.08	.16
Direction*Rand.Error*TimeInvesting	1	.04	.85
Session*Rand.Error*TimeInvesting	1	1.42	.24
Error	46		
Total	72		
Corrected Total	71		

Frequency = frequency conditions between subjects; Direction = direction of change-upward or downward-between earnings in the last reported period and the forecasted period; Session = morning or evening session of experiment; Rand.Error = two different random error draws used to create earnings series: TimeInvesting = Amount of investing experience in months.

Table 4-Cell means and Standard Deviations for
Absolute Prediction Errors in Task 1 and Task 2

Reporting Frequency in 1st Task	**Task 1 Single Frequency**	**Task 2 Joint Frequency**
Less Frequent	Cell 1	Cell 2
Mean	.09	.17
(s.d.)	(.08)	(.17)
[n]	[31]	[31]
More Frequent	Cell 3	Cell 4
Mean	.14	.11
(s.d.)	(.13)	(.09)
[n]	[41]	[41]

Planned Pairwise Comparisons For Research Question 2
Dependent Variable = Absolute Prediction Errors

Less frequent reporting in task 1 = both more and less frequent reporting in task 2.
Cell 2 = Cell 1, ($F = 1.15$, $p < .30$)

More frequent reporting in task 1 = both more and less frequent reporting in task 2.
Cell 3 = Cell 4, ($F = 4.51$, $p < .04$)

Less frequent reporting = both more and less frequent reporting.
Cell 1 = Cell 4, ($F = 1.30$, $p < .26$)

Both more and less frequent reporting received 2nd task = both more and less frequent reporting received 2nd task. Cell 2 = Cell 4 ($F = 1.22$, $p < .27$)

Table 5-Analysis of Effects of Reporting Frequency
on Absolute Prediction Error

Between-Subjects ANOVA with Absolute Prediction Error as DV

Source	df	F-value	p-value
Corrected Model	15	3.11	.00
Intercept	1	100.89	.00
Frequency	1	4.04	.05
Direction	1	15.83	.00
Experience	1	1.99	.16
Rand.Error	1	25.16	.00
Frequency*Direction	1	.20	.66
Frequency*Experience	1	1.02	.32
Direction*Experience	1	1.04	.31
Frequency*Direction*Experience	1	.37	.54
Frequency*Rand.Error	1	1.54	.22
Direction*Rand.Error	1	3.95	.05
Frequency*Direction*Rand.Error	1	.00	.97
Experience*Rand.Error	1	2.68	.11
Frequency*Experience*Rand.Error	1	1.98	.16
Direction*Experience*Rand.Error	1	.83	.37
Frequency*Direction*Experience*Rand.Error	1	.56	.46
Error	56		
Total	72		
Corrected Total	71		

Descriptions same as Table 3

Table 6-Cell Variances for Task 1 and Task 2

Reporting Frequency in 1st Task	Task 1 Single Frequency	Task 2 Joint Frequency
Less Frequent	Cell 1	Cell 2
Variance [n]	.006 [31]	.028 [31]
More Frequent	Cell 3	Cell 4
Variance [n]	.016 [41]	.008 [41]

Result of Between-Subjects Hypotheses Test-H3

Less Frequent reporting in task 1 < More frequent reporting in task 2
($F = 2.56$, $p < .00$)

Planned Pairwise Comparisons For of Research Question 3
Dependent Variable = Variance

Less frequent reporting in task 1 > Less frequent reporting in task 2.
Cell 2 = Cell 1, ($F = 4.73$, $p < .00$)

More frequent reporting in task 1 > More frequent reporting in task 2.
Cell 3 = Cell 4, ($F = 1.87$, $p < .03$)

Less frequent reporting = both more and less frequent reporting.
Cell 1 = Cell 4, ($F= 1.37$, $p < .19$)

Less frequent reporting received 1st = more frequent reporting received 1st.
Cell 2 = Cell 4 ($F = 3.27$, $p < .00$)

Table 7-Analysis of Effects of Frequency on Confidence Intervals

Panel A
Repeated Measure ANOVA with Confidence Interval as DV in Task 1 and Task 2

Source	df	F-value	p-value
Intercept	1	169.16	.00
Frequency	1	.357	.55
Direction	1	.273	.60
Rand.Error	1	.431	.51
Frequency*Direction	1	2.05	.16
Frequency*Rand.Error	1	.243	.62
Direction*Rand.Error	1	1.27	.26
Frequency*Direction*Rand.Error	1	.01	.92
Task	1	.28	.60
Task*Frequency	1	.69	.41
Task*Direction	1	3.45	.04
Task*Rand. Error	1	19.53	.00
Task*Frequency*Direction	1	3.32	.07
Task*Frequency*Rand.Error	1	1.32	.26
Task*Direction*Error	1	.62	.43
Task*Frequency*Direction*Rand.Error	1	.08	.78
Error	64		

Task = 2 tasks consisting of 2 predictions (confidence intervals).
Freq = Frequency conditions between subjects: more and less reporting in forecasting tasks; Direction = Direction of change-upward or downward-between earnings in the last reported period and the forecasted period; Rand-Error = Two different random error draws used to create earnings series.

Table 8-Analysis of Effects of Frequency on Absolute Prediction Error*

Panel A

Repeated Measure ANOVA with Absolute Prediction Error in Task 1 and Task 2

Source	df	F-value	p-value
Interecept	1	143.36	.00
Frequency	1	.16	.69
Direction	1	.53	.47
Error	1	.56	.46
Experience	1	.04	.84
Frequency*Direction	1	.33	.57
Frequency*Rand.Error	1	3.58	.06
Direction*Rand.Error	1	3.98	.06
Frequency*Direction*Rand.Error	1	.44	.51
Frequency*Experience	1	1.83	.18
Direction*Experience	1	.02	.88
Frequency*Direction*Experience	1	.34	.56
Rand.Error*Experience	1	3.49	.07
Frequency*Rand.Error*Experience	1	.49	.49
Direction*Rand.Error*Experience	1	.16	.69
Freqency*Direction*Rand.Error*Experience	1	.24	.63
Task	1	.16	.69
Task*Frequency	1	4.76	.03
Task*Direction	1	19.32	.00
Task*Rand.Error	1	32.67	.00
Task*Experience	1	4.18	.05
Task*Experience*Direction	1	1.40	.24
Task*Frequency*Rand.Error	1	.15	.70
Task*Direction*Rand.Error	1	.22	.64
Task*Frequency*Direction*Rand.Error	1	.42	.52
Task*Frequency*Experience	1	.01	.91
Task*Direction*Experience	1	2.20	.14
Task*Frequency*Direction*Experience	1	.03	.86
Task*Rand.Error*Experience	1	.02	.88
Task*Frequency*Rand.Error*Exerience	1	1.19	.28
Task*Direction*Rand.Error*Experience	1	.57	.45
Task*Frequency*Direction*Rand.Error*Experience	1	2.20	.14
Error	56		

*Description of variables is the same as in Table 7

APPENDIX 1

Appendix 1-Example of Less Frequent Reporting Instrument

The current date is December 31, 2003. You own stock in ALPHA, Inc. and want to predict earnings per share for the next quarter (January – March 2004, a total of 13 weeks). The following pages contain a history of earnings per share for the past three years along with graphs to aid in your decision. You can review the pages in any order you desire and you can revisit pages if you desire. The disk contains a copy of the data tables presented below. The earnings data in the worksheet is protected and you cannot make changes to it. However, you can use the adjacent areas in the worksheet for any calculations you wish to make.

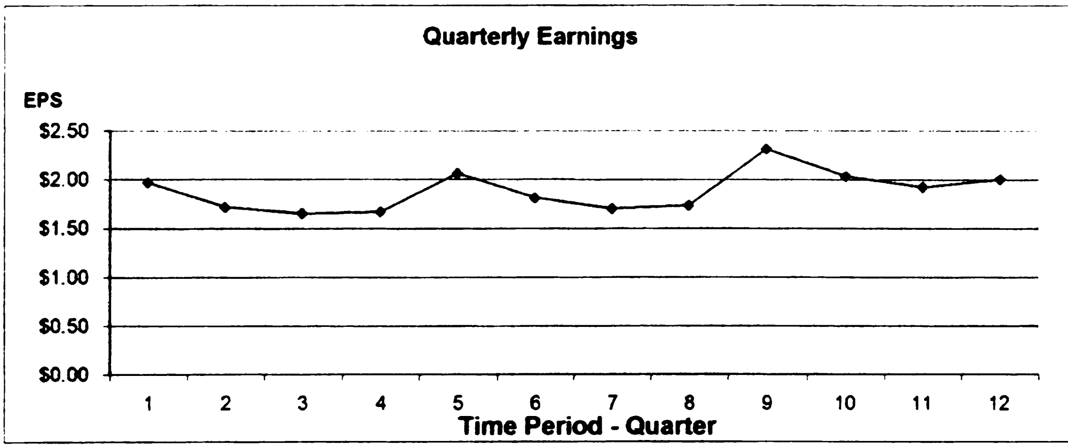
Based on the information provided on the following pages,
please provide your best prediction of earnings per share for Quarter 1, 2004
[January 1, 2004 - March 31, 2004].

1. Your prediction of earnings per share is: $ ______________

2. The actual earnings per share may not turn out to be exactly the same as you predicted in your answer to the previous question. But you probably have some idea of the range within which earnings per share is likely to fall. With this in mind, please answer the following questions:

   a. "I would be extremely surprised (no more than a 5% chance of occurring) if next quarter's earnings were **<u>higher</u>** than $______________"

   b. "I would be extremely surprised (no more than a 5% chance of occurring) if next quarter's earnings were **<u>lower</u>** than $________________"



	2001	2002	2003
Qtr. 1	$1.95	$2.04	$2.32
Qtr. 2	$1.72	$1.81	$2.03
Qtr. 3	$1.65	$1.69	$1.91
Qtr.4	$1.66	$1.74	$2.00

Appendix 1-Example of More Frequent Reporting Instrument

The current date is December 31, 2003. You own stock in ALPHA, Inc. and want to predict earnings per share for the next quarter (January – March 2004, a total of 13 weeks). The following pages contain a history of earnings per share for the past three years along with graphs to aid in your decision. You can review the pages in any order you desire and you can revisit pages if you desire. In the past, we have discovered that some students like to make calculations. Because we value your time, we have included a disk that contains a copy of the data tables presented below. The earnings data in the worksheet is protected and you cannot make changes to it. Although it is not required, you can use the adjacent areas in the worksheet for any calculations you wish to make.

Based on the information provided on the following pages,
please provide your best prediction of earnings per share for Quarter 1, 2004
[January 1, 2004 - March 31, 2004].

3. Your prediction of earnings per share is: $ ______________
(Please make sure you give a prediction for 13 weeks of earnings, not a single week)

4. The actual earnings per share may not turn out to be exactly the same as you predicted in your answer to the previous question. But you probably have some idea of the range within which earnings per share is likely to fall. With this in mind, please answer the following questions:

   a. "I would be extremely surprised (no more than a 5% chance of occurring) if next quarter's earnings were **higher** than $_____________"

   b. "I would be extremely surprised (no more than a 5% chance of occurring) if next quarter's earnings were **lower** than $_______________"

Year
2001

	Qtr. 1		Qtr. 2		Qtr. 3		Qtr.4		
1/1	Week1	0.16	Week 14	0.13	Week 27	0.11	Week 40	0.13	
	Week 2	0.16	Week 15	0.14	Week 28	0.13	Week 41	0.12	
	Week 3	0.14	Week 16	0.14	Week 29	0.14	Week 42	0.13	
	Week 4	0.14	Week 17	0.13	Week 30	0.12	Week 43	0.14	
	Week 5	0.16	Week 18	0.12	Week 31	0.13	Week 44	0.14	
	Week 6	0.15	Week 19	0.13	Week 32	0.14	Week 45	0.13	
	Week 7	0.15	Week 20	0.14	Week 33	0.12	Week 46	0.11	
	Week 8	0.15	Week 21	0.13	Week 34	0.13	Week 47	0.12	
	Week 9	0.15	Week 22	0.11	Week 35	0.11	Week 48	0.13	
	Week 10	0.15	Week 23	0.12	Week 36	0.16	Week 49	0.13	
	Week 11	0.13	Week 24	0.14	Week 37	0.13	Week 50	0.14	
	Week 12	0.16	Week 25	0.14	Week 38	0.11	Week 51	0.13	
	Week 13	0.15	Week 26	0.15	Week 39	0.12	Week 52	0.11	12/31

Year
2002

	Qtr. 1		Qtr. 2		Qtr. 3		Qtr.4		
1/1	Week 1	0.16	Week 14	0.15	Week 27	0.14	Week 40	0.15	
	Week 2	0.15	Week 15	0.14	Week 28	0.14	Week 41	0.13	
	Week 3	0.16	Week 16	0.15	Week 29	0.12	Week 42	0.11	
	Week 4	0.15	Week 17	0.15	Week 30	0.13	Week 43	0.15	
	Week 5	0.15	Week 18	0.13	Week 31	0.13	Week 44	0.13	
	Week 6	0.16	Week 19	0.14	Week 32	0.13	Week 45	0.13	
	Week 7	0.15	Week 20	0.13	Week 33	0.13	Week 46	0.11	
	Week 8	0.17	Week 21	0.14	Week 34	0.12	Week 47	0.13	
	Week 9	0.17	Week 22	0.14	Week 35	0.13	Week 48	0.14	
	Week 10	0.15	Week 23	0.14	Week 36	0.11	Week 49	0.14	
	Week 11	0.17	Week 24	0.14	Week 37	0.14	Week 50	0.14	
	Week 12	0.16	Week 25	0.13	Week 38	0.14	Week 51	0.15	
	Week 13	0.14	Week 26	0.13	Week 39	0.13	Week 52	0.13	12/31

Year
2003

	Qtr. 1		Qtr. 2		Qtr. 3		Qtr.4		
1/1	Week 1	0.17	Week 14	0.13	Week 27	0.14	Week 40	0.15	
	Week 2	0.16	Week 15	0.14	Week 28	0.15	Week 41	0.16	
	Week 3	0.20	Week 16	0.17	Week 29	0.15	Week 42	0.15	
	Week 4	0.18	Week 17	0.17	Week 30	0.15	Week 43	0.15	
	Week 5	0.17	Week 18	0.15	Week 31	0.14	Week 44	0.16	
	Week 6	0.18	Week 19	0.14	Week 32	0.14	Week 45	0.14	
	Week 7	0.19	Week 20	0.15	Week 33	0.15	Week 46	0.14	
	Week 8	0.18	Week 21	0.17	Week 34	0.15	Week 47	0.14	
	Week 9	0.17	Week 22	0.16	Week 35	0.15	Week 48	0.17	
	Week 10	0.19	Week 23	0.16	Week 36	0.16	Week 49	0.16	
	Week 11	0.17	Week 24	0.15	Week 37	0.15	Week 50	0.16	
	Week 12	0.18	Week 25	0.16	Week 38	0.13	Week 51	0.16	
	Week 13	0.18	Week 25	0.18	Week 39	0.15	Week 52	0.16	12/31

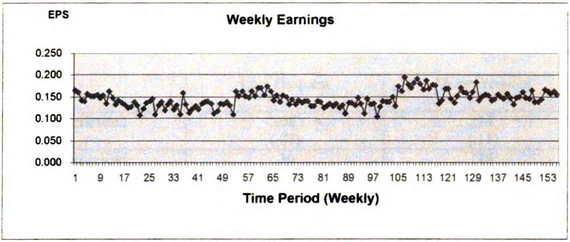

EPS
Weekly Earnings
0.250
0.200
0.150
0.100
0.050
0.000
1 9 17 25 33 41 49 57 65 73 81 89 97 105 113 121 129 137 145 153
Time Period (Weekly)

Table 9-Means and Standard Deviations,First Task

Categorized by Experience in Investing

	Less Frequent	More Frequent
Experienced	.08 (.07)	.14 (.14)
No experience	.10 (.09)	.14 (13)

Table 10-Analysis of Effects of Frequency on Signed Prediction Error

Panel A
Between Subjects ANOVA with Signed Prediction Error as DV

Source	df	F-value	p-value
Corrected Model	1	1.92	.04
Intercept	1	1.54	.22
Frequency	1	.00	.95
Direction	1	3.65	.06
Rand.Error	1	14.75	.00
Experience	1	4.32	.04
Frequency*Direction	1	.00	.92
Frequency*Rand.Error	1	.38	.54
Direction*Rand.Error	1	12.04	.00
Frequency*Experience*Rand.Error	1	.06	.80
Frequency*Experience	1	2.81	.09
Direction*Experience	1	.92	.34
Frequency*Direction*Experience	1	.06	.80
Rand.Error*Experience	1	3.73	.06
Frequency*Rand.Error*Experience	1	1.81	.18
Direction*Rand.Error*Experience	1	.99	.33
Frequency*Direction*Rand.Error*Experience	1	.27	.61
Error	56		
Total			

Frequency = frequency conditions between subjects,First task; Direction = direction of change-upward or downward-between earnings in the last reported period and the forecasted period; Rand.Error = two different random error draws used to create earnings series; Experience = yes or no to prior investing experience

Table 11-Correlations, Post-Experiment Question and Judgment Performance

	Perceived Volatility	***Perceived Difficulty***	***Absolute Prediction Error***	***Absolute Uncertainty***
Perceived Volatility	1			
Perceived Difficulty	.24*	1		
Absolute Prediction Error	-.04	-.04	1	
Absolute Uncertainty (Confidence Interval)	.07	.03	.27	1

*Significance < .05
Perceived Difficulty captures the perceived difficult in the prediction task.
Perceived Volatility captures how volatile investors perceived the reporting earnings

Table 12-Means and Standard Deviations for Uncertainty in Task 1 and Task 2 Controlling for Direction of Change in Earnings in Prediction Period

	Less Frequent	More Frequent
Positive Direction	.60 (.43)	.54 (.40)
Negative Direction	.53 (.38)	.57 (.35)

Table 13-Analysis of Effects of Reporting Frequency on Confidence Intervals When the Prediction Period Change in Earnings is Positive

Repeated Measures ANOVA with Confidence Interval as DV

Source	df	F-value	p-value
Task	1	2.92	.10
Task*Frequency	1	.50	.48
Task *Rand.Error	1	6.73	.02
Task*Frequency*Error	1	.39	.54
Error	29		

Description same as in Table 7

Table 14-Analysis of Effects of Reporting Frequency on Confidence Intervals When the Prediction Period Change in Earnings is Negative

Repeated Measures ANOVA with Confidence Interval as DV

Source	df	F-value	p-value
Task	1	.90	.35
Task*Frequency	1	3.61	.07
Task *Rand.Error	1	13.93	.00
Task*Frequency*Error	1	1.04	.31
Error	29		

Description same as in Table 7

Table 15-Means and Standard Deviations of Confidence Intervals in Task 1 and Task 2 Controlling for Random Error Draw

	Less Frequent	More Frequent
Random Error Draw One	.61 (.38)	.44 (.29)
Random Error Draw Two	.52 (.42)	.66 (.41)

Table 16-Analysis of Effects of Reporting Frequency on Confidence Intervals For Random Error Draw One

Repeated Measures ANOVA with Confidence Interval as DV

Source	df	F-value	p-value
Task	1	15.84	.00
Task*Frequency	1	2.52	.123
Task *Rand.Error	1	.74	.397
Task*Frequency*Error	1	2.85	.102
Error	30		

Description same as in Table 7

Table 17-Analysis of Effects of Reporting Frequency on Confidence Intervals For Random Error Draw Two

Repeated Measures ANOVA with Confidence Interval as DV

Source	df	F-value	p-value
Task	1	6.64	.01
Task*Frequency	1	.04	.83
Task *Rand.Error	1	3.08	.08
Task*Frequency*Error	1	1.05	.31
Error	30		

Description same as in Table 7

Table 18-Analysis of Effects of Reporting Frequency on Signed Prediction Error

Repeated Measures ANOVA with Signed Prediction Error as DV

Source	df	F-value	p-value
Task	1	.69	.41
Task*Frequency	1	.09	.76
Task *Rand.Error	1	14.66	.00
Task*Direction	1	1.70	.20
Task*Experience	1	4.73	.03
Task*Frequency*Rand.Error	1	.27	.60
Task*Frequency*Direction	1	.16	.69
Task*Error*Direction	1	.48	.49
Task*Frequency*Rand.Error.*Direction	1	.74	.34
Task*Frequency*Experience	1	.18	.67
Task*Rand.Error*Experience	1	.99	.32
Task*Frequency*Rand.Error*Direction	1	2.42	.13
Task*Direction*Experience	1	.34	.56
Task*Frequency*Direction*Experience	1	.00	.95
Task*Rand.Error*Direction*Experience	1	.67	.43
Task*Frequency*Rand.Error*Direction* Experience	1	.12	.73
Error	56		

Description same as in Table 7

Table 19-Analysis of Effects of Reporting Frequency on Signed Prediction Error for Those Who Received Less Frequent Reporting in the 1st Task

Repeated Measures ANOVA with Signed Prediction Error as DV

Source	df	F-value	p-value
Task	1	.11	.74
Task*Direction	1	.32	.58
Task*Rand.Error	1	4.33	.05
Task*Experience	1	1.22	.28
Task*Direction*Rand.Error	1	.95	.34
Task*Direction*Experience	1	.11	.75
Task*Rand.Error*Experience	1	.12	.73
Task*Direction*Rand.Error*Experience	1	.54	.47
Error	23		

Description same as in Table 7

Table 20-Analysis of Effects of Reporting Frequency on Signed Prediction Error for Those Who Received More Frequent Reporting in the 1st Task

Repeated Measures ANOVA with Signed Prediction Error as DV

Source	df	F-value	p-value
Task	1	.78	.38
Task*Direction	1	1.78	.19
Task*Rand.Error	1	11.64	.00
Task*Experience	1	4.15	.05
Task*Direction*Rand.Error	1	.02	.90
Task*Direction*Experience	1	.26	.61
Task*Rand.Error*Experience	1	4.00	.05
Task*Direction*Rand.Error*Experience	1	.13	.72
Error	23		

Description same as in Table 7

Table 21-Means and Standard Deviations for Prediction Error in Task 1 and Task 2 Controlling for Direction of Prediction Period Change in Earnings

	Less Frequent	More Frequent
Random Error Draw One	.16 (.12)	.10 (.12)
Random Error Draw Two	.08 (.09)	.17 (.14)

Table 22-Analysis of Effects of Reporting Frequency on Prediction Error When the Prediction Period Change in Earnings is Positive

Repeated Measures ANOVA with Prediction Error as DV

Source	df	F-value	p-value
Task	1	7.83	.01
Task*Frequency	1	3.86	.06
Task *Rand.Error	1	13.05	.00
Task*Experience	1	4.24	.05
Task*Frequency*Rand.Error	1	.02	.88
Task*Frequency*Experience	1	.00	.96
Task*Rand.Error*Experience	1	.28	.60
Task*Frequency*Rand.Error*Experience	1	2.26	.15
Error	25		

Description same as in Table 7

Table 23-Analysis of Effects of Reporting Frequency on Prediction Error When the Prediction Period Change in Earnings is Negative

Repeated Measures ANOVA with Prediction Error as DV

Source	df	F-value	p-value
Task	1	12.38	.00
Task*Frequency	1	.77	.39
Task *Rand.Error	1	21.28	.00
Task*Experience	1	.24	.66
Task*Frequency*Rand.Error	1	.83	.37
Task*Frequency*Experience	1	.07	.80
Task*Rand.Error*Experience	1	.28	.60
Task*Frequency*Rand.Error*Experience	1	.12	.73
Error	25		

Description same as in Table 7

Table 24-Means and Standard Deviations for Prediction Error in Task 1 and Task 2 Controlling for Random Error Draw

	Less Frequent	More Frequent
Random Error Draw One	.17 (.13)	.08 (.06)
Random Error Draw Two	.07 (.06)	.19 (.16)

Table 25-Analysis of Effects of Reporting Frequency on Prediction Error for Random Error Draw One

Repeated Measures ANOVA with Prediction Error as DV

Source	df	F-value	p-value
Task	1	18.29	.00
Task*Frequency	1	1.58	.22
Task *Experience	1	2.37	.14
Task*Direction	1	11.60	.00
Task*Frequency*Experience	1	.46	.50
Task*Frequency*Direction	1	1.65	.21
Task*Experience*Direction	1	2.45	.13
Task*Frequency*Experience*Direction	1	1.34	.26
Error	25		

Description same as in Table 7

Table 26-Analysis of Effects of Reporting Frequency on Prediction Error for Random Error Draw Two

Repeated Measures ANOVA with Prediction Error as DV

Source	df	F-value	p-value
Task	1	17.25	.00
Task*Frequency	1	4.03	.05
Task *Experience	1	2.18	.15
Task*Direction	1	9.39	.00
Task*Frequency*Experience	1	.89	.35
Task*Frequency*Direction	1	.17	.68
Task*Experience*Direction	1	.33	.57
Task*Frequency*Experience*Direction	1	1.05	.32
Error	25		

Description same as in Table 7

Table 27-Means and Standard Deviations for Prediction Error in Task 1 and Task 2

Controlling for Experience

	Less Frequent	More Frequent
Experienced	.11 (.12)	.13 (.15)
Non-Experienced	.12 (.11)	.14 (.13)

Table 28-Analysis of Effects of Reporting Frequency on Prediction Error for Investors with Investing Experience

Repeated Measures ANOVA with Prediction Error as DV

Source	df	F-value	p-value
Task	1	1.89	.19
Task*Frequency	1	1.35	.26
Task *Direction	1	10.96	.00
Task*Rand.Error	1	10.93	.00
Task*Frequency*Direction	1	.59	.46
Task*Frequency*Rand.Error	1	.16	.70
Task*Experience*Direction*Rand.Error	1	.48	.50
Task*Frequency*Direction*Rand.Error	1	1.45	.25
Error	25		

Description same as in Table 7

Table 29-Analysis of Effects of Reporting Frequency on Prediction Error for Investors with No Investing Experience

Repeated Measures ANOVA with Prediction Error as DV

Source	df	F-value	p-value
Task	1	2.70	.11
Task*Frequency	1	5.27	.03
Task *Direction	1	8.43	.00
Task*Rand.Error	1	30.77	.00
Task*Frequency*Direction	1	1.02	.32
Task*Frequency*Rand.Error	1	2.17	.15
Task*Experience*Direction*Rand.Error	1	.08	.78
Task*Frequency*Direction*Rand.Error	1	.69	.41
Error	25		

Description same as in Table 7

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