Using Cognitive Load Theory to Explain the Accrual Anomaly

Max R. Hewitt

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2007

Program Authorized to Offer Degree:
Business School

University of Washington
Graduate School

This is to certify that I have examined this copy of a doctoral dissertation by

Max R. Hewitt

and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
examining committee have been made.

Chair of the Supervisory Committee:

S. Jane Kennedy

Reading Committee:

Frank D. Hodge

S. Jane Kennedy

Terence J. Shevlin

Date: 5/31/07

In presenting this dissertation in partial fulfillment of the requirements for the doctoral degree at the University of Washington, I agree that the Library shall make its copies freely available for inspection. I further agree that extensive copying of the dissertation is allowable only for scholarly purposes, consistent with "fair use" as prescribed in the U.S. Copyright Law. Requests for copying or reproduction of this dissertation may be referred to ProQuest Information and Learning, 300 North Zeeb Road, Ann Arbor, MI 48106-1346, 1-800-521-0600, to whom the author has granted "the right to reproduce and sell (a) copies of the manuscript in microform and/or (b) printed copies of the manuscript made from microform."

Signature 

Date 5/31/07

University of Washington

Abstract

Using Cognitive Load Theory to Explain the Accrual Anomaly

Max R. Hewitt

Chair of the Supervisory Committee:
Professor S. Jane Kennedy
Accounting

The accrual anomaly represents the positive abnormal returns generated by a trading strategy that seeks to exploit investors' failure to accurately forecast earnings when the accrual and cash components of earnings (earnings components) are differentially persistent. This dissertation investigates: (i) whether analysts and nonprofessional investors accurately forecast earnings when the earnings components are differentially persistent; and, (ii) a behavioral process that contributes to the accrual anomaly. I find that the earnings forecasts of analysts and nonprofessional investors are less accurate when the earnings components are differentially persistent relative to when the earnings components are equally persistent. Using cognitive load theory as a framework, I consider the effect of two hurdles (i.e., intrinsic and extraneous cognitive load) that investors need to overcome to accurately forecast earnings of firms with differentially persistent earnings components. I investigate how task decomposition and disclosure format combine to enable analysts and nonprofessional investors to overcome the cognitive load hurdles and more accurately forecast earnings when the earnings components are differentially persistent. I predict and find that the earnings forecasts of analysts and nonprofessional investors are only more accurate when analysts and nonprofessional investors attend to the earnings components and this information is disclosed in a format that minimizes their information processing costs.

TABLE OF CONTENTS

TABLE OF FIGURES

TABLE OF TABLES

Table Number Page

ACKNOWLEDGEMENTS

The author wishes to express sincere appreciation to his dissertation committee members, Jane Kennedy (chairperson), Ted Beauchaine, Frank Hodge, Terry Mitchell, Ed Rice, and Terry Shevlin for their guidance and valuable comments. The author also wishes to thank Sudipta Basu, Sarah Bonner, Bob Bowen, Dave Burgstahler, Marty Butler, Andy Call, Brooke Elliott, Pat Hopkins, Kathryn Kadous, Todd Kravet, Susan Krische, Laureen Maines, Dawn Matsumoto, Rick Mergenthaler, Jeff Miller, Mark Nelson, Derek Oler, Shiva Rajgopal, D. Shores, Stephanie Sikes, Jane Thayer, Kristy Towry, Ryan Wilson and workshop participants at Emory University, Indiana University, University of Illinois, University of Notre Dame, University of Southern California, and University of Washington for helpful comments. Finally, the author wishes to thank the financial analysts and MBA students who generously donated their time and effort.

1. INTRODUCTION

The accrual anomaly represents the positive abnormal returns generated by a trading strategy that seeks to exploit investors' failure to accurately forecast earnings when the accrual and cash components of earnings (earnings components) are differentially persistent (Sloan 1996).[1] This dissertation investigates: (i) whether analysts and nonprofessional investors accurately forecast earnings when the earnings components are differentially persistent; and, (ii) a behavioral process that contributes to the accrual anomaly. Consistent with Sloan (1996), I define 'persistence' as the implications of the earnings components on future earnings.[2] In this study, 'persistence' represents the time-series patterns of earnings and its components.

When the earnings components have different time-series patterns, the aggregation of these components can lead to a more complex earnings time-series pattern. In this instance, the persistence of earnings is more difficult to determine from the aggregated earnings time series than the individual time series of each earnings component. Sloan (1996) suggests that fixation on the aggregated earnings time series leads to investors' failure to accurately forecast earnings when

---

[1] Recent research often limits the implications of Sloan's findings to accrual mispricing (e.g., Kothari, Loutskina and Nikolaev 2007; Kraft, Leone and Wasley 2006; Desai, Rajgopal and Venkatachalam 2004). However, Sloan (1996) addresses how investors implicitly estimate the persistence of the accrual and cash components of earnings in their investment decisions. The implications of Sloan's findings are not limited to accrual mispricing (Call, Hewitt and Shevlin 2007).

[2] Sloan (1996) measures the persistence of the earnings components as the regression coefficients on the earnings components when future earnings is regressed on the contemporaneous values of the earnings components for time-series data.

the earnings components are differentially persistent. In this dissertation, I directly investigate the behavioral process that underlies investors' failure to accurately forecast earnings when the earnings components are differentially persistent. I provide further evidence of this deficiency and its potential source. Using cognitive load theory as a framework, I investigate two hurdles that analysts and nonprofessional investors need to overcome to accurately forecast earnings of firms with differentially persistent earnings components.

Prior research suggests that investors do not accurately estimate the persistence of the earnings components (e.g., Sloan 1996; Bradshaw, Richardson and Sloan 2001; Hirshleifer and Teoh 2003).[3] In my experiment, analysts and MBA students are required to forecast next-year earnings for two firms. One firm has differentially persistent accrual and cash components of earnings (Firm DIFF), while the other firm does not (Firm SAME).[4] I predict and find that participants' forecasts are relatively less accurate when the earnings components are differentially persistent than when the components are equally persistent. I also find that participants are significantly less confident in the accuracy of their forecasts when the earnings components are differentially persistent.

Prior research also considers whether investors' knowledge is related to the mispricing of securities (e.g., Collins, Gong and Hribar 2003; Balsam, Bartov and

---

[3] As shown by Hirshleifer and Teoh (2003), this setting may be generalized to other settings where multiple components of earnings (e.g., earnings of various segments, core earnings and special items) with different implications for future earnings are aggregated.

[4] In the materials distributed to participants, "Firm DIFF" and "Firm SAME" are labeled "Alps" and "Dolomites," respectively.

Marquardt 2002; Bradshaw et al. 2001; Bartov, Radhakrishnan and Krinsky 2000). Bonner, Walther and Young (2003) claim knowledgeable investors have relatively more forecasting experience than less knowledgeable investors. Greater knowledge allows investors to use available information to more accurately forecast earnings (Bonner et al. 2003). However, Bradshaw et al. (2001) find little evidence to suggest that analysts' forecasts reflect the low persistence of large accruals. In this study, I compare the forecast accuracy of analysts and MBA students.

I do not find a significant difference in the earnings forecast accuracy of analysts and MBA students. This finding is supported by analyses that show analysts and MBA students have similar task-specific knowledge when the task involves the recognition of time-series patterns. While analysts have considerably greater forecasting experience relative to MBA students, both groups of participants are equally prone to forecasting errors when the earnings components are differentially persistent.

However, MBA students are more confident in the accuracy of their forecasts than analysts. In this experiment, participants are only given financial statements before being asked to provide earnings forecasts. The higher confidence of MBA students in the accuracy of their forecasts relative to analysts may indicate that nonprofessional investors are more confident basing their earnings forecasts on financial statements alone. Nonprofessional investors' higher confidence in the accuracy of their forecasts relative to analysts may lead to them placing too much

weight on these forecasts in certain trading contexts (Bloomfield, Libby and Nelson 1999).

In this dissertation, I also consider a potential behavioral mechanism that contributes to the decrease in forecast accuracy when the earnings components are differentially persistent. When the earnings components are differentially persistent, cognitive load theory suggests that investors face intrinsic cognitive load and extraneous cognitive load in order to accurately forecast earnings. Intrinsic cognitive load is the number of cues required to be processed in working memory to successfully complete a task. When the earnings components are differentially persistent, investors who fixate on earnings face intrinsic cognitive load due to the need to process multiple time-series patterns that give rise to the aggregated earnings time series. Extraneous cognitive load is the format of the cues required to be processed to complete a task. When the earnings components are differentially persistent, investors face extraneous cognitive load due to the need to attend to information not placed on the income statement and to use this information to discern the persistence of the earnings components. Using cognitive load theory as a framework, I investigate how task decomposition and disclosure format ameliorate investors' forecast accuracy when the earnings components are differentially persistent.

I predict investors' earnings forecasts will only be more accurate when investors are required to attend to the earnings components and the information is disclosed in a format that minimizes investors' information processing costs.

Investors face excessive cognitive load when they fixate on the aggregated earnings time series and the earnings components are differentially persistent. Requiring investors to attend to the earnings components reduces the intrinsic cognitive load of the forecasting task because attending to the earnings components allows investors to discern the persistence of each component. However, making investors attend to the earnings components also requires them to process information on the statement of cash flows. As a result, investors that attend to the earnings components also face extraneous cognitive load due to the presentation format of the statement of cash flows (Hodder, Hopkins and Wood 2007). Therefore, in order to improve 'fixated' investors' forecast accuracy when the earnings components are differentially persistent, I predict both intrinsic and extraneous cognitive load must be reduced. Consistent with my predictions, I find that the earnings forecasts of analysts and MBA students are significantly more accurate when the task is decomposed and the information concerning the earnings components is disclosed in a format that minimizes investors' information processing costs.

This study attempts to examine the issue of whether analysts and nonprofessional investors incorporate the differential persistence of the earnings components in their earnings forecasts and the possible hurdles to investors' use of this information. This examination is motivated by the extant literature concerning the accrual anomaly that suggests investors do not attend to the earnings components. The literature implicitly assumes that the information in the earnings

components is value relevant and investors' valuation models should incorporate this information. The results of this study are also subject to the assumption that the persistence of the earnings components is relevant to investors when forecasting earnings. However, investors may employ other valuation models based on other decompositions of earnings (e.g., revenues and expenses), and other financial and nonfinancial information.

The contributions of this study are threefold. First, it provides empirical evidence demonstrating how cognitive load theory explains investors' forecast accuracy when the accrual and cash components of earnings are differentially persistent. This study responds to the suggestion of Libby, Bloomfield and Nelson (2002 p.791-792) for future research to provide a direct test of Sloan's archival evidence by varying the "ease with which the information can be analyzed, ... as well as the traders' knowledge and training." In doing so, it is one of the first experimental studies to directly investigate the behavioral process that contributes to the accrual anomaly. In documenting a key deficiency in investor behavior, as well as the source and remedy for this deficiency, this study incorporates the key features of Bonner's (1999) framework for judgment and decision-making research in accounting.

Second, this study presents the role of disclosure format in reducing trading anomalies. In doing so, it provides empirical evidence concerning part of Hirshleifer and Teoh's (2003) model describing the effects of limited attention and disclosure format when financial information is aggregated. My study has

implications for regulators, in particular, the Joint Financial Statement Presentation Project conducted by the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB). While prior research demonstrates that disclosure format affects investors' judgments and decisions (e.g., Maines and McDaniel 2000; Hirst and Hopkins 1998; Hopkins 1996), this study presents cognitive load theory as a framework that explains how and when disclosure format leads to improvements in investors' forecast accuracy when the underlying firm is characterized by differentially persistent accrual and cash components of earnings.

Finally, this study adds to the growing body of literature investigating psychology-based theories explaining market inefficiency (Chan, Frankel and Kothari 2004; Libby et al. 2002). Consistent with cognitive load theory, this study provides evidence that investors' forecasts are affected by the structure of the task and the way that information is disclosed. These findings suggest that investors' cognitive limitations may lead to inefficient markets when barriers (e.g., arbitrage costs) restrict the ability of these markets to correct the mispricing of securities of firms characterized by differentially persistent accrual and cash components of earnings.

The remainder of this dissertation is presented as follows. Section 2 provides a summary of the background literature and develops the hypotheses. Section 3 explains the experimental method employed in this study. Sections 4 and 5 discuss the results and conclude the dissertation, respectively.

2. BACKGROUND AND HYPOTHESES

2.1 The accrual anomaly

To estimate the persistence of the earnings components, Sloan (1996) regresses future earnings on the two current period components of earnings for a sample of firm-years between 1962 and 1991:

$$EARN_{t+1} = \gamma_0 + \gamma_{acc} \cdot ACC_t + \gamma_{cash} \cdot CASH_t + \varepsilon_{t+1}$$

where γ_{acc} and γ_{cash} represent the persistence of accrual component of earnings (ACC_t) and the cash component of earnings ($CASH_t$), respectively, and $EARN_{t+1}$ is next-period earnings.

Sloan (1996) predicts that the persistence of the accrual component of earnings is relatively lower than the persistence of the cash component of earnings (i.e., $\gamma_{acc} < \gamma_{cash}$). Sloan bases his prediction on the greater use of managerial discretion in measuring and reporting accruals relative to cash flows from operating activities. This assertion is supported by Xie (2001) who finds discretionary accruals are significantly less persistent than nondiscretionary accruals and cash flows from operating activities.

On average, Sloan finds that the accrual component of earnings is significantly less persistent than the cash component of earnings. Sloan also investigates whether stock prices reflect that investors accurately estimate the persistence of the two earnings components when forecasting earnings. Citing results using the Mishkin (1983) test and significant abnormal buy-hold returns from a trading strategy where he takes short (long) positions on firms with high

(low) accruals, Sloan concludes that investors overweight (underweight) the persistence of the accrual (cash) component of earnings.[5]

Sloan (1996) attributes the accrual anomaly to investors' fixation on earnings. He presents two analyses that rule out the alternative systematic risk explanation for the anomaly. First, he shows that his trading strategy generates positive abnormal returns for almost all sample years. It is unlikely that a risk-based explanation for the accrual anomaly would consistently generate positive abnormal annual returns throughout a period of time characterized by both high and low stock markets. Second, Sloan shows that over 40% of the positive abnormal returns to his trading strategy are concentrated around subsequent earnings announcements. If the accrual anomaly is due to risk, it is not obvious why these returns would concentrate around the following earnings announcements.

Recent research also promotes a behavioral explanation for the accrual anomaly by providing evidence against the risk explanation. For example, Hirshleifer, Hou and Teoh (2007) control for several known risk factors (e.g., market-to-book, size, and beta) when examining the profitability of an accrual-

---

[5] Francis and Smith (2005) suggest that only 13% of firms have significantly different levels of persistence for the two earnings components. The lack of pervasiveness of the differential persistence of the earnings components potentially threatens the external validity and importance of this study. In other words, the external validity of this study is limited to the context where firms have differentially persistent earnings components. However, as observed in Sloan, the accrual anomaly is sufficiently pervasive to allow significant abnormal positive one-year returns to be earned in excess of 10%. In addition, the power of the tests employed by Francis and Smith (2005) may account for the seemingly low percentage of firms with significantly different levels of persistence for the earnings components. Using an alternative measurement for differential persistence, Call et al. (2007) estimate that at least 40% of all firm-year observations possess differential persistence.

based trading strategy. The authors find that the accrual anomaly still exists after controlling for these risk factors.

2.2 Forecasting earnings when its components are differentially persistent

Sloan (1996) proposes that "investors 'fixate' on earnings and fail to distinguish between the accrual and cash flow components of current earnings." Given that prior research also suggests investors fixate on earnings (e.g., Libby et al. 2002; Hand 1990; Abdel-khalik and Keller 1979), this study investigates the accuracy of investors' forecasts when the earnings components are differentially persistent and how investors' forecast accuracy may be ameliorated in these situations.

Consistent with prior research, I assume that investors fixate on the aggregated earnings time series and do not attend to the components of earnings. In other words, investors use the following information set (ψ^{fix}) to forecast earnings:

$$\psi^{fix} = (EARN_1, EARN_2, ..., EARN_t)$$

where t represents the number of years of annual data available to investors. Sloan (1996) suggests investors' earnings forecasts will be less accurate if investors rely upon ψ^{fix} to forecast earnings when the earnings components are differentially persistent.

To illustrate the problems associated with investors relying upon ψ^{fix} to forecast earnings when the earnings components are differentially persistent, I consider the following tasks requiring the completion of two number series: a

triangular number series (i.e., 1,3,6,10,15,?) and an oscillating number series (i.e., 1,3,1,3,1,?). Assume that these number series are analogous to earnings components characterized by different time-series patterns. These time-series patterns enable the prediction of the earnings components. The number series can also be combined to form an aggregated number series (i.e., 2,6,7,13,16,?). When these number series represent the earnings components, the aggregated number series is analogous to earnings.

Table 1 indicates that both analysts and MBA students find it relatively straight-forward to solve a triangular number series and an oscillating number series, in isolation. Over 90% of all participants solved each of these number series and most participants required less than 20 seconds to solve each of these number series. However, Table 1 indicates that it is much more difficult for analysts and MBA students to solve the aggregated number series. Most participants took more than 100 seconds to provide a solution to the aggregated number series and only 42% of analysts and 37% of MBA students solved this number series correctly. These findings illustrate the difficulties that 'fixated' investors face when trying to forecast earnings when its components have differential persistence.

To accurately forecast earnings, Hirshleifer and Teoh (2003) recommend that investors attend to the following information set (ψ^*) when the earnings components are differentially persistent:

$$\psi^* = (ACC_1, ACC_2,..., ACC_t; CASH_1, CASH_2,..., CASH_t) .$$

Hirshleifer and Teoh (2003) propose that investors' forecasts will only be less accurate through their use of ψ^{fix} when the earnings components are differentially persistent (i.e., $\gamma_{acc} \neq \gamma_{cash}$).[6]

Consistent with Hirshleifer and Teoh (2003), I hypothesize that investors' forecasts will be less accurate when the earnings components are differentially persistent relative to when these components are not differentially persistent.

H1: *Investors' earnings forecasts will be relatively less accurate when the earnings components are differentially persistent than when the earnings components are equally persistent.*

2.3 Forecast accuracy of analysts and nonprofessional investors

I use three reasons to motivate my investigation of the forecast accuracy of multiple groups of capital markets participants. First, research in psychology and accounting generally shows that experience results in greater task-specific knowledge, which in turn leads to improved judgments and decisions (Rikers and Paas 2005; Libby and Luft 1993; Bonner 1990). When the earnings components are differentially persistent, I expect analysts' forecasts to be only significantly more accurate, relative to MBA students' forecasts, if analysts are less prone to earnings fixation or analysts' experience with forecasting leads to them possessing greater knowledge concerning time-series pattern recognition. If there is no difference between both the levels of earnings fixation and knowledge concerning

[6] Appendix A illustrates the effect of using ψ^{fix} to forecast earnings when the earnings components are differentially persistent. Hirshleifer and Teoh's (2003) analysis is based on the assumption that information aggregation leads to information loss in the aggregated information set (Lev 1968). Consistent with this assumption, I construct an experimental setting where information aggregation leads to a more complex earnings persistence pattern than the persistence patterns for the earnings components.

time-series pattern recognition of analysts and MBA students, I would expect no difference between the forecast accuracy of the two groups when the earnings components are differentially persistent. Table 1 suggests that analysts and MBA students have similar knowledge concerning number-series pattern recognition. If both groups are similarly fixated on earnings, these results suggest no difference should be observed between the forecast accuracy of analysts and MBA students when the earnings components are differentially persistent.

Accounting research using archival methods has provided mixed evidence on the effect of investor sophistication on the magnitude of earnings-based anomalies (using institutional ownership as a proxy for investor sophistication). Bartov et al. (2000) and Collins et al. (2003) show that securities held by relatively large percentages of institutional investors are significantly less likely to be mispriced. Bartov et al. (2000) and Collins et al. (2003) demonstrate the role of institutional ownership in relation to the post-earnings announcement drift and the accrual anomaly, respectively. However, Bradshaw et al. (2001) find no evidence to suggest that analysts' forecasts reflect the relatively lower persistence of large accruals. One explanation for this result is that analysts possess the same knowledge concerning time-series pattern recognition as other capital markets participants.

Prior research suggesting that stock prices are set by the marginal investor provides a second reason for investigating the forecast accuracy of multiple groups of capital markets participants. The extant literature proposes professional

investors (e.g., analysts) will set stock prices in some circumstances, while nonprofessional investors will set stock prices in other circumstances (Hand 1990; Collins et al. 2003). Further, Kachelmeier and King (2002) and Libby et al. (2002) provide arguments for why individual judgment biases can persist in market settings. For example, the cost to arbitrage the resultant security mispricing from relatively naïve investors may be sufficiently high to dissuade arbitragers from trading the mispriced security (Mashruwala, Rajgopal and Shevlin 2006).

If analysts are subject to the same judgment biases as nonprofessional investors, research may seek to explain and improve the judgments of both groups of investors. I state my second hypothesis in the null form due to the absence of evidence concerning the relative levels of fixation of analysts and nonprofessional investors, and my findings concerning the similar task-specific knowledge of analysts and MBA students with respect to time-series pattern recognition.

H2: *Analysts will not provide significantly more accurate earnings forecasts relative to nonprofessional investors when the earnings components are differentially persistent.*

2.4 Cognitive load theory

I now consider the underlying mechanism that leads to investors' inaccurate earnings forecasts when the earnings components are differentially persistent. Cognitive load theory provides a behavioral explanation for why individuals make erroneous forecasts. This theory suggests that a task will not be successfully

completed when the decision maker faces excessive cognitive load.[7] There are two sources of cognitive load that may present hurdles to decision makers when attempting to successfully complete a task. These are intrinsic cognitive load and extraneous cognitive load (Sweller 1988; Sweller, Chandler, Tierney and Cooper 1990).

This study considers how both intrinsic and extraneous cognitive load prevent investors from accurately forecasting earnings when the earnings components are differentially persistent. Intrinsic cognitive load is the number of cues required to be held in working memory in order to successfully complete a task. In this study, cues are represented by the time-series patterns in earnings and its components. When the earnings components are differentially persistent, participants who limit their attention to the aggregated earnings time series must process two cues (i.e., time-series patterns) to successfully forecast earnings. In contrast, investors who attend to the earnings components are only required to process one cue (i.e., time-series pattern) at a time in working memory to successfully forecast earnings. Extraneous cognitive load is the complexity of the format through which cues are communicated to the decision maker.[8] In this study, extraneous cognitive load is represented by the disclosure format of the financial

---

[7] Cognitive load theory hypothesizes a negative relation between cognitive load and performance. It is silent on the form (i.e., linear or curvilinear) of this negative relation.

[8] Cognitive load theorists use the word "extraneous" to label the cognitive load due to the disclosure format of the information provided to the decision maker. By using this label, they do not intend to suggest that this aspect of cognitive load is irrelevant or unimportant to their analysis of cognitive load. Rather, their intention is to identify the aspect of cognitive load that does not result from the intrinsic requirements of the task.

statements given to participants. Cognitive load theory suggests that reforms aimed at improving investors' forecast accuracy need to consider both of these hurdles when the earnings components are differentially persistent.

2.5 Improving forecast accuracy when the earnings components are differentially persistent

Section 2.2 recommends that investors attend to ψ^* in order to accurately forecast earnings when the earnings components are differentially persistent. Prior research suggests that investors fixate on earnings and often fail to consider other information when forecasting earnings (e.g., Libby et al. 2002; Hand 1990; Abdel-khalik and Keller 1979). Reforms seeking to improve investors' forecast accuracy when the earnings components are differentially persistent need to increase the attention that investors pay to the earnings components (i.e., increase investors' attention to ψ^* and decrease investors' attention to ψ^{fix}).

Reforms that require investors to attend to ψ^* will only increase forecast accuracy if investors can easily locate and accurately estimate ψ^*. The earnings components information needs to be obtained from the statement of cash flows or a combination of the balance sheet and the income statement. I expect investors to have difficulty forecasting earnings of firms with differentially persistent earnings components when they find it difficult to use the statement of cash flows to estimate ψ^*. Investors may find it difficult to use the statement of cash flows due to the indirect presentation format used by most firms to present cash flows from operating activities. For example, investors may not understand the intuition

underlying the use of accruals to reconcile earnings to cash flows from operating activities. In this study, I consider the efficacy of two manipulations aimed at encouraging investors to incorporate the persistence of the earnings components in their earnings forecasts when the earnings components are differentially persistent.

2.6 The interaction effect of task decomposition and disclosure format

Using cognitive load theory as a framework, I investigate how task decomposition and disclosure format ameliorate investors' forecast accuracy when the earnings components are differentially persistent. I expect that decomposing the task and disclosing information concerning the earnings components in a format that minimizes investors' information processing costs will enable investors to overcome the hurdles presented by the intrinsic and extraneous cognitive load of firms with differentially persistent earnings components. In this study, I consider the interaction effect of task decomposition and disclosure format on investors' forecast accuracy when the earnings components are differentially persistent.

Prior research proposes that task decomposition reduces the number of cues required to be held in working memory (Kleinmuntz, Fennema and Peecher 1996; Kleinmuntz 1988; Morera and Budescu 2001; Wilks and Zimbelman 2004). This research is based upon the "divide and conquer" principle. This principle suggests that: "(1) complex decision problems should be decomposed into smaller, more manageable parts; and, (2) these smaller parts should be logically aggregated to derive an overall value for each alternative" (Morera and Budescu 1998).

The decomposed task requires investors to attend to information set, ψ^*, rather than relying on information set, ψ^{fix}. Investors using ψ^* face lower intrinsic cognitive load than those using ψ^{fix}. This lower intrinsic cognitive load results from ψ^* requiring investors to only process one time-series pattern in working memory at a time in order to accurately forecast earnings. In contrast, ψ^{fix} requires investors to discern and process the aggregation of two time-series patterns in working memory to accurately forecast earnings when the earnings components are differentially persistent. When the earnings components are differentially persistent, aggregation of the earnings components obscures the time-series patterns of the earnings components. Therefore, attending only to ψ^{fix} makes it more difficult for investors to discern the time-series pattern of earnings.

However, I predict that decomposing the task, in isolation, does not improve investors forecast accuracy when the earnings components are differentially persistent. While task decomposition enables investors to attend to the earnings components, it also requires investors to locate and calculate these components. This requirement may present difficulties to investors who are not used to locating and calculating the earnings components. In other words, the extraneous cognitive load associated with the disclosure format of the traditional financial statements makes it difficult for investors to locate and accurately calculate the inputs required for ψ^*.

Hodder et al. (2007) find that investors have difficulties interpreting the operating activities section of the statement of cash flows due to the disclosure

format of this financial statement. Most firms use the indirect method to present cash flows from operating activities. This method presents cash flows from operating activities by adding back accruals to earnings. Some difficulties that the indirect method may pose to investors include the need for investors to understand what the line items represent that are used to reconcile earnings and cash flows from operating activities, the need to locate cash flows from operating activities on the statement of cash flows, and the need to aggregate the accrual items to arrive at the accrual component of earnings. Hodder et al. (2007) find that investors' forecasts are less accurate when the statement of cash flows is presented using the indirect method relative to when it is presented using the direct method. Therefore, investors also need to overcome the extraneous cognitive load hurdle presented by the disclosure format of the statement of cash flows (in particular, the indirect presentation of cash flows from operating activities) to accurately forecast earnings.

In this study, I vary the disclosure format of the financial statements. Reforms addressing the disclosure format of the financial statements are predominantly concerned with reducing extraneous cognitive load. The Joint Financial Statement Presentation Project conducted by FASB and IASB argues that improving the disclosure format of the financial statements will lead to improvements in investors' judgments and decisions (IASB 2005). The chairman of the FASB recently proposed dramatic changes to the income statement through altering the "display and disaggregation [of information] to give a richer picture of what's really going on" (Reason 2005). The chairman stated his belief that changes

to the disclosure format will "allow users to see that the income statement and cash flow statement are two different ways of looking at performance – one on an accrual basis and one on a cash basis – and use them together" (Reason 2005).

To demonstrate the effect of the Joint Financial Statement Presentation Project's possible reforms in a context where the accrual and cash components of earnings are differentially persistent, I incorporate three of the theoretical suggestions of Maines and McDaniel (2000). These suggestions are: (i) disaggregating earnings into its accrual and cash components; (ii) linking the accrual and cash components of earnings; and, (iii) placing these components on the income statement. These suggestions motivate the "Disaggregated Disclosure Format" that I use in this study to manipulate the disclosure format of the financial statements. The "Disaggregated Disclosure Format" of the income statement is presented in Figure 1. Investors presented with the "Disaggregated Disclosure Format" face lower extraneous cognitive load than investors that acquire ψ^* from the traditional financial statements.

Given that prior research shows that investors fixate on earnings, I expect that presenting the disaggregated earnings components on the income statement without directing investors to this information will not reduce the cognitive load of the forecasting task. When investors fixate on earnings, cognitive load will not be reduced because investors neglect to attend to the disaggregated earnings information (ψ^*) when forecasting earnings. Therefore, intrinsic cognitive load is unchanged when investors only attend to the aggregated earnings time series.

When the earnings components are differentially persistent, I predict that investors will accurately forecast earnings only when they are required to attend to the earnings components (i.e., task decomposition) and the information is disclosed in a format that minimizes investors' information processing costs (i.e., disaggregated disclosure format). With this combination, investors benefit from being required to attend to the earnings components, while not needing to locate and calculate the earnings components from the statement of cash flows. This combination allows investors to overcome the hurdles presented by intrinsic cognitive load and extraneous cognitive load.

This reasoning leads to the predicted interaction effect of task decomposition and disclosure format on investors' forecast accuracy when the earnings components are differentially persistent. Figure 2 depicts the predicted pattern of participants' mean forecast accuracy when the earnings components are differentially persistent.

H3: *When the earnings components are differentially persistent, investors' forecasts will only be more accurate when the task is decomposed and the disaggregated earnings components are disclosed on the income statement.*

Traditional disclosure format

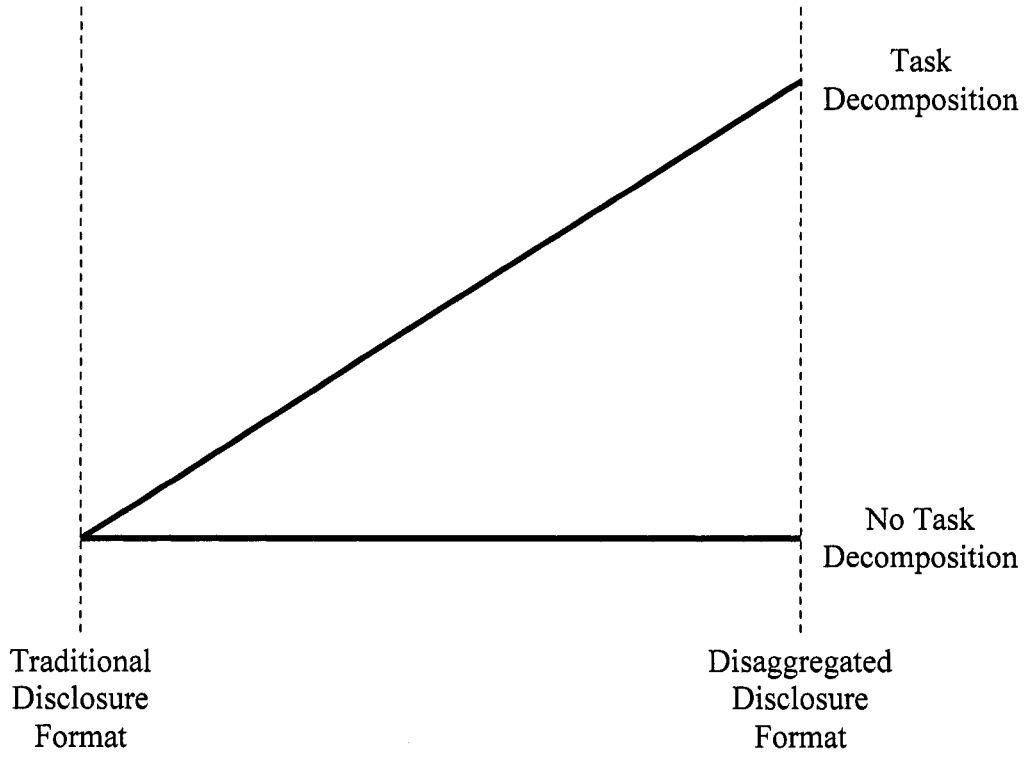
	Year ended December 31				
	2005	**2004**	**2003**	**2002**	**2001**
NET OPERATING REVENUES	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
Cost of Goods Sold	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
GROSS PROFIT	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
Selling, General and Administrative Expenses					
Depreciation	(XXX)	(XXX)	(XXX)	(XXX)	(XXX)
Other	(XXX)	(XXX)	(XXX)	(XXX)	(XXX)
NET INCOME	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX

Disaggregated disclosure format (amendment to "traditional" format is highlighted)

	Year ended December 31				
	2005	**2004**	**2003**	**2002**	**2001**
NET OPERATING REVENUES	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
Cost of Goods Sold	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
GROSS PROFIT	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
Selling, General and Administrative Expenses					
Depreciation	(XXX)	(XXX)	(XXX)	(XXX)	(XXX)
Other	(XXX)	(XXX)	(XXX)	(XXX)	(XXX)
NET INCOME	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
Components of Net Income:					
Cash Flows From Operating Activities	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX
Non-cash Component of Net Income	(XXX)	(XXX)	(XXX)	(XXX)	(XXX)
Net Income	X,XXX	X,XXX	X,XXX	X,XXX	X,XXX

Figure 1 – Examples of Income Statement Disclosure Formats

(Dependent variable: Forecast Accuracy)



This figure depicts the predicted pattern of participants' mean forecast accuracy when the earnings components are differentially persistent (Firm DIFF).

To test this hypothesized interaction I use the following contrast weights for each condition:

"No Task Decomposition / Traditional Disclosure Format" = -1
"Task Decomposition / Traditional Disclosure Format" = -1
"No Task Decomposition / Disaggregated Disclosure Format" = -1
"Task Decomposition / Disaggregated Disclosure Format" = +3.

Figure 2 – Hypothesis 3: Predicted Forecast Accuracy (Firm DIFF)

Table 1 – Number Series Tasks

Panel A: Analyst sample

	Total Time (sec)		Percentage of Correct Responses				
Type of Number Series	**Mean (SD)**	**Median**	**(1) n=20**	**(2) n=16**	**(3) n=18**	**(4) n=20**	**Overall n=74**
Linear	12 (11)	9	93	100	92	98	95
Triangular	30 (42)	15	90	94	89	95	92
Oscillating	17 (58)	8	95	100	94	100	97
Triangular & Oscillating	143 (153)	102	55	56	33	25	42

Panel B: MBA student sample

	Total Time (sec)		Percentage of Correct Responses				
Type of Number Series	**Mean (SD)**	**Median**	**(1) n=30**	**(2) n=33**	**(3) n=32**	**(4) n=33**	**Overall n=128**
Linear	11 (7)	9	100	95	92	91	95
Triangular	30 (46)	18	97	94	84	91	91
Oscillating	9 (6)	8	100	94	94	94	95
Triangular & Oscillating	151 (157)	100	47	30	25	45	37

This table reports the mean, median, and standard deviation for the total time (seconds) it took participants to complete each type of number series. It also shows the percentage of participants who successfully completed each type of number series by condition. The conditions are labeled as follows: "No Task Decomposition / Traditional Disclosure Format": (1); "Task Decomposition / Traditional Disclosure Format" (2); "No Task Decomposition / Disaggregated Disclosure Format" (3); and, "Task Decomposition / Disaggregated Disclosure Format" (4). The number series given to participants were as follows (the number in parentheses represents the correct answer to the number series): "Linear"=1,2,3,4,(5) and 4,8,12,16,20,(24); "Triangular"=1,3,6,10,15,(21); "Oscillating"=8,4,8,4,8,(4); and, "Triangular & Oscillating"=2,6,7,13,16,(24).

3. EXPERIMENTAL METHOD

3.1 Design overview

All participants complete forecasts and confidence assessments for two firms via the study's website. Firm DIFF is characterized by differentially persistent accrual and cash components of earnings. Firm SAME is characterized by accrual and cash components of earnings that have the same persistence. Figure 3 provides the persistence for earnings and the earnings components of Firm DIFF and Firm SAME. All participants are presented with five years of financial information and asked to provide forecasts for the following year.

3.2 Participants

Participants in this study consist of 74 financial analysts and 128 MBA students. These participants were randomly allocated to conditions as they were recruited. I recruited the analyst participants from four large investment advisory firms, two investment banks, and the treasury department of a large commercial bank. The analyst participants average 8 years of professional experience working as financial analysts and, on average, 47% of their professional responsibilities involve analyzing equity securities. These analyst participants cover 16 different industries and 53% of the financial analysts are chartered financial analysts. Almost three-quarters of the analyst participants work on the sell-side. I recruited the MBA student participants from the first-year MBA class of a large public university. Previous research uses MBA students as proxies for nonprofessional

investors (e.g., Elliott 2006; Hodge, Kennedy and Maines 2004). Elliott, Hodge, Kennedy and Pronk (2007) provide evidence that suggests MBA students undertaking the 'core' component of their studies attend to the same financial information as nonprofessional investors.[9] In this regard, MBA students are an appropriate proxy for nonprofessional investors as I investigate whether investors attend to information concerning the earnings components to forecast earnings.

3.3 Manipulation of task decomposition

I manipulate the task decomposition variable by informing participants in the "Task Decomposition" conditions that "Net Income" (i.e., earnings) consists of non-cash and cash components and then requiring them to forecast next-year "Non-cash Component of Net Income" and "Cash Flows From Operating Activities." I use the label "Non-cash Component of Net Income" in the materials as it is arguably more descriptive than the potentially ambiguous "Accruals" label. Participants in the "No Task Decomposition" conditions are required to forecast next-year "Net Income."

3.4 Manipulation of disclosure format

I manipulate disclosure format across two levels. Participants in the "Traditional Disclosure Format" conditions are presented with a set of financial statements including the income statement in its traditional presentation format. Participants in the "Disaggregated Disclosure Format" conditions are presented

[9] However, Hodge et al. (2007) also show that MBA students integrate financial information differently from nonprofessional investors when completing complex tasks.

with a set of financial statements disclosing earnings information disaggregated into its accrual and cash components on the income statement. This disclosure format of the income statement reconciles net income to cash flows from operating activities by adding back accruals. See Figure 1 for the manipulation of disclosure format on the income statement.

The "Disaggregated Disclosure Format" adopts the recommendations of Maines and McDaniel (2000) and mirrors some of the recent reforms proposed by standard-setters (IASB 2005; Reason 2005). Importantly, there is no differential information across the disclosure format conditions because the information placed at the bottom of the income statement in the "Disaggregated Disclosure Format" conditions can be calculated either directly from the statement of cash flows, or indirectly from the change in accrual accounts as presented on the balance sheet and depreciation expense as presented as a separate line item on the income statement. Therefore, I manipulate the disclosure format rather than the total amount of information given to participants.

3.5 Materials

The financial statements for both firms are presented in Figures 4 to 6. The income statements presented in Figure 4 are those given to participants in the "Disaggregated Disclosure Format" conditions. All participants receive the same disclosure format for the balance sheet (Figure 5) and the statement of cash flows (Figure 6).

I embed differential persistence of the accrual and cash components of earnings in Firm DIFF's financial statements. Figure 3 shows the patterns for the accrual and cash components of earnings for Firm DIFF and the time-series pattern for earnings for Firm SAME. Earnings are predictable for Firm DIFF and Firm SAME in 2006 taking into account the time-series patterns of the two earnings components and earnings, respectively. Firm DIFF's financial statements are characterized by a cash component of earnings that is increasing at an increasing rate and an oscillating pattern for the accrual component of earnings. This time-series pattern for the cash component of earnings is established by embedding a triangular number series in this earnings component. These time-series patterns create a scenario where the contemporaneous cash (accrual) component of earnings has a relatively high (low) level of persistence into Firm DIFF's earnings in 2006. Firm SAME's financial statements are characterized by a linear time-series pattern that has the same effect on the accrual and cash components of earnings.

I embed stochastic percentage errors into the data so that earnings are not perfectly predictable from inspection of both firms' financial statements. This avoids demand effects that may result in participants relying more on the earnings components than (i) other items in the experimental materials that are not perfectly predictable; or, (ii) they would in reality when the earnings components are not perfectly predictable. Consistent with Ackert, Church and Shehata (1997), stochastic percentage errors were determined for the earnings components by

sampling from a distribution in which +5%, 0%, and -5% occurred with probabilities of 0.2, 0.6, and 0.2, respectively.

The financial statements given to the participants are constructed so that the accrual component of earnings represents the difference between net income and cash flows from operating activities. This calculation of the accrual component of earnings is also consistent with the balance sheet method accrual component calculations used by Sloan (1996) and Hirshleifer, Hou, Teoh and Zhang (2004). Embedding these relationships in the financial statements ensures that participants in the "Traditional Disclosure Format" conditions can calculate the accrual component of earnings and are not disadvantaged through the content of the financial statements that they receive.

3.6 Procedure

The experiment proceeds as follows. After being briefed on the experiment, participants complete the forecasting task for either Firm DIFF or Firm SAME. I randomize across participants whether they first complete the forecasting task for Firm DIFF or Firm SAME, before completing the other firm's forecasting task. Each forecasting task involves the receipt of a firm's financial statements followed by the request for participants to provide their forecasts. In addition to providing forecasts, participants are also asked how confident they are in the accuracy of their forecasts (0-100%). Prior research has shown an association between investor confidence and trading activity (Hirshleifer 2001; Bloomfield et al. 1999). Therefore, I measure participants' confidence in the accuracy of their forecasts to

infer the probability of these forecasts being used to trade the associated firm's securities. After providing their forecasts, participants complete a series of debriefing questions. These questions include items addressing their ability to complete various number series patterns (linear, triangular, and oscillating), as well as questions addressing their professional and investing experience to ensure that any significant variation in these factors across the conditions is incorporated into the statistical analyses.

3.7 Measurement of dependent variable

This study uses forecast accuracy as a dependent variable. I report forecast accuracy as a percentage and I calculate it by subtracting the percentage forecast error from 100%. Forecast error is calculated as the absolute value of the difference between each participant's next-year earnings forecast and the actual value of next-year earnings divided by the actual value of next-year earnings. I use the number series embedded in the materials to determine actual earnings for the forecast year.

$$\text{Forecast accuracy (\%)} = 1 - [\,|\,\text{Forecast} - \text{Actual}\,|\,/\,\text{Actual}\,]$$

Firm DIFF

Item	Pattern	Formula
Accrual Component of Earnings	Oscillating	$ACC_t = -274 + 150(-1)^t$
Cash Component of Earnings	Triangular Number Series	$CASH_t = 1,022 + 100 \cdot [\sum_{k=0}^{t-1} k]$
Earnings	Oscillating and Triangular Number Series	$EARN_t = 748 + 100 \cdot [\sum_{k=0}^{t-1} k] + (150)(-1)^t$

Firm SAME

Item	Pattern	Formula
Accrual Component of Earnings	Linear	$ACC_t = -7 - 50(t)$
Cash Component of Earnings	Linear	$CASH_t = 269 + 350(t)$
Earnings	Linear	$EARN_t = 262 + 300(t)$

$EARN_t$ is earnings (net income) in year t.
ACC_t is the accrual component of earnings in year t, and represents the difference between net income and cash flows from operating activities. This calculation of the accrual component of earnings is also consistent with the balance sheet method accrual component calculations. In the experiment, accruals were labeled "Non-cash Component of Net Income."
$CASH_t$ is the cash component of earnings (cash flows from operating activities) in year t.

I embed stochastic percentage errors into the data so that earnings is not perfectly predictable from inspection of both firms' financial statements. Consistent with Ackert et al. (1997), stochastic percentage errors were determined for the earnings components by sampling from a distribution in which +5%, 0%, and -5% occurred with probabilities of 0.2, 0.6, and 0.2, respectively.

Figure 3 – Persistence of Earnings and the Accrual and Cash Components of Earnings

Firm DIFF

FIRM DIFF
Income Statement
For the year ended December 31, 2005

	Year ended December 31				
	2005	**2004**	**2003**	**2002**	**2001**
NET OPERATING REVENUES	5,369	5,033	3,017	3,353	2,009
Cost of Goods Sold	(2,684)	(2,516)	(1,508)	(1,676)	(1,005)
GROSS PROFIT	2,684	2,516	1,508	1,676	1,005
Selling, General and Administrative Expenses					
Depreciation	(334)	(309)	(302)	(303)	(363)
Other	(773)	(704)	(374)	(376)	(13)
NET INCOME	1,577	1,504	832	998	628
Components of Net Income:					
Cash Flows From Operating Activities	2,022	1,622	1,256	1,122	1,073
Non-cash Component of Net Income	(445)	(118)	(424)	(124)	(445)
Net Income	1,577	1,504	832	998	628

Firm SAME

FIRM SAME
Income Statement
For the year ended December 31, 2005

	Year ended December 31				
	2005	**2004**	**2003**	**2002**	**2001**
NET OPERATING REVENUES	5,408	4,683	3,933	3,233	2,508
Cost of Goods Sold	(2,704)	(2,342)	(1,967)	(1,617)	(1,254)
GROSS PROFIT	2,704	2,342	1,967	1,617	1,254
Selling, General and Administrative Expenses					
Depreciation	(364)	(379)	(362)	(352)	(357)
Other	(490)	(501)	(443)	(360)	(363)
NET INCOME	1,850	1,462	1,162	905	534
Components of Net Income:					
Cash Flows From Operating Activities	2,120	1,669	1,319	1,017	588
Non-cash Component of Net Income	(270)	(207)	(157)	(112)	(54)
Net Income	1,850	1,462	1,162	905	534

Figure 4 – Income Statement ("Disaggregated Disclosure Format" Conditions)

Firm DIFF

FIRM DIFF
Balance Sheet
As of December 31, 2005

	As of December 31				
	2005	2004	2003	2002	2001
ASSETS					
CURRENT ASSETS					
Cash	12,008	11,529	10,276	8,254	6,655
Accounts Receivable	2,419	2,399	2,291	2,878	2,714
Inventory	5,418	5,387	5,131	5,216	5,386
TOTAL CURRENT ASSETS	19,845	19,315	17,698	16,348	14,755
LONG-TERM ASSETS	59,897	59,519	59,234	60,193	60,766
TOTAL ASSETS	79,742	78,834	76,932	76,541	75,521
LIABILITIES					
CURRENT LIABILITIES					
Accounts Payable	10,480	10,318	10,145	10,696	10,880
TOTAL CURRENT LIABILITIES	10,480	10,318	10,145	10,696	10,880
LONG-TERM LIABILITIES	61,653	62,484	62,259	62,149	61,943
TOTAL LIABILITIES	72,133	72,802	72,404	72,845	72,823
SHAREOWNERS' EQUITY					
Common Stock	2,000	2,000	2,000	2,000	2,000
Retained Earnings	5,609	4,032	2,528	1,696	698
TOTAL SHAREOWNERS' EQUITY	7,609	6,032	4,528	3,696	2,698
TOTAL LIABILITIES AND SHAREOWNERS' EQUITY	79,742	78,834	76,932	76,541	75,521

Firm SAME

FIRM SAME
Balance Sheet
As of December 31, 2005

	As of December 31				
	2005	2004	2003	2002	2001
ASSETS					
CURRENT ASSETS					
Cash	11,438	10,727	9,310	7,216	5,594
Accounts Receivable	2,643	2,356	2,253	2,420	2,532
Inventory	8,004	7,854	8,004	8,089	8,004
TOTAL CURRENT ASSETS	22,085	20,937	19,567	17,725	16,130
LONG-TERM ASSETS	58,817	58,526	58,377	59,346	60,000
TOTAL ASSETS	80,902	79,463	77,944	77,071	76,130
LIABILITIES					
CURRENT LIABILITIES					
Accounts Payable	10,652	10,309	10,528	10,985	11,252
TOTAL CURRENT LIABILITIES	10,652	10,309	10,528	10,985	11,252
LONG-TERM LIABILITIES	61,521	62,275	61,999	61,831	61,528
TOTAL LIABILITIES	72,173	72,584	72,527	72,816	72,780
SHAREOWNERS' EQUITY					
Common Stock	2,000	2,000	2,000	2,000	2,000
Retained Earnings	6,729	4,879	3,417	2,255	1,350
TOTAL SHAREOWNERS' EQUITY	8,729	6,879	5,417	4,255	3,350
TOTAL LIABILITIES AND SHAREOWNERS' EQUITY	80,902	79,463	77,944	77,071	76,130

Figure 5 – Balance Sheet (All Conditions)

Firm DIFF

FIRM DIFF
Statement of Cash Flows
For the year ended December 31, 2005

	Year ended December 31				
	2005	2004	2003	2002	2001
CASH FLOWS FROM OPERATING ACTIVITIES					
Net Income	1,577	1,504	832	998	628
Adjustments to Reconcile Net Income to Net Cash Provided by Operating Activities:					
Depreciation	334	309	302	303	363
(Increase) Decrease in Accounts Receivable	(20)	(108)	587	(164)	31
(Increase) Decrease in Inventory	(31)	(256)	85	170	(58)
Increase (Decrease) in Accounts Payable	162	173	(551)	(184)	109
Net Cash Provided by Operating Activities	2,022	1,622	1,256	1,122	1,073
CASH FLOWS FROM INVESTING ACTIVITIES	(712)	(594)	656	271	(357)
CASH FLOWS FROM FINANCING ACTIVITIES	(831)	225	110	206	651
CASH AND CASH EQUIVALENTS					
Net Increase (Decrease) During the Period	479	1,253	2,022	1,599	1,367
Balance at Beginning of Period	11,529	10,276	8,254	6,655	5,288
Balance at End of Period	12,008	11,529	10,276	8,254	6,655

Firm SAME

FIRM SAME
Statement of Cash Flows
For the year ended December 31, 2005

	Year ended December 31				
	2005	2004	2003	2002	2001
CASH FLOWS FROM OPERATING ACTIVITIES					
Net Income	1,850	1,462	1,162	905	534
Adjustments to Reconcile Net Income to Net Cash Provided by Operating Activities:					
Depreciation	364	379	362	352	357
(Increase) Decrease in Accounts Receivable	(287)	(103)	167	112	125
(Increase) Decrease in Inventory	(150)	150	85	(85)	(319)
Increase (Decrease) in Accounts Payable	343	(219)	(457)	(267)	(109)
Net Cash Provided by Operating Activities	2,120	1,669	1,319	1,017	588
CASH FLOWS FROM INVESTING ACTIVITIES	(655)	(528)	607	302	(453)
CASH FLOWS FROM FINANCING ACTIVITIES	(754)	276	168	303	603
CASH AND CASH EQUIVALENTS					
Net Increase (Decrease) During the Period	711	1,417	2,094	1,622	738
Balance at Beginning of Period	10,727	9,310	7,216	5,594	4,856
Balance at End of Period	11,438	10,727	9,310	7,216	5,594

Figure 6 – Statement of Cash Flows (All Conditions)

4. RESULTS AND DISCUSSION

Table 2, Panels A and B (Panels C and D) report the descriptive statistics related to participants' forecasts for Firm DIFF (Firm SAME) for the analyst and MBA student samples, respectively. I exclude participants' net income forecasts from the analyses when they exceed the overall mean net income forecast for a firm by over four standard deviations.[10] In the post-experiment questions, I ask participants to identify the income statement they were presented with in the experiment. This question assesses whether participants in the "Disaggregated Disclosure Format" conditions are aware that they were presented with the accrual and cash components of earnings information on the income statement. Eighty-five (eighty-three) percent of the analyst participants (MBA student participants) correctly identified the income statement that they were given in the experiment. This percentage does not significantly differ across conditions and the reported results are insensitive to the exclusion of the forecasts of participants who failed to correctly identify the income statement they were given in the experiment. In addition, I observe that the order in which participants provide forecasts for the two firms is not significant when included as a covariate in the statistical analyses.

[10] No forecasts are excluded for the analyst sample for Firm DIFF. Two forecasts are excluded for the analyst sample for Firm SAME. It appears that at least one of these two analysts forecasted "Net Operating Revenues" for Firm SAME. Five forecasts are excluded for the MBA student sample for Firm DIFF. Nine forecasts are excluded for the MBA student sample for Firm SAME. It appears that at least eight of these MBA students' forecasts are based upon "Net Operating Revenues."

4.1 Hypothesis 1

Hypothesis 1 states that investors' forecasts will be less accurate when the earnings components are differentially persistent than when these components are equally persistent. To test this hypothesis, I perform paired-sample t-tests for participants in the "No Task Decomposition / Traditional Disclosure Format" (control) condition for both the analyst and the MBA student samples. Consistent with my prediction, participants' forecasts are relatively less accurate when the earnings components are differentially persistent (Table 2). Table 3 documents that this finding is significant for both samples (analysts: $t_{18} = 6.726$; $p = 0.000$, one-tailed; MBA students: $t_{27} = 11.464$; $p = 0.000$, one-tailed).

I also find that participants are less confident in the accuracy of their forecasts when the earnings components are differentially persistent than when these components are equally persistent (Table 2). This finding is significant for both samples (analysts: $t_{18} = 2.840$; $p = 0.011$, two-tailed; MBA students: $t_{27} = 4.043$; $p = 0.000$, two-tailed; Table 3), suggesting that participants were aware of the inherent difficulty in providing accurate forecasts for Firm DIFF.

4.2 Hypothesis 2

In its null form, Hypothesis 2 states that analysts will not provide relatively more accurate earnings forecasts compared to nonprofessional investors when the earnings components are differentially persistent. I perform independent samples t-tests for participants in the "No Task Decomposition / Traditional Disclosure

Format" (control) conditions to test for differences between the analyst and MBA student samples.

I find that the mean forecast accuracy of the analyst sample does not differ from the mean forecast accuracy of the MBA students when the earnings components are differentially persistent (Table 2: analysts: 70.97%; MBA students: 70.44%).[11] This result is consistent with the finding that analyst participants and MBA student participants performed similarly on the number series tasks. These results are also consistent with prior research that suggests investors find it difficult to accurately forecast earnings when the earnings components are differentially persistent (e.g., Sloan 1996; Bradshaw et al. 2001; Hirshleifer and Teoh 2003). In particular, these results are also consistent with Bradshaw et al. (2001) who find that analysts only partially adjust their forecasts to correct for the differential persistence of large accruals. However, these results are inconsistent with the prior literature that suggests investor sophistication is negatively related to security mispricing (Bonner et al. 2003; Collins et al. 2003) and the expertise literature in psychology (Rikers and Paas 2005).

The two samples differ with respect to participants' confidence in the accuracy of their forecasts (Table 4). Comparing the confidence assessments for participants in the "No Task Decomposition / Traditional Disclosure Format" (control) conditions, I find that the analyst participants are significantly less

[11] The mean forecast accuracy of the analyst sample also does not differ from the mean forecast accuracy of the MBA student sample when the earnings components are equally persistent (Table 2: analysts: 92.44%; MBA students: 92.22%).

confident than MBA students in the accuracy of their forecasts (Firm DIFF: t_{47} = 2.125; p = 0.039, two-tailed; Firm SAME: t_{46} = 2.278; p = 0.027, two-tailed; Table 4). The higher confidence of MBA students in the accuracy of their forecasts relative to analysts may indicate that nonprofessional investors are more confident basing their earnings forecasts on financial statements alone.

4.3 Hypothesis 3

This study provides a basis for investigating the efficacy of measures that enable investors to overcome hurdles related to both intrinsic and extraneous cognitive load when they are required to forecast earnings of firms with differentially persistent earnings components. This study's findings with respect to the first two hypotheses suggest both analysts and nonprofessional investors (i.e., investors with less investing experience) could benefit from measures that reduce the cognitive burden associated with forecasting earnings of firms with differentially persistent earnings components.

Hypothesis 3 investigates the role of cognitive load as a behavioral mechanism underlying investors' difficulty to accurately forecast earnings of firms with differentially persistent earnings components. I predict an interaction effect between task decomposition and disclosure format on investors' forecast accuracy. Figure 2 presents the predicted pattern of condition means.

Bobko (1986) recommends the use of planned contrast analysis to test a hypothesized ordinal interaction to increase the power of the statistical test. Using ANOVA to test the predicted pattern of means depicted in Figure 2 is likely to

result in spurious significant main effects (Buckless and Ravenscroft 1990; Rosnow and Rosenthal 1995).[12] These spurious main effects are evident in the ANOVA presented in Panel A of Table 5. This ANOVA suggests that main effects exist for "Task Decomposition" and "Disclosure Format." However, inspection of the two-way comparisons reveals that the "Task Decomposition / Traditional Disclosure Format" condition is not significantly different from the ""No Task Decomposition / Traditional Disclosure Format" condition ($t_{96} = 0.762$; $p = 0.448$). It is arguably invalid to conclude that a main effect exists for "Task Decomposition" because I do not observe significantly higher forecast accuracy for "Task Decomposition" relative to "No Task Decomposition" across both levels of the "Disclosure Format" variable. The same conclusion applies to the "Disclosure Format" main effect.

My contrast coding reflects the predicted pattern of investors' forecast accuracy for Firm DIFF (Figure 2). I use the following contrast weights for each condition: "No Task Decomposition / Traditional Disclosure Format" = -1; "Task Decomposition / Traditional Disclosure Format" = -1; "No Task Decomposition / Disaggregated Disclosure Format" = -1; and, "Task Decomposition / Disaggregated Disclosure Format" = +3. These contrast weights are appropriate because the mean forecast accuracy of the "Task Decomposition / Disaggregated Disclosure Format" condition is expected to be significantly greater than the overall mean forecast

[12] Other recent accounting studies that have adopted planned contrast analysis to test ordinal interactions include Sedor (2002) and Hodge et al. (2004).

accuracy of the other three conditions. As required, these contrast weights sum to zero.

Figure 7 depicts the condition means for all participants. Participants in the "Task Decomposition / Disaggregated Disclosure Format" condition had a mean forecast accuracy of 80.24% compared with participants in the "No Task Decomposition / Traditional Disclosure Format," "Task Decomposition / Traditional Disclosure Format," and "No Task Decomposition / Disaggregated Disclosure Format" conditions, which had means of 70.66%, 72.72%, and 71.89%, respectively. Table 5, Panel C provides evidence supporting Hypothesis 3 (t_{193} = 3.936; p = 0.000, one-tailed). The hypothesized interaction holds for both groups of participants (analysts: t_{70} = 2.187; p = 0.016, one-tailed; MBA students: t_{119} = 3.320; p = 0.001, one-tailed).[13]

These results are consistent with cognitive load representing an underlying behavioral mechanism contributing to investors' inaccurate earnings forecasts when the earnings components are differentially persistent. This study's findings suggest that investors must overcome intrinsic cognitive load and extraneous cognitive load to accurately forecast earnings when the earnings components are differentially persistent. Decomposing the task or disclosing the disaggregated earnings

[13] Closer inspection of the data reveals that four analyst participants appear to have forecasted the mean of the time series for Firm DIFF. Removing these participants' forecasts from the analyses leads to condition means for the "Task Decomposition / Disaggregated Disclosure Format," "No Task Decomposition / Traditional Disclosure Format," "Task Decomposition / Traditional Disclosure Format," and "No Task Decomposition / Disaggregated Disclosure Format" conditions of 70.97%, 71.52%, 73.27% and 81.79%, respectively. This sample also supports Hypothesis 3 (t_{66} = 3.957; p = 0.000, one-tailed; not tabulated).

components on the income statement is insufficient in isolation to increase investors' forecast accuracy when the earnings components are differentially persistent. This finding suggests neither manipulation, in isolation, reduces both intrinsic and extraneous cognitive load.

4.4 Additional analyses

4.4.1 The role of task decomposition in reducing fixation

Table 6 reports that over two-thirds of participants in each condition chose to first access the income statement after being given the task. Independent of the condition that participants were assigned to, participants appear to prefer to view the income statement when given an earnings forecasting task. Due to the absence of information concerning the cash component of earnings on the traditional income statement, this fixation on the income statement makes these participants susceptible to inaccurately forecasting earnings when its components are differentially persistent. Interestingly, Table 6 also shows that analysts in the "Task Decomposition" conditions were more likely to first access the income statement relative to MBA student participants in the "Task Decomposition" conditions. This finding is contrary to the commonly held belief that sophisticated users of financial statements (e.g., analysts) may be less fixated on earnings than less sophisticated users of financial statements. As one analyst participant succinctly stated "analytically, we are all creatures of habit when assessing relationships and quantitatively estimating prospective financial performance."

Table 7, Panel A reports the relative percentage of time participants spent viewing each of Firm DIFF's financial statements. Analyst participants in the "Task Decomposition" conditions spent significantly less time viewing the income statement ($t_{72} = 4.474$; $p = 0.000$, one-tailed; not tabulated) and significantly more time viewing the statement of cash flows ($t_{72} = 5.478$; $p = 0.000$, one-tailed; not tabulated). Table 7, Panel B documents the same pattern for the MBA students.

Decomposing the task for participants requires them to forecast each of the earnings components separately and, in doing so, reduces the intrinsic cognitive load of the task. The statement of cash flows contains information concerning both earnings components and, in particular, shows the link between earnings and cash flows from operating activities through the indirect presentation of cash flows from operating activities. Participants in the "Task Decomposition" conditions attend relatively more to the disaggregated components information on the statement of cash flows (ψ^*) and participants in the "No Task Decomposition" conditions attend relatively more to the aggregated earnings information reported on the income statement (ψ^{fix}). This finding is consistent with my theoretical framework.

4.4.2 The role of disclosure format in reducing extraneous cognitive load

When the earnings components are differentially persistent, I predict that the mean forecast accuracy of participants in the "Task Decomposition / Traditional Disclosure Format" condition will not be greater than that of participants in the control condition ("No Task Decomposition / Traditional Disclosure Format"). This prediction holds for both samples (analysts: $t_{34} = 0.472$; $p = 0.640$, two-tailed;

not tabulated; MBA students: $t_{60} = 1.016$; $p = 0.314$, two-tailed; not tabulated). I attribute these results to the extraneous cognitive load presented by the financial statements when participants are trying to locate and calculate the earnings components.

I analyze the role of disclosure format in reducing extraneous cognitive load by comparing participants' forecasts of the earnings components for the "Task Decomposition / Traditional Disclosure Format" and "Task Decomposition / Disaggregated Disclosure Format" conditions.[14] When the earnings components are differentially persistent, analysts' forecasts of cash flows from operating activities are significantly more accurate when the disclosure format presents the disaggregated earnings components on the income statement ($\chi^2 = 3.667$; $p = 0.028$, one-tailed; not tabulated). However, there is no significant difference between the "Task Decomposition" conditions for analysts' forecast accuracy of the accrual component of earnings ($\chi^2 = 0.159$; $p = 0.345$, one-tailed; not tabulated). MBA students' forecasts of both components are significantly more accurate when the disclosure format presents the disaggregated earnings components on the income statement (cash flows from operating activities: $\chi^2 = 2.373$; $p = 0.062$, one-tailed; not tabulated; accrual component of earnings: $\chi^2 = 4.029$; $p = 0.024$, one-tailed; not tabulated).

[14] Due to the limited degrees of freedom and the non-normality of these data samples, I perform these analyses using Kruskal-Wallis non-parametric tests for independent samples.

Table 6 allows for the comparison between the "Task Decomposition" conditions of the percentage of participants viewing each financial statement when they submit their forecasts. Participants in the "Task Decomposition / Disaggregated Disclosure Format" condition have the choice of using either the income statement or the statement of cash flows to simultaneously consider the earnings components before submitting their forecasts. Table 6, Panels A and B suggests that participants in the "Task Decomposition / Disaggregated Disclosure Format" condition are more (less) likely than participants in the "Task Decomposition / Traditional Disclosure Format" to view the income statement (statement of cash flows) immediately before they submit their forecasts. Further, the mean forecast accuracy of participants in the "Task Decomposition / Disaggregated Disclosure Format" condition is significantly greater than the mean forecast accuracy of participants in the "Task Decomposition / Traditional Disclosure Format" ($t_{99} = 2.334$; $p = 0.011$, one-tailed, Table 5). These results suggest that the extraneous cognitive load presented by traditional financial statements contributes to the difficulties investors face when trying to locate and calculate the earnings components. Consistent with Maines and McDaniel (2000), this study suggests that disaggregating the components and placing these components on the income statement reduces the extraneous cognitive load associated with forecasting earnings of firms with differentially persistent earnings components.

4.4.3 The 'benefit' of fixating on aggregated numbers

This study investigates the hurdles that investors face forecasting earnings of firms with differentially persistent earnings components. My results suggest that investors limit their attention to the aggregated earnings time series (ψ^{fix}) to forecast earnings. While this approach may minimize cognitive processing costs, it leads to inaccurate forecasts when the earnings components are differentially persistent. However, when the earnings components are equally persistent, this approach leads to forecasts that compare favorably to those of investors required to use information set, ψ^{*}. The mean forecast accuracy of participants' forecasts for Firm SAME in the "No Task Decomposition / Traditional Disclosure Format" condition is not significantly different than the mean forecast accuracy of the other conditions (analysts: $t_{70} = 1.208$; $p = 0.231$, two-tailed; MBA students: $t_{117} = 1.479$; $p = 0.142$, two-tailed; not tabulated). Consistent with my theory, these results suggest that investors' forecast accuracy will only be adversely affected by using ψ^{fix} when the earnings components are differentially persistent.

4.4.4 The effect of task decomposition and disclosure format on investment decisions

After completing their forecasts, participants made an investment decision based on the relative earnings potential of the two firms. Firm DIFF's financial statements reflect key aspects of Sloan's findings concerning the relative persistence, sign, and size of the accrual and cash components of earnings. On average, he finds that earnings are less (more) persistent than the cash (accrual)

component of earning. Therefore, if participants use the historical persistence of earnings to forecast future earnings, they underweight (overweight) the persistence of the cash (accrual) component of earnings.

On average, Sloan finds that the accrual component of earnings is less persistent, and smaller relative to the cash component of earnings. While the cash component of earnings tends to be positive, the accrual component of earnings tends to be negative. Therefore, if participants underweight (overweight) the persistence of a positive and relatively large cash component of earnings (negative and relatively small accrual component of earnings), I would expect them to provide relatively lower earnings forecasts for Firm DIFF than Firm SAME. In contrast, participants who do attend to the persistence of accruals and cash flows from operating activities would most likely believe that Firm DIFF has relatively greater earnings potential than Firm SAME.

Table 8 reports the percentage of participants who decided to invest in Firm DIFF. This table suggests that participants' investment decisions do not directly mirror their earnings forecasts. These findings suggest that investors based their investment decisions on information other than their earnings forecasts. In particular, I do not observe the same cognitive load effect on investment decisions as I observe for earnings forecasts. Some analyst participants commented that the scarcity of information provided in the experiment made an investment decision difficult, e.g., "... your survey forced me to pick one of the companies to invest in

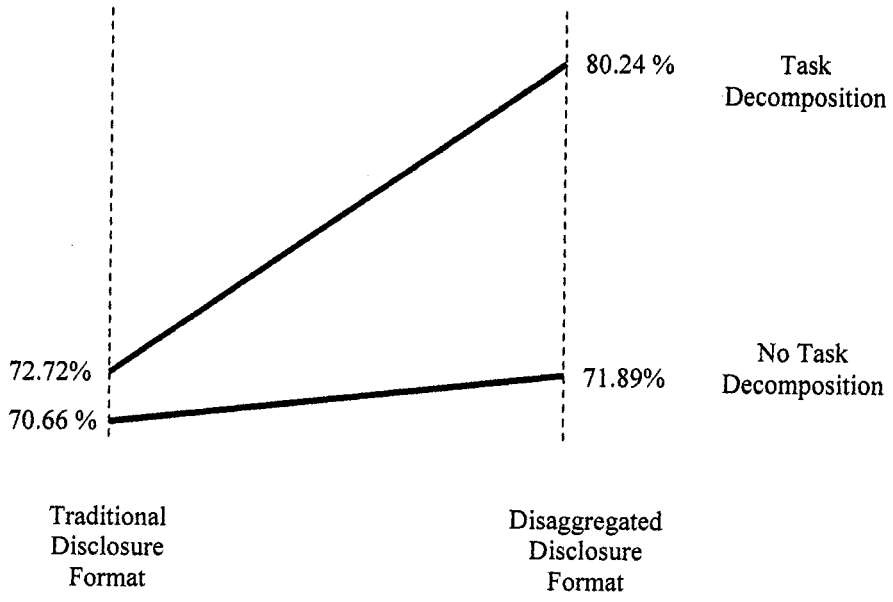
without information on the price of the stock. Obviously, without this information (as well as other important data) I would be indifferent."

However, two findings in Table 8 are noteworthy. When the forecasting task is not decomposed, analysts are significantly more likely to invest in Firm DIFF relative to MBA students ($\chi^2 = 8.431$; $p = 0.004$, two-tailed; not tabulated). In contrast, when the forecasting task is decomposed, there is almost no difference between the investment decisions of analysts and MBA students. Although inconsistent with the findings concerning earnings forecasts, these results provide preliminary evidence that nonprofessional investors are less likely to consider properties of the earnings components in arriving at their investment decisions (e.g., persistence of the earnings components), when the task is not decomposed.

Table 8 also suggests that the percentage of MBA students willing to invest in Firm DIFF is twice as large in the "Task Decomposition / Disaggregated Disclosure Format" condition relative to the "No Task Decomposition / Traditional Disclosure Format" (control) condition ($\chi^2 = 2.267$; $p = 0.132$, two-tailed; not tabulated). This result provides weak evidence of the effect of cognitive load on investment decisions when one of the investment choices has differentially persistent earnings components. When cognitive load is reduced through task decomposition and disclosing the disaggregated earnings components on the income statement, nonprofessional investors (i.e., in this study, MBA students) are more likely to incorporate the persistence of the earnings components into their investment decisions.

It is possible that these results reflect that participants use information other than their earnings forecasts to arrive at their investment decisions. For instance, Table 2 shows participants are significantly more confident in the accuracy of their forecasts for Firm SAME relative to Firm DIFF. Further, this difference in confidence does not significantly vary across conditions. This lack of confidence in the accuracy of their Firm DIFF forecasts may have led to some participants being reluctant to select this firm in their investment decisions. This finding may explain why relatively fewer MBA students chose to invest in Firm DIFF across all conditions compared with the proportion that decided to invest in Firm SAME.

(Dependent variable: Forecast Accuracy)



This figure depicts the observed pattern of participants' mean forecast accuracy when the earnings components are differentially persistent (Firm DIFF).

Figure 7 – Hypothesis 3: Observed Forecast Accuracy (Firm DIFF)

Table 2 – Forecasting Tasks

Panel A: Firm DIFF – Analyst sample

		Forecast		Forecast Accuracy (%)		
Condition	**n**	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Mean (SD) Confidence in Forecast Accuracy**
No Task Decomp./ Traditional	20	1,724 (274)	1,650	70.97 (8.61)	68.81	37 (24)
Task Decomp./ Traditional	16	1,664 (274)	1,650	69.39 (11.41)	68.81	48 (27)
No Task Decomp./ Disaggregated	18	1,721 (217)	1,700	71.76 (9.04)	70.89	39 (30)
Task Decomp./ Disaggregated	20	1,868 (419)	1,863	77.69 (17.23)	77.69	43 (29)

Panel B: Firm DIFF – MBA student sample

		Forecast		Forecast Accuracy (%)		
Condition	**n**	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Mean (SD) Confidence in Forecast Accuracy**
No Task Decomp./ Traditional	29	1,761 (377)	1,650	70.44 (8.54)	68.81	51 (21)
Task Decomp./ Traditional	33	1,782 (454)	1,830	74.33 (18.95)	76.31	51 (22)
No Task Decomp./ Disaggregated	29	1,808 (423)	1,625	71.97 (11.22)	67.76	49 (26)
Task Decomp./ Disaggregated	32	1,967 (351)	2,038	81.84 (14.40)	84.99	51 (28)

Table 2 – Forecasting Tasks (cont.)

Panel C: Firm SAME – Analyst sample

		Forecast		Forecast Accuracy (%)		
Condition	**n**	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Mean (SD) Confidence in Forecast Accuracy**
No Task Decomp./ Traditional	19	2,175 (172)	2,175	92.44 (6.42)	93.55	52 (22)
Task Decomp./ Traditional	16	2,126 (227)	2,139	91.17 (6.96)	91.51	58 (24)
No Task Decomp./ Disaggregated	17	2,054 (339)	2,165	89.71 (12.59)	93.31	47 (34)
Task Decomp./ Disaggregated	20	2,120 (320)	2,210	87.92 (9.76)	87.81	50 (31)

Panel D: Firm SAME – MBA student sample

		Forecast		Forecast Accuracy (%)		
Condition	**n**	**Mean (SD)**	**Median**	**Mean (SD)**	**Median**	**Mean (SD) Confidence in Forecast Accuracy**
No Task Decomp./ Traditional	29	2,178 (146)	2,203	92.22 (4.49)	92.34	66 (20)
Task Decomp./ Traditional	30	2,125 (311)	2,165	89.83 (11.39)	90.88	60 (28)
No Task Decomp./ Disaggregated	27	2,281 (317)	2,216	87.79 (14.09)	91.90	63 (26)
Task Decomp./ Disaggregated	33	2,071 (306)	2,140	89.05 (9.87)	90.35	59 (26)

Table 2 – Forecasting Tasks (cont.)

Notes to Table 2:

Participants were asked to forecast net income. Participants in the "Task Decomposition" conditions were informed that net income consists of non-cash and cash components and were then required to forecast "Non-cash Component of Net Income" and "Cash Flows From Operating Activities" for the next year. These forecasts of the earnings components were aggregated for participants in the "Task Decomposition" conditions. Participants in the "No Task Decomposition" conditions were asked to forecast "Net Income" for the next year. Participants in the "Traditional Disclosure Format" conditions were presented with a set of financial statements including the income statement in its traditional presentation format. Participants in the "Disaggregated Disclosure Format" conditions were presented with a set of financial statements disclosing earnings information disaggregated into its accrual and cash components on the income statement. This disclosure format of the income statement reconciles net income to cash flows from operating activities by adding back accruals. See Figure 2 for the manipulation of disclosure format on the income statement. This table reports the mean, standard deviation, and median for the net income forecast variable for each condition for both the analyst and MBA student samples.

Forecast accuracy (%) is calculated as 1 – [|Forecasted Net Income – Actual Net Income| / Actual Net Income]. This table reports the mean, standard deviation, and median for the forecast accuracy variable for each condition for both the analyst and MBA student samples.

After completing their forecasts, participants were shown their forecasts and asked "How confident are you in the accuracy of this forecast of net income?" Participants provided percentage confidence assessments in response to this question. This table reports the mean and standard deviation for the confidence assessment variable for each condition for both the analyst and MBA student samples.

Panels A and B report the descriptive statistics for the Firm DIFF (Alps) forecasting task. Panels C and D report the descriptive statistics for the Firm SAME (Dolomites) forecasting task.

Table 3 – Tests of Hypothesis 1

	df	t-statistic	p-value
Forecast Accuracy			
Analyst sample	18	6.726	0.000 (1T)
MBA student sample	27	11.464	0.000 (1T)
Combined sample	46	12.766	0.000 (1T)
Confidence in Forecast Accuracy			
Analyst sample	18	2.840	0.011 (2T)
MBA student sample	27	4.043	0.000 (2T)
Combined sample	46	4.933	0.000 (2T)

Hypothesis 1 states: "investors' earnings forecasts will be relatively less accurate when the earnings components are differentially persistent than when the earnings components are equally persistent."

To test Hypothesis 1, I use a paired-sample t-test of participants' forecasts in the "No Task Decomposition / Traditional Disclosure Format" condition. I perform this analysis for the analyst and MBA student samples separately.

One-tailed p-values are labeled "(1T)." Two-tailed p-values are labeled "(2T)."

Table 4 – Tests of Hypothesis 2

	df	t-statistic	p-value
Forecast Accuracy			
Firm DIFF	47	0.211	0.834 (2T)
Firm SAME	46	0.143	0.887 (2T)
Confidence in Forecast Accuracy			
Firm DIFF	47	2.125	0.039 (2T)
Firm SAME	46	2.278	0.027 (2T)

Hypothesis 2 states: "analysts will not provide significantly more accurate earnings forecasts relative to nonprofessional investors when the earnings components are differentially persistent."

To test Hypothesis 2, I use an independent samples t-test of participants' responses in the "No Task Decomposition / Traditional Disclosure Format" conditions.

Two-tailed p-values are labeled "(2T)."

Table 5 – Tests of Hypothesis 3

Panel A: Analysis of Variance

Source of variance	df	F-statistic	p-value
Main effects:			
Investor type (INVESTOR)	1	1.230	0.269 (2T)
Task decomposition (TD)	1	5.246	0.023 (2T)
Disclosure format (DF)	1	5.262	0.023 (2T)
Two-way interaction effects:			
INVESTOR *x* TD	1	1.413	0.236 (2T)
INVESTOR *x* DF	1	0.000	0.995 (2T)
TD *x* DF	1	0.000	0.045 (1T)
Three-way interaction effect			
INVESTOR *x* TD *x* DF	1	0.037	0.847 (2T)

Panel B: Two-way Comparisons

	df	t-statistic	p-value
No TD / Traditional DF *(control)*			
vs. TD / Traditional DF	96	0.762	0.448 (2T)
vs. No TD / Disaggregated DF	94	0.641	0.523 (2T)
vs. TD / Disaggregated DF	99	3.819	0.000 (1T)
TD / Traditional DF			
vs. No TD / Disaggregated DF	94	0.287	0.775 (2T)
vs. TD / Disaggregated DF	99	2.334	0.011 (1T)
No TD / Disaggregated DF			
vs. TD / Disaggregated DF	97	3.117	0.001 (1T)

Panel C: Cognitive Load Planned Contrasts

	df	t-statistic	p-value
Analyst sample	70	2.187	0.016 (1T)
MBA student sample	119	3.320	0.001 (1T)
Combined sample	193	3.936	0.000 (1T)

To test the predicted interaction for Hypothesis 3, I use the following contrast weights for each condition: "No Task Decomposition / Traditional Disclosure Format" = -1; "Task Decomposition / Traditional Disclosure Format" = -1; "No Task Decomposition / Disaggregated Disclosure Format" = -1; and, "Task Decomposition / Disaggregated Disclosure Format" = +3. One-tailed p-values are labeled "(1T)." Two-tailed p-values are labeled "(2T)."

Table 6 – Process Information: Firm DIFF Forecasting Task

Panel A: Analyst sample

		Percentage of Participants Choosing to View Statement First			Percentage of Participants Viewing Statement When Submitting Forecast		
Condition	**n**	**IS**	**BS**	**SCF**	**IS**	**BS**	**SCF**
No Task Decomp./ Traditional	20	80	15	5	95	0	5
Task Decomp./ Traditional	16	81	19	0	19	19	62
No Task Decomp./ Disaggregated	18	83	17	0	89	6	6
Task Decomp./ Disaggregated	20	85	5	10	60	15	25

Panel B: MBA student sample

		Percentage of Participants Choosing to View Statement First			Percentage of Participants Viewing Statement When Submitting Forecast		
Condition	**n**	**IS**	**BS**	**SCF**	**IS**	**BS**	**SCF**
No Task Decomp./ Traditional	30	90	7	3	77	13	10
Task Decomp./ Traditional	33	70	15	15	33	0	67
No Task Decomp./ Disaggregated	32	94	6	0	81	3	16
Task Decomp./ Disaggregated	33	67	27	6	76	12	12

This table reports the percentage of participants viewing each financial statement first/last by condition. This analysis is for the Firm DIFF forecasting task. The income statement, balance sheet, and statement of cash flows are labeled "IS," "BS," and "SCF," respectively.

Table 7 – Time Information: Firm DIFF Forecasting Task

Panel A: Analyst sample

		Total Time (seconds)		Percentage of Total Time Mean (SD)		
Condition	**n**	**Mean (SD)**	**Median**	**IS**	**BS**	**SCF**
No Task Decomp./ Traditional	20	186 (125)	169	78 (22)	12 (14)	10 (11)
Task Decomp./ Traditional	16	452 (317)	323	37 (20)	19 (15)	44 (22)
No Task Decomp./ Disaggregated	18	408 (360)	287	72 (25)	18 (23)	10 (10)
Task Decomp./ Disaggregated	20	602 (641)	354	58 (29)	15 (19)	27 (25)

Panel B: MBA student sample

		Total Time (seconds)		Percentage of Total Time Mean (SD)		
Condition	**n**	**Mean (SD)**	**Median**	**IS**	**BS**	**SCF**
No Task Decomp./ Traditional	30	461 (544)	265	61 (32)	24 (28)	15 (18)
Task Decomp./ Traditional	33	813 (885)	487	33 (27)	11 (10)	56 (29)
No Task Decomp./ Disaggregated	32	377 (757)	160	68 (28)	16 (21)	16 (19)
Task Decomp./ Disaggregated	33	541 (550)	300	52 (32)	17 (25)	30 (27)

This table reports the mean, median and standard deviation for the total time (seconds) that participants spent viewing Firm DIFF's financial statements before submitting their forecasts and the mean and standard deviation for the percentage of total time that participants spent viewing each financial statement. The income statement, balance sheet, and statement of cash flows are labeled "IS," "BS," and "SCF," respectively.

Table 8 – Investment Decision

	Analyst sample		MBA student sample	
Condition	**n**	**Percentage Invest in Firm DIFF**	**n**	**Percentage Invest in Firm DIFF**
No Task Decomp./ Traditional	20	45	30	17
Task Decomp./ Traditional	16	25	33	25
No Task Decomp./ Disaggregated	18	44	32	19
Task Decomp./ Disaggregated	20	35	33	33

This table reports the percentage of participants who chose to invest in Firm DIFF based on the relative earnings potential of Firm DIFF and Firm SAME.

5. CONCLUSIONS AND FUTURE RESEARCH

Archival research reports that investors do not correctly estimate the differential persistence of the earnings components when forecasting earnings (Sloan 1996). My study confirms that investors' earnings forecasts are significantly less accurate when the earnings components are differentially persistent relative to when these components are equally persistent. I also show that investors are relatively less confident in the accuracy of their forecasts when the earnings components are differentially persistent. This evidence lends empirical support to the existence of the accrual anomaly and part of the theoretical model presented by Hirshleifer and Teoh (2003) describing the effects of limited attention and disclosure format when financial information is aggregated.

These results hold for separate samples of analysts and MBA students. I find no significant difference between the mean forecast accuracy of these two groups when the earnings components are differentially persistent. This result is consistent with the findings of Bradshaw et al. (2001) who show that analysts do not appear to incorporate the lower persistence of large accruals into their forecasts. Therefore, both analysts and MBA students appear to be susceptible to the underlying behavioral mechanism that leads to the accrual anomaly. I also find no significant difference between the mean forecast accuracy of the two samples when the earnings components are equally persistent.

My study presents cognitive load theory as a behavioral explanation for investors' inaccurate earnings forecasts for firms with differentially persistent

earnings components. When the earnings components are differentially persistent, I show that investors need to overcome both intrinsic and extraneous cognitive load to more accurately forecast earnings. In this study, I show how task decomposition and disclosure format enable analysts and MBA students to overcome these hurdles and improve their forecast accuracy. When the earnings components are differentially persistent, I find that the earnings forecasts of analysts and MBA students are only more accurate when the forecasting task is decomposed and the earnings components are disaggregated on the income statement.

This study is relevant to investors, regulators and standard-setters. My results highlight to investors the limitations of fixating on the aggregated earnings time series. Also, my study investigates the role of disclosure format in reducing trading anomalies and accordingly has implications for regulators and standard-setters. I document the efficacy of combining task decomposition and disclosure format as a mechanism for overcoming cognitive load and improving investors' forecast accuracy when the earnings components are differentially persistent.

Regulators and standard-setters may seek to educate investors about the accrual anomaly and the need to attend to the earnings components when forecasting earnings. This education agenda may lead to an increase in the awareness of investors to attend to the earnings components when forecasting earnings. This knowledge may allow investors to more accurately forecast earnings without task decomposition and altering the disclosure format of the financial statements. In this sense, knowledge may replace either task

decomposition or disclosure format to affect forecast accuracy. Therefore, knowledge concerning the importance of attending to the earnings components arguably enables investors to decrease cognitive load without requiring the reforms considered in this study.

Several limitations potentially affect the interpretability of my results and provide avenues for future research. Analysts and nonprofessional investors normally forecast earnings in a different setting than that presented in this study. For example, analysts and nonprofessional investors normally face numerous incentives that are not replicable in an experimental setting. Also analysts and nonprofessional investors have considerably more information available to them when they make their forecasts than what they were provided with in this experiment. Several analysts commented on the lack of information provided to them in the experiment. For example, one analyst stated "we don't know what industry the company is in, and therefore the cyclical and sector influences on the company. The cash flow statement and balance sheet do not contain detail on whether the sales growth seen over the period shown has come from acquisitions or it is organic." Another analyst commented "analysts cannot forecast future operating cash flows, etc., based purely on historical financial statement information." In light of these responses, future research may consider how incentives and different information sources interact with the variables manipulated in this study to affect the accuracy of the forecasts of analysts and nonprofessional investors.

I find no significant difference between the mean forecast accuracy of the analyst and MBA student samples when the earnings components are differentially persistent. This finding may stem from the limited information made available to participants in the study which may affect the two groups of participants differently. Analysts may use information other than the information presented in the financial statements to discern the differential persistence of the earnings components (e.g., industry affiliation, firm age). Therefore, the limited information presented in the experiment may not alert analysts to the differential persistent of the earnings components because they may typically use other information to discern differential persistence. Future research may consider other ways that knowledge and experience can affect the forecasting task when the earnings components are differentially persistent. For example, does familiarity with particular firms/industries and nonfinancial information alert analysts to the differential persistence of the earnings components?

Finally, while I motivate this study using the extant literature examining the accrual anomaly, this experiment does not involve active trading by investors. As the accrual anomaly is a 'trading' anomaly, my findings are limited by the assumption that investors' earnings forecasts are linked to their trading decisions. Future research could extend my study by considering the effect of cognitive load on investors' trading activity in a laboratory market setting.

REFERENCES

Abdel-khalik, A.R., and T.F. Keller. 1979. Earnings or cash flows: an experiment on functional fixation and the valuation of the firm. *Studies in Accounting Research* 21, American Accounting Association.

Ackert, L.F., B.K. Church, and M. Shehata. 1997. An experimental examination of the effects of forecast bias on individuals' use of forecasted information. *Journal of Accounting Research* 35(1): 25-42.

Balsam, S., E. Bartov, and C. Marquardt. 2002. Accruals management, investor sophistication, and equity valuation: evidence from 10–Q filings. *Journal of Accounting Research* 40(4): 987-1012.

Bartov, E., S. Radhakrishnan, and I. Krinsky. 2000. Investor sophistication and patterns in stock returns after earnings announcements. *The Accounting Review* 75(1): 43-63.

Bloomfield, R., R. Libby, and M.W. Nelson. 1999. Confidence and the welfare of less-informed investors. *Accounting, Organizations and Society* 24: 623-647.

Bobko, P. 1986. A solution to some dilemmas when testing hypotheses about ordinal interactions. *Journal of Applied Psychology* 71(2): 323-326.

Bonner, S.E. 1990. Experience effects in auditing: the role of task-specific knowledge. *The Accounting Review* 65(1): 72-92.

Bonner, S.E. 1999. Judgment and decision-making research in accounting. *Accounting Horizons* 13(4): 385-398.

Bonner, S.E., B.R. Walther, and S.M. Young. 2003. Sophistication-related differences in investors' models of the relative accuracy of analysts' forecast revisions. *The Accounting Review* 78(3): 679-706.

Bradshaw, M.T., S.A. Richardson, and R.G. Sloan. 2001. Do analysts and auditors use information in accruals? *Journal of Accounting Research* 39(1): 45-75.

Buckless, F.A., and S.P. Ravenscroft. 1990. Contrast coding: A refinement of ANOVA in behavioral analysis. *The Accounting Review* 65 (4): 933-945.

Call, A., M. Hewitt, and T. Shevlin. 2007. Investors' mispricing of earnings: a model of persistence and the stock price consequences. Working paper, University of Washington.

Chan, W.S., R. Frankel, and S.P. Kothari. 2004. Testing behavioral theories using trends and consistency in financial performance. *Journal of Accounting and Economics* 38(Conference Issue on Research on Market Efficiency, Valuation, and Mispricing: Risk, Behavioral, and Alternative Explanations): 3-50.

Collins, D.W., G. Gong, and P. Hribar. 2003. Investor sophistication and the mispricing of accruals. *Review of Accounting Studies* 8(2-3): 251-276.

Desai, H., S. Rajgopal, and M. Venkatachalam. 2004. Value-glamour and accruals mispricing: one anomaly or two? *The Accounting Review* 79(2): 355-385.

Elliott, W.B. 2006. Are investors influenced by pro forma emphasis and reconciliations in earnings announcements? *The Accounting Review* 81(1):113-133.

Elliott, W.B., F.D. Hodge, S.J. Kennedy, and M. Pronk. 2007. Are graduate business students a reasonable proxy for nonprofessional investors? *The Accounting Review* Forthcoming.

Francis, J., and M. Smith. 2005. A reexamination of the persistence of accruals and cash flows. *Journal of Accounting Research* 43(3): 413-451.

Hand, J.R.M. 1990. A test of the extended functional fixation hypothesis. *The Accounting Review* 65(4): 740-763.

Hirshleifer, D. 2001. Investor psychology and asset pricing. *The Journal of Finance* 56(4): 1533-1597.

Hirshleifer, D., K. Hou, and S.H. Teoh. 2007. The accrual anomaly: risk or mispricing? Working paper, The Ohio State University.

Hirshleifer, D., K. Hou, S.H. Teoh, and Y. Zhang. 2004. Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38(Conference Issue on Research on Market Efficiency, Valuation, and Mispricing: Risk, Behavioral, and Alternative Explanations): 297-331.

Hirshleifer, D., and S.H. Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36: 337-386.

Hirst, D.E., and P.E. Hopkins. 1998. Comprehensive income reporting and analysts' judgments. *Journal of Accounting Research* 36(Supplement): 47-75.

Hodder, L., P.E. Hopkins, and D.A. Wood. 2007. The effects of financial statement and informational complexity on cash flow forecasts. Working paper, Indiana University.

Hodge, F.D., S.J. Kennedy, and L.A. Maines. 2004. Does search-facilitating technology improve the transparency of financial reporting? *The Accounting Review* 79(3): 687-703.

Hopkins, P.E. 1996. The effect of financial statement classification of hybrid financial instruments on financial analysts' valuation judgments. *Journal of Accounting Research* 34(Supplement): 33-50.

International Accounting Standards Board (IASB). 2005. *Performance Reporting.* Project Update. December 8.

Jiambalvo, J., and W. Waller. 1984. Decomposition and assessments of audit risk. *Auditing: A Journal of Practice and Theory* 3(2): 80-88.

Kachelmeier, S.J., and R.R. King. 2002. Using laboratory experiments to evaluate accounting policy issues. *Accounting Horizons* 16(3): 219-232.

Kleinmuntz, D.N. 1988. Decomposition and the control of errors in decision analytic models. Presentation at Conference on Insights in Decision Making: Theory and Applications, University of Chicago, June 12-14, 1998.

Kleinmuntz, D.N., M.G. Fennema, and M.E. Peecher. 1996. Conditioned assessment of subjective probabilities: identifying the benefits of decomposition. *Organizational Behavior and Human Decision Processes* 66(1): 1-15.

Kothari, S.P., E. Loutskina, and V. Nikolaev. 2007. Agency theory of overvalued equity as an explanation for the accrual anomaly. Working paper, MIT.

Kraft, A., A.J. Leone, and C. Wasley. 2006. An analysis of the theories and explanations offered for the mispricing of accruals and accrual components. *Journal of Accounting Research* 44(2): 297-339.

Lev, B. 1968. The aggregation problem in financial statements: an informational approach. *Journal of Accounting Research* 6(2): 247-261.

Libby, R., R.J. Bloomfield, and M.W. Nelson. 2002. Experimental research in financial accounting. *Accounting, Organizations and Society* 27(8): 775–810.

Libby, R., and J. Luft. 1993. Determinants of judgment performance in accounting settings: ability, knowledge, motivation and environment. *Accounting, Organizations and Society* 18(5): 425-450.

Maines, L.A., and L.S. McDaniel. 2000. Effects of comprehensive-income characteristics on nonprofessional investors' judgments: the role of financial statement format. *The Accounting Review* 75(2): 179-207.

Mashruwala, C., S. Rajgopal, and T. Shevlin. 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. *Journal of Accounting and Economics* 42(1-2): 3-33.

Mishkin, F. 1983. *A Rational Expectations Approach to Macroeconomics: Testing Policy Effectiveness and Efficient-Markets Models*. Chicago, IL: University of Chicago Press.

Morera, O.F., and D.V. Budescu. 1998. A psychometric analysis of the "divide and
conquer" principle in multicriteria decision making. *Organizational Behavior and Human Decision Processes* 75(3): 187-206.

Morera, O.F., and D.V. Budescu. 2001. Random error reduction in analytic hierarchies: a comparison of holistic and decompositional decision strategies. *Journal of Behavioral Decision Making* 14(3): 223-242.

Reason, T. 2005. Convergence of accounting rules: the narrowing GAAP. *CFO Magazine* December 27.

Rikers, R.M.J.P., and F. Paas. 2005. Recent advances in expertise research. *Applied Cognitive Psychology* 19: 145-149.

Rosnow, R., and R. Rosenthal. 1995. "Some things you learn aren't so": Cohen's paradox, Asch's paradigm, and the interpretation of interaction. *Psychological Science* 6: 3-9.

Sedor, L.M. 2002. An explanation for unintentional optimism in analysts' earnings forecasts. *The Accounting Review* 77(4): 731-753.

Sloan, R.G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings. *The Accounting Review* 71(3): 289-315.

Sweller, J. 1988. Cognitive load during problem solving: effects on learning. *Cognitive Science* 12: 257-285.

Sweller, J., P. Chandler, P. Tierney, and M. Cooper. 1990. Cognitive load as a factor in the structuring of technical material. *Journal of Experimental Psychology: General* 119(2): 176-192.

Wilks, T.J., and M.F. Zimbelman. 2004. Decomposition of fraud-risk assessments and auditors' sensitivity to fraud cues. *Contemporary Accounting Research* 21(3): 719-745.

Xie, H. 2001. The mispricing of abnormal accruals. *The Accounting Review* 76(3): 357–373.

Appendix A – Example Demonstrating Effect of Differentially Persistent Earnings Components

The following example represents an application of part of the model presented by Hirshleifer and Teoh (2003 p. 370-373).

Consider a setting where the persistence of the earnings components (i.e., γ_{acc} and γ_{cash}) are time-series constants such that:

$$EARN_0 = ACC + CASH$$
$$EARN_1 = \gamma_{acc} \cdot ACC + \gamma_{cash} \cdot CASH$$
$$EARN_2 = (\gamma_{acc})^2 \cdot ACC + (\gamma_{cash})^2 \cdot CASH$$

Let ψ^{fix} represent the information set used by investors that fixate on earnings to forecast year 2 earnings at the end of year 1:

$$\psi^{fix} = (EARN_0, EARN_1) .$$

Let ψ^* represent the information set used by investors that attend to the earnings components to forecast year 2 earnings at the end of year 1:

$$\psi^* = (ACC, \gamma_{acc} \cdot ACC; CASH, \gamma_{cash} \cdot CASH) .$$

At the end of year 1, investors would accurately forecast year 2 earnings by attending to the differential persistence of the earnings components (ψ^*):

$$E_1^*[EARN_2] = (\gamma_{acc})^2 \cdot ACC + (\gamma_{cash})^2 \cdot CASH \qquad (A1)$$

In contrast, investors who limit their attention to ψ^{fix} would forecast year 2 earnings using a common earnings persistence parameter (γ_{fix}) derived from observing reported earnings at the end of year 0 and year 1, i.e.,

$$\gamma_{fix} = \frac{EARN_1}{EARN_0} = \frac{\gamma_{acc} \cdot ACC + \gamma_{cash} \cdot CASH}{ACC + CASH}$$

Using γ_{fix}, investors who limit their attention to ψ^{fix} would forecast earnings for year 2 as:

$$E_1^{fix}[EARN_2] = \gamma_{fix} \cdot EARN_1 . \qquad (A2)$$

Now $E_1^*[EARN_2]$ will only equal $E_1^{fix}[EARN_2]$ when $\gamma_{acc} = \gamma_{cash}$.

Proof:

Assuming $E_1^*[EARN_2] = E_1^{fix}[EARN_2]$, let Equation (A1) = Equation (A2).

$$(\gamma_{acc})^2 \cdot ACC + (\gamma_{cash})^2 \cdot CASH = \gamma_{fix} \cdot EARN_1 \quad (A3)$$

Substitute $\gamma_{fix} = EARN_1 / EARN_0$ into Equation (A3).

$$(\gamma_{acc})^2 \cdot ACC + (\gamma_{cash})^2 \cdot CASH = (EARN_1)^2 / EARN_0 \quad (A4)$$

Therefore, by rearranging Equation (A4):

$$(ACC + CASH)[(\gamma_{acc})^2 \cdot ACC + (\gamma_{cash})^2 \cdot CASH] = (\gamma_{acc} \cdot ACC + \gamma_{cash} \cdot CASH)^2 \quad (A5)$$

By expanding and simplifying Equation (A5):

$$(\gamma_{acc})^2 + (\gamma_{cash})^2 = 2\,(\gamma_{acc}) \cdot (\gamma_{cash}) . \quad (A6)$$

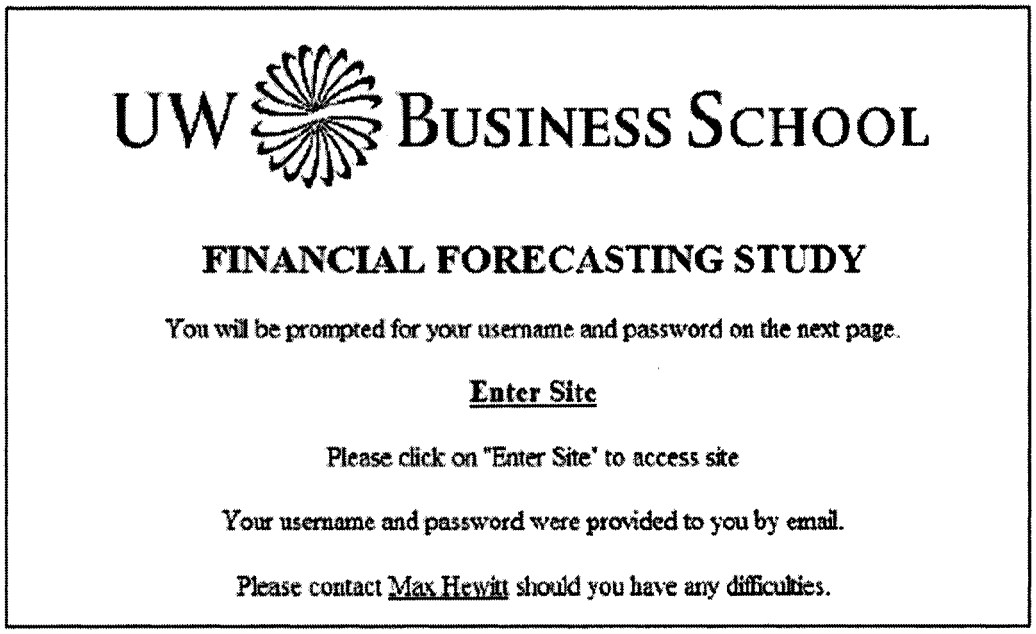
As Equation (A6) only holds when $\gamma_{acc} = \gamma_{cash}$, $E_1^*[EARN_2]$ will only equal $E_1^{fix}[EARN_2]$ when $\gamma_{acc} = \gamma_{cash}$. Therefore, to accurately forecast earnings when $\gamma_{acc} \neq \gamma_{cash}$, investors need to attend to ψ^*.

In this study, Firm DIFF is characterized with a γ_{acc} (γ_{cash}) equivalent to -1 (>1). In this instance, investors need to attend to ψ^* to accurately forecast earnings. In this study, Firm SAME is characterized with a γ_{acc} (γ_{cash}) equivalent to +1 (+1). In this instance, investors do not need to attend to ψ^* to accurately forecast earnings.

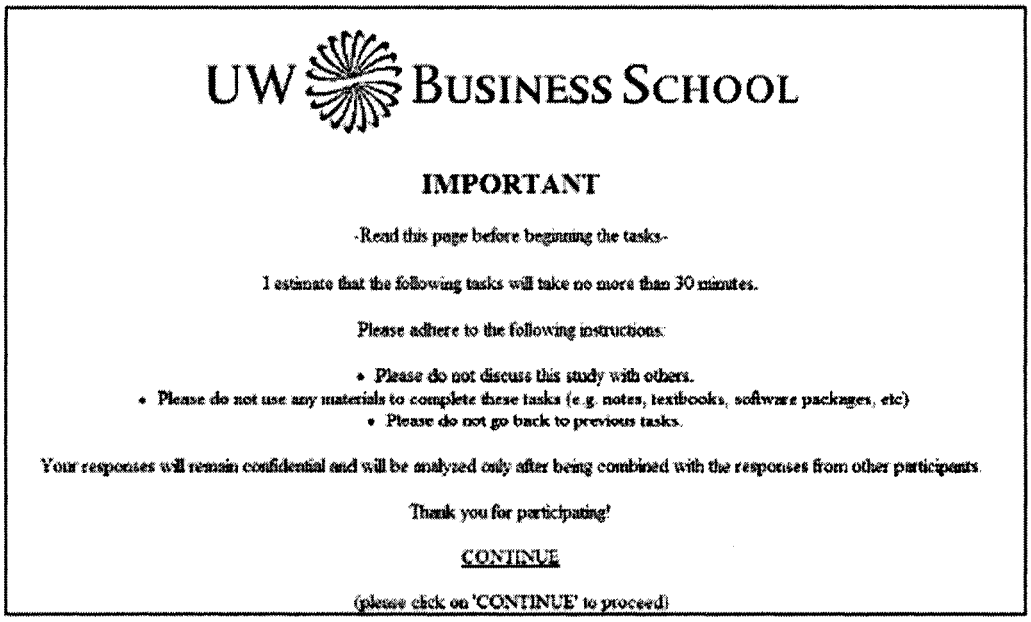
$EARN_t$ is earnings in year *t*.
ACC is the accrual component of earnings for year 0, and represents the difference between net income and cash flows from operating activities.
CASH is the cash component of earnings (cash flows from operating activities) for year 0.
ψ^{fix} is the information set used by investors that fixate on earnings to forecast year 2 earnings at the end of year 1. ψ^* is the information set used by investors that attend to the earnings components to forecast year 2 earnings at the end of year 1.
γ_{acc} is the persistence of the accrual component of earnings. γ_{cash} is the persistence of the cash component of earnings. γ_{fix} is the common earnings persistence parameter used by investors who limit their attention to the aggregated earnings time series.
$E_1^*[EARN_2]$ is the expectation of year 2 earnings at the end of year 1 of investors who attend to the differential persistence of the earnings components. $E_1^{fix}[EARN_2]$ is the expectation of year 2 earnings at the end of year 1 of investors who limit their attention to the aggregated earnings time series.

Appendix B – Example of Online Materials

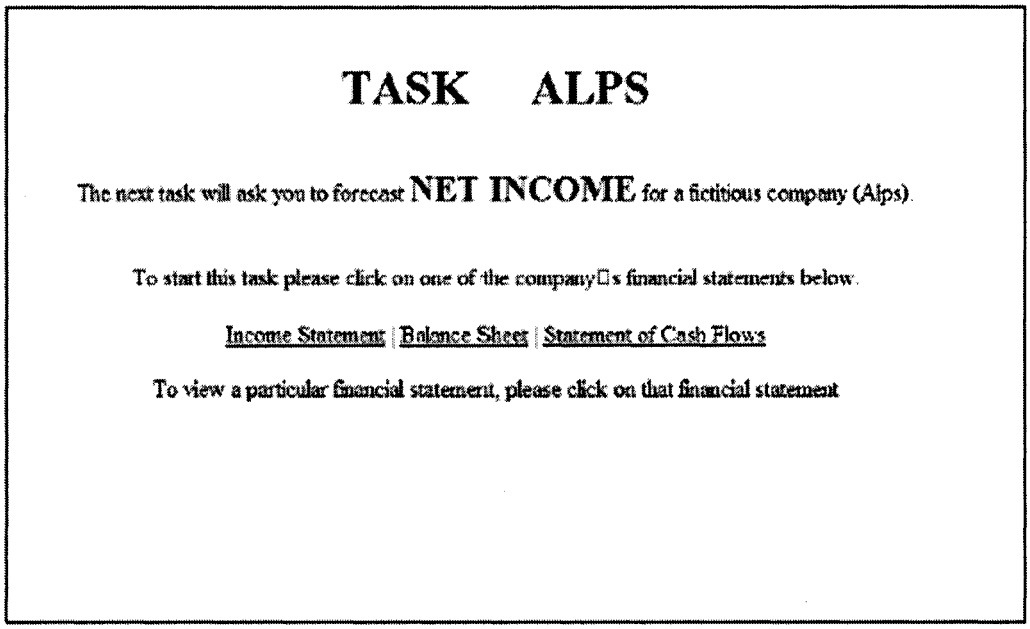
Screen 1: Introduction



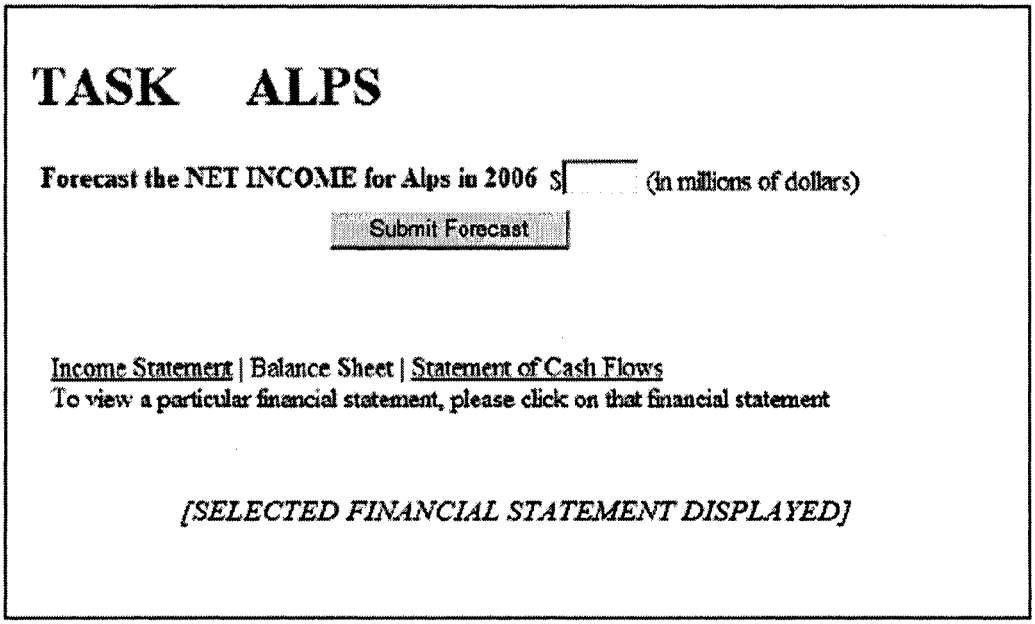
Screen 2: Instructions



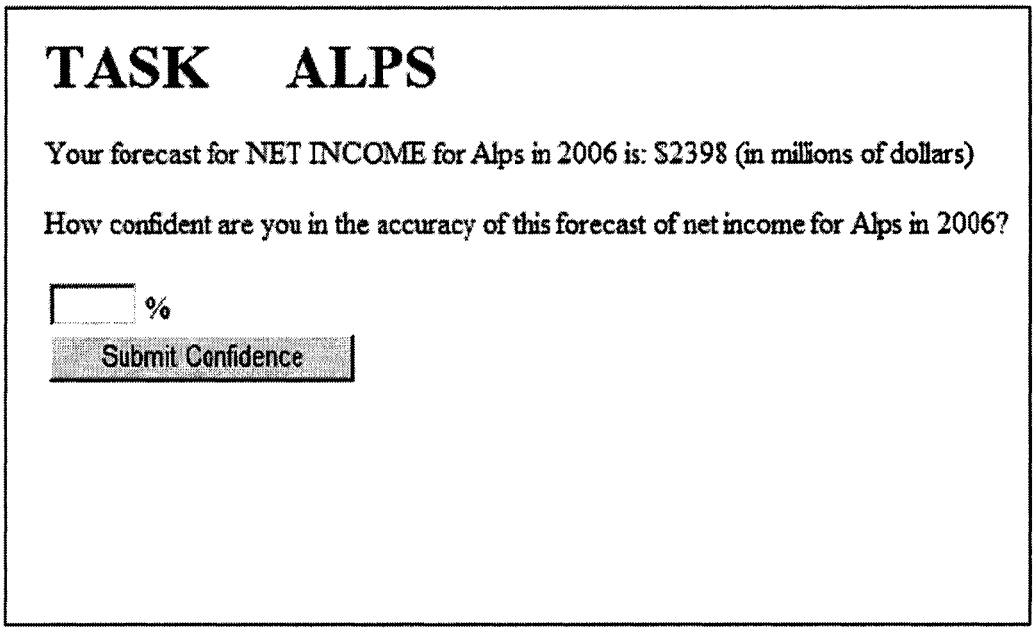
Screen 3: Forecast instructions – First Firm



Screen 4: Forecast task – First Firm

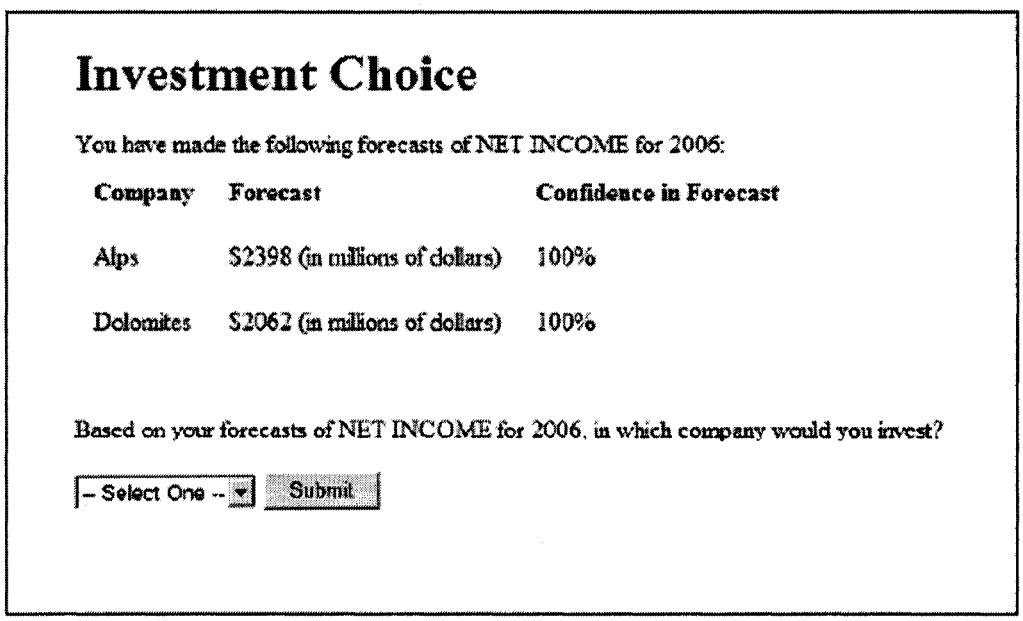


Screen 5: Confidence assessment – First Firm

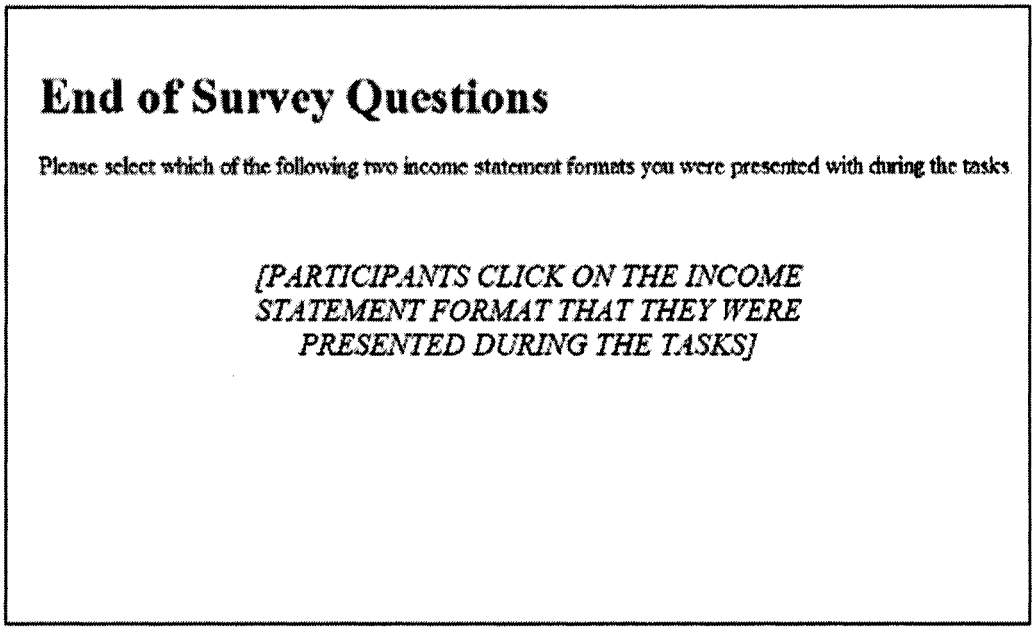


[Screens 6-8: Repeat Screens 3-5 with Second Firm]

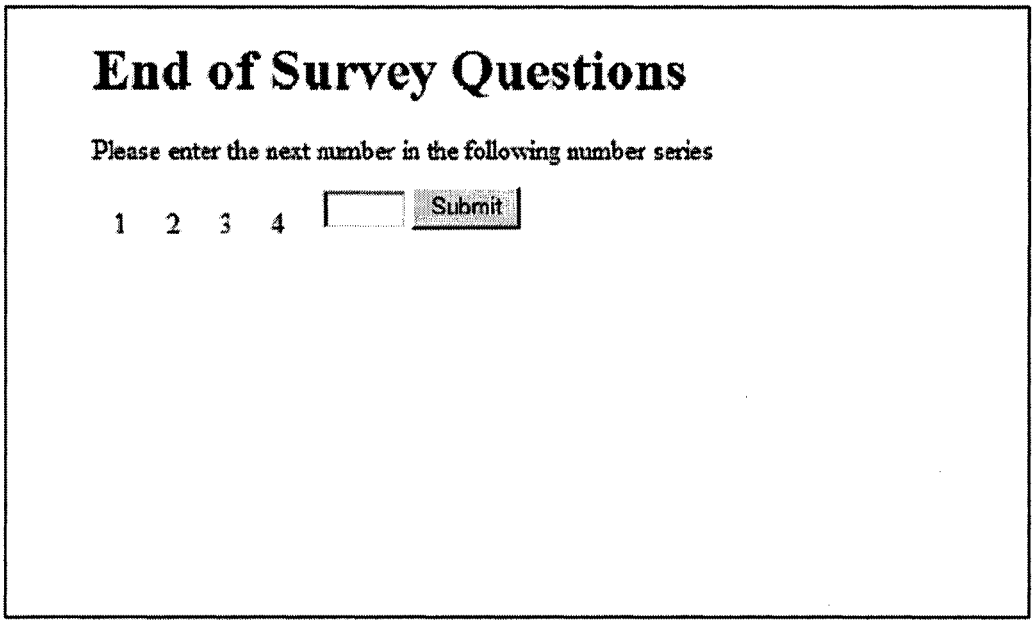
Screen 9: Investment choice



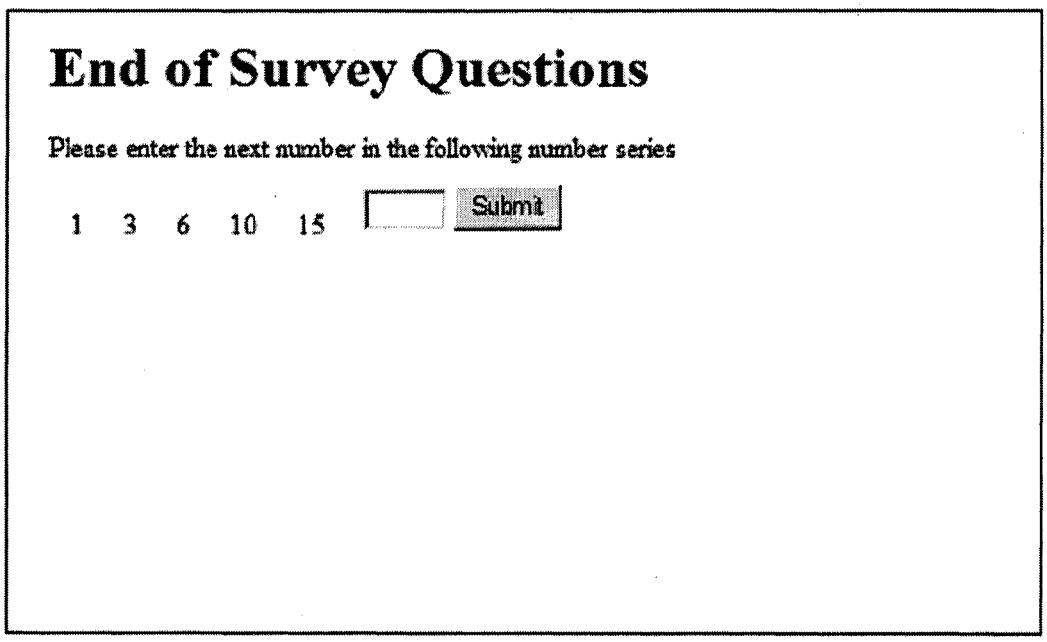
Screen 10: End of survey questions – Identification of disclosure format



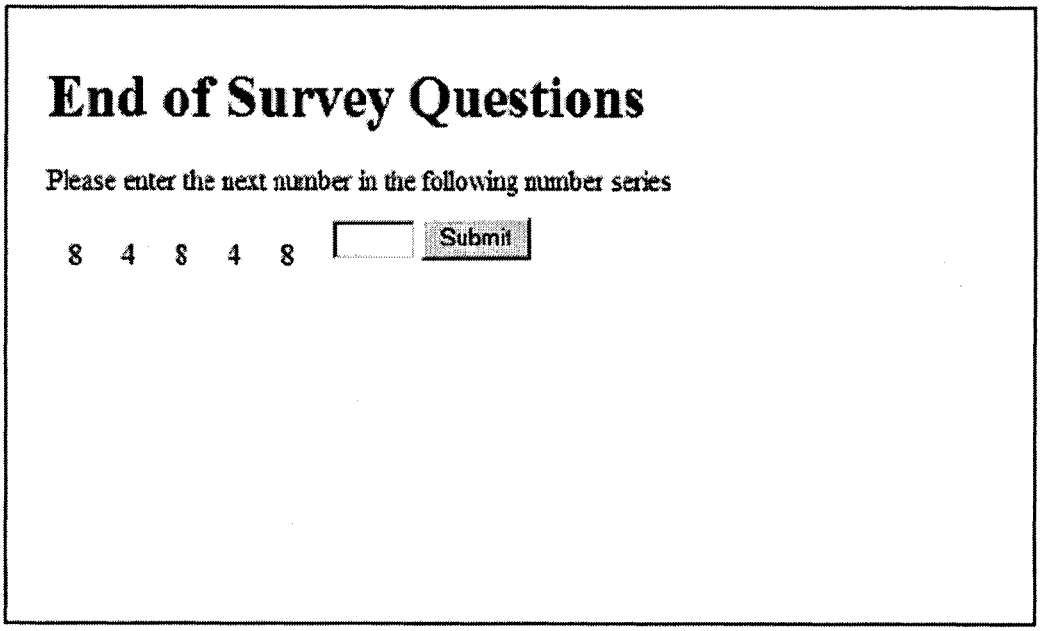
Screen 11: End of survey questions – Number series 1



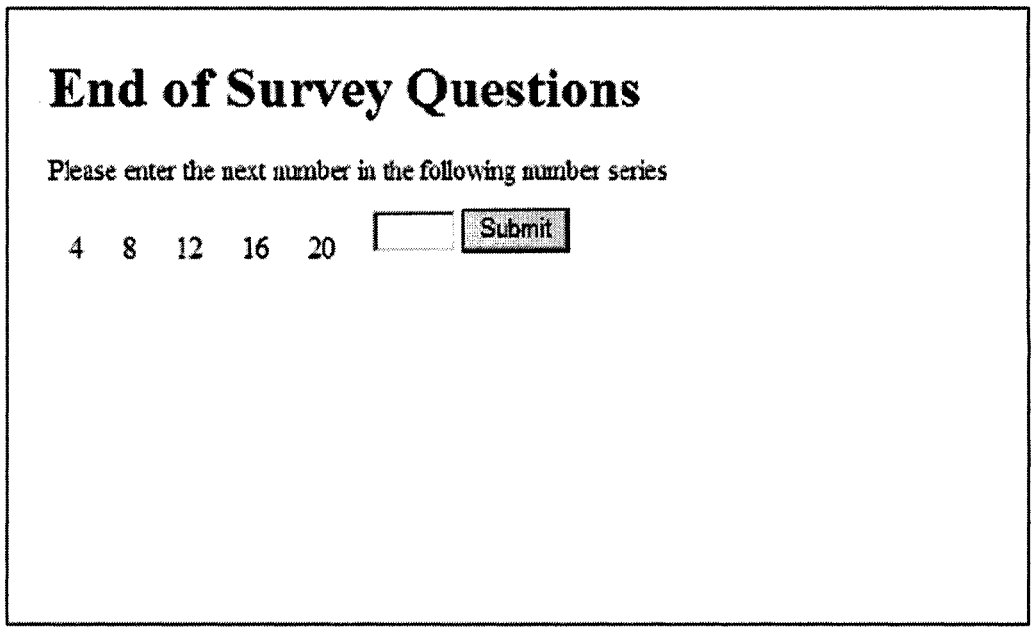
Screen 12: End of survey questions – Number series 2



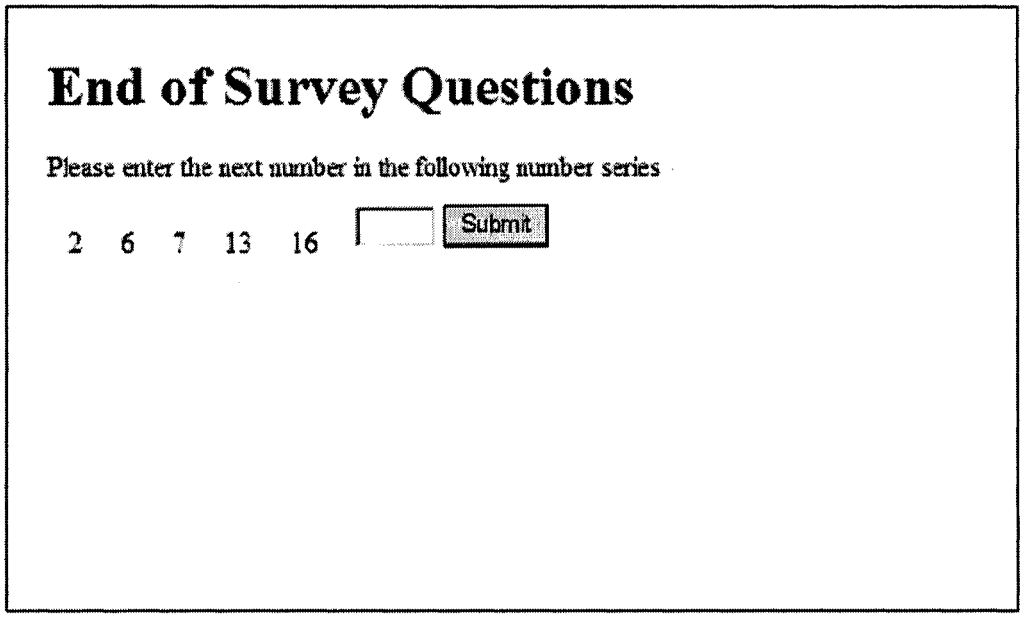
Screen 13: End of survey questions – Number series 3



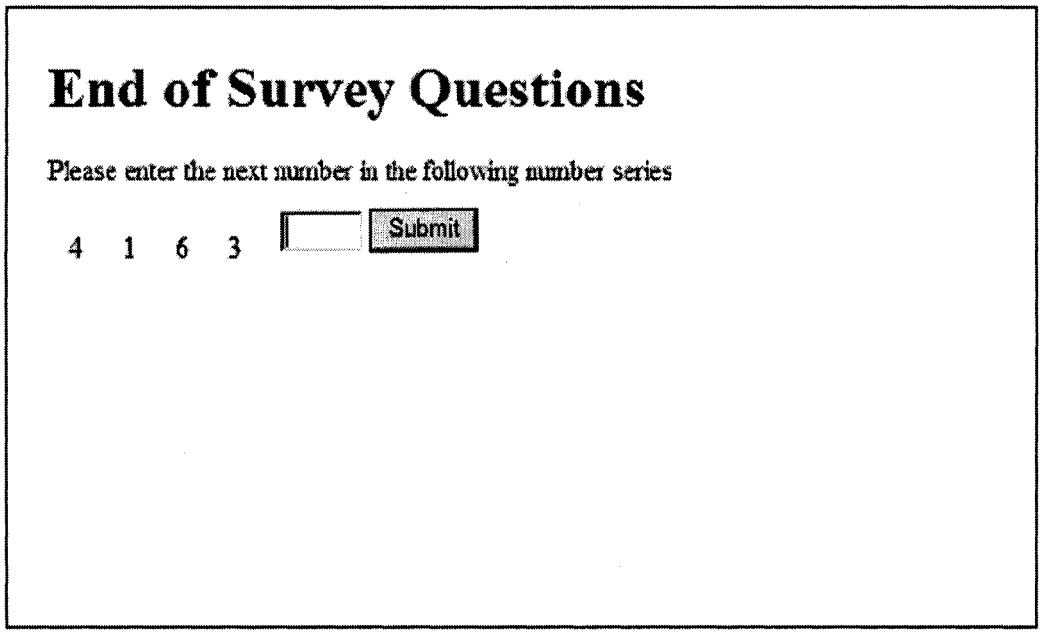
Screen 14: End of survey questions – Number series 4



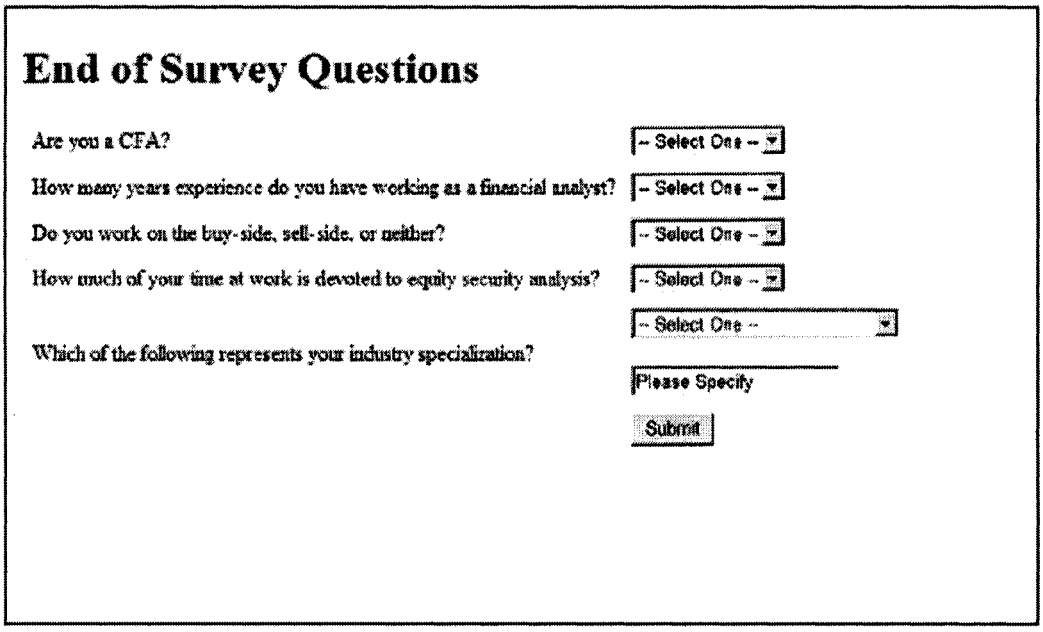
Screen 15: End of survey questions – Number series 5



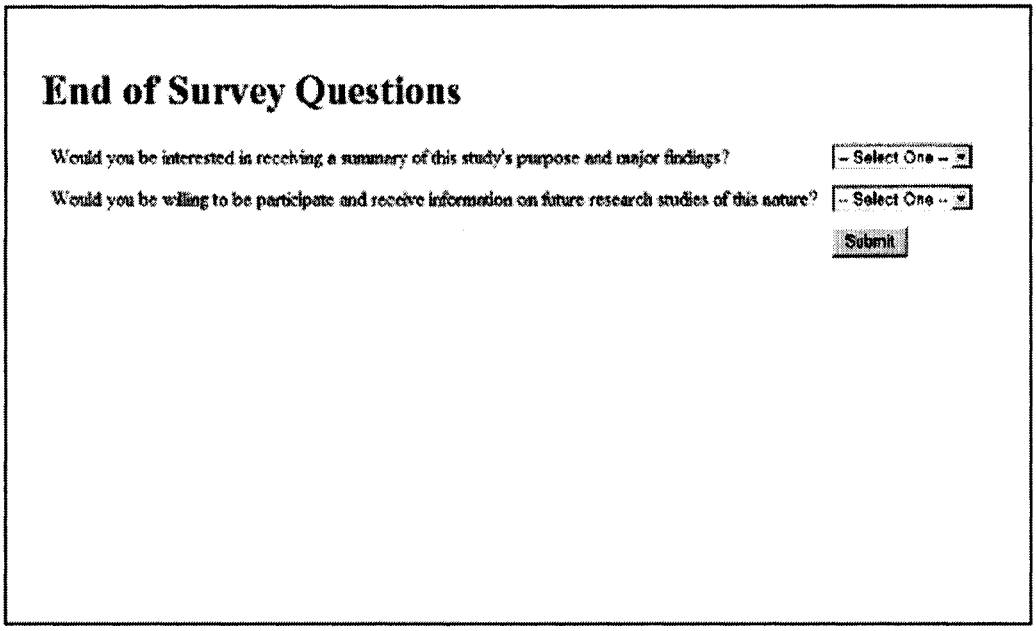
Screen 16: End of survey questions – Number series 6



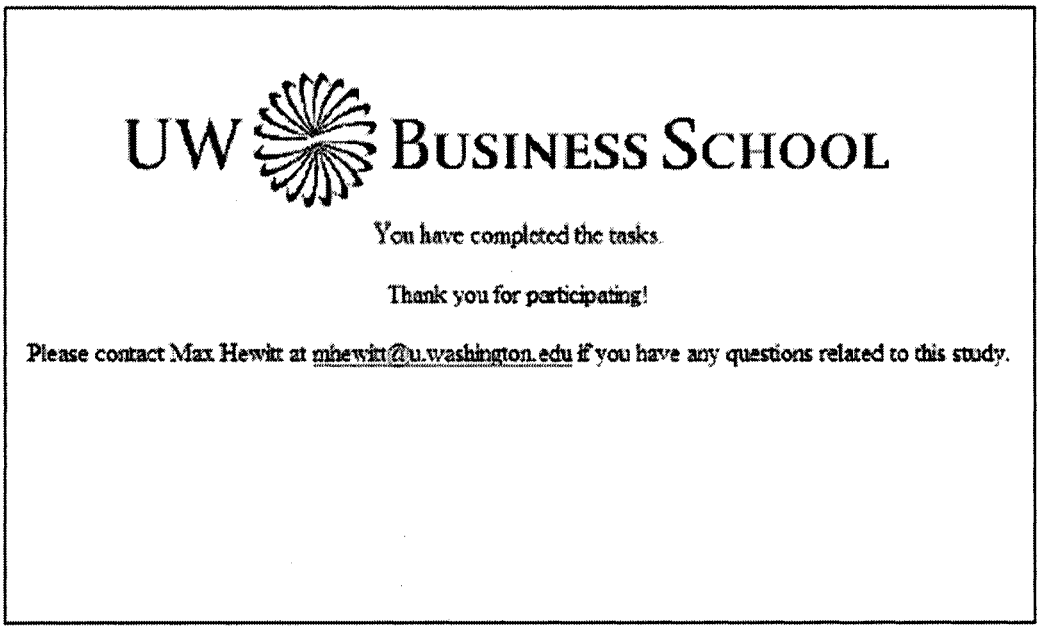
Screen 17: End of survey questions – Demographic questions



Screen 18: End of survey questions – Future participation



Screen 19: Conclusion



VITA

Max Hewitt was born in Sydney, Australia. He earned a Bachelor of Economics at Macquarie University, a Master of Teaching (Honours Class I) at the University of Sydney, a Master of Commerce (Honours) at the University of New South Wales, and a Graduate Diploma at the Institute of Chartered Accountants in Australia. He is also a Chartered Accountant. In 2007, he earned a Doctor of Philosophy at the University of Washington in Business Administration.