Disaggregating Operating and Financing Activities versus Disaggregating Unusual and/or Infrequent Income Items: Implications for Forecasts of Future Profitability

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ABSTRACT

Academic research and financial statement analysis textbooks have relied on the notion that disaggregating financial statements into operating and financing activities improves profitability forecasts. Consistent with this notion, the accounting standard-setting Boards recently proposed the requirement that financial statements be disaggregated into operating and financing activities. In addition, the Boards' proposals retract the current U.S. GAAP requirement that firms disaggregate unusual and/or infrequent items in the income statement. In this study, we examine whether the Boards' proposals lead to accuracy improvements in out-of-sample forecasts of future profitability. We find that, relative to a naïve prediction model, disaggregating the financial statements into operating and financing activities fails to improve forecasts of future profitability. In contrast, disaggregating income into unusual and/or infrequent items leads to relatively more accurate forecasts of future profitability than disaggregating operating and financing activities. We consider whether supplementing the operating/financing disaggregation with the unusual and/or infrequent item disaggregation rectifies the relative ineffectiveness of the operating/financing disaggregation for forecasting future profitability, but find no supporting evidence. This study's findings question the merits of the Boards' proposed financial statement disaggregation.

Keywords: *disaggregation; operating; financing; unusual or infrequent; profitability.*

Data Availability: *Available from the public sources identified in the text.*

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I. INTRODUCTION

Prior analytical accounting research has emphasized the importance of disaggregating financial statements into operating and financing activities (Feltham and Ohlson 1995). Recent research on financial statement analysis has relied on the importance of this disaggregation in models of forecasting profitability (e.g., Nissim and Penman 2001; Fairfield and Yohn 2001; Fairfield Ramnath and Yohn 2009). Further, various textbooks provide a structured approach to financial statement analysis based on this disaggregation (e.g., Penman 2009; Lundholm and Sloan 2009).

The notion that the disaggregation of financial statements into operating and financing activities is important for financial statement analysis is also influencing standard setting. In particular, the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB) recently outlined proposals to change the presentation of the financial statements. In their discussion paper, "Preliminary Views on Financial Statement Presentation," the Boards propose to require firms to disaggregate the statement of comprehensive income and the statement of financial position based on operating and financing activities (FASB 2008; IASB 2008). Underlying the Boards' proposal are the assertions, consistent with prior analytical work (e.g., Feltham and Ohlson 1995), that disaggregating the income statement and balance sheet into operating and financing activities is useful for valuation and improves forecasts of future profitability. In addition to requiring the operating/financing disaggregation, the

Boards also propose the removal of the U.S. GAAP requirement for firms to identify unusual and/or infrequent items in the income statement (FASB 1973).[1]

The Boards' proposals represent a significant departure from the existing financial statement presentation format. However, before requiring such radical changes, it is important to assess the incremental usefulness of the proposed financial statement disaggregation models. This assessment is especially necessary in light of the concerns expressed by many that the proposed changes will increase preparers' costs as well as the level of detail and complexity faced by financial statement users (PwC 2009; AICPA 2009).

Currently, little or no empirical evidence exists on the incremental information content of a model that disaggregates operating and financing activities over an aggregated model for profitability forecasting. Research on the usefulness of the Feltham and Ohlson (1995) model over the aggregated Ohlson (1995) model for explaining firm value provides very limited evidence that the disaggregated model yields greater information content for explaining *stock prices* than the aggregated model (Myers 1999; Ahmed et al. 2000; Callen and Segal 2005). In addition, while research has examined the information content of the operating/financing disaggregation for valuation, the information content of the disaggregation for forecasting future profitability has not been examined. In contrast, prior financial statement analysis research has examined the

[1] APB Opinion No. 30, paragraph 26, states that "extraordinary items are events and transactions that are distinguished by their unusual nature and by the infrequency of their occurrence." The extraordinary items should be reported as a separate component of net income after income from continuing operations on the face of the income statement. APB Opinion No. 30 also states that a "material event or transaction that is unusual or infrequent in nature or occurs infrequently but not both, and therefore does not meet both criteria for classification as an extraordinary item, should be reported as a separate component of income from continuing operations" (FASB 1973, 6). Researchers commonly refer to these items as "special items" presumably due to Compustat's use of this label. We refer to the special items and/or extraordinary items as unusual and/or infrequent items.

information content of the financial statement disaggregations currently required under U.S. GAAP for forecasting future profitability. Research has documented that the segregation of unusual and/or infrequent items from other income items improves forecasts of future profitability (Fairfield, Sweeney and Yohn 1996). The research suggests that the unusual and/or infrequent items are differentially persistent from other income items (e.g., Dechow and Ge 2005) and that these items have different implications for forecasts of future profitability (Fairfield, Kitching and Tang 2009).

Bernard (1995, 736) suggests that profitability prediction "is tantamount to the ability to approximate current value," highlighting the importance of examining the information content of the operating/financing disaggregation for forecasting future profitability in assessing the efficacy of the Boards' financial statement presentation proposal. In addition, given the prior research that supports the current U.S. GAAP disaggregation, we examine the information content of the proposed operating/financing disaggregation relative to the current unusual and/or infrequent item disaggregation for forecasting purposes. This study provides direct evidence on this issue by examining whether the operating/financing disaggregation is incrementally useful over the aggregated model for forecasting future profitability.

In summary, to provide empirical evidence to the Boards related to the proposed changes in disaggregation included in the Financial Statement Presentation project, this study examines the relative usefulness of disaggregating operating and financing activities versus disaggregating unusual and/or infrequent income items for forecasting future profitability. Specifically, we consider three research questions: (1) does disaggregating the financial statements into operating and financing activities (hereafter, the *OPFIN* disaggregation) improve forecasts of future profitability over aggregated financial statements?, (2) does the *OPFIN* disaggregation provide more accurate forecasts of future profitability than the unusual and/or infrequent item disaggregation of the income statement (hereafter, the *UNINFREQ* disaggregation) currently required under U.S. GAAP?, and (3) does the combination of the *OPFIN* and the *UNINFREQ* disaggregations provide more accurate forecasts than the *UNINFREQ* disaggregation currently required under U.S. GAAP?

Consistent with prior research (e.g., Fairfield et al. 1996; Fairfield et al. 2009), we rely on parsimonious forecasting models that incorporate different disaggregations of the financial statement information. We calculate in-sample coefficient estimates for each of the models from 10-year rolling regressions. We then use these estimates to predict return-on-equity (*ROE*) in the out-of-sample period and analyze accuracy improvements in out-of-sample forecasts of one-year-ahead *ROE* to assess the relative accuracy of the *OPFIN* and *UNINFREQ* models.

We begin by comparing the disaggregated models to a naïve *ROE* prediction model. We find little to no evidence of an incremental benefit from the *OPFIN* disaggregation relative to the naïve *ROE* prediction model. While we observe significant mean improvement arising from the *OPFIN* disaggregation, we fail to document a median improvement or a mean or median improvement using rank regression prediction models. In addition, the *OPFIN* disaggregation leads to improved median forecasts of future profitability in only seven years of the 25-year sample period while it leads to *significantly less* accurate median forecasts of future profitability in nine years of the 25-year sample period.

In contrast, we find that the *UNINFREQ* disaggregation consistently outperforms the naïve *ROE* prediction model. We document significant mean and median improvements in forecasts of future profitability using this disaggregation. Furthermore, the *UNINFREQ* disaggregation leads to improved median forecasts of future profitability in 24 years of the 25-year sample period. A direct comparison of the *OPFIN* and *UNINFREQ* disaggregations reveals that the *UNINFREQ* disaggregation yields significantly more accurate forecasts of future profitability in 23 years of the 25-year sample period relative to the *OPFIN* disaggregation. Using the continuous variable specification, there is no year in our sample period in which the *OPFIN* disaggregation outperforms the *UNINFREQ* disaggregation.

Finally, we examine whether combining the *OPFIN* and *UNINFREQ* disaggregations (i.e., *COMBINED*) improves forecasts of future profitability relative to the *UNINFREQ* disaggregation alone. We find no evidence that supplementing the *OPFIN* disaggregation with the *UNINFREQ* disaggregation improves forecasts of future profitability. In fact, the *UNINFREQ* disaggregation yields significantly more accurate forecasts of future profitability in 23 years of the 25-year sample period relative to the *COMBINED* disaggregation model. This result suggests that simply supplementing the *OPFIN* disaggregation with a requirement for firms to identify unusual and/or infrequent items is unlikely to improve forecasts of future profitability relative to the disaggregation currently required under U.S. GAAP.

In further analyses, we show that our results are robust across groupings of firms based on the magnitude of leverage, the difference in return on net operating assets and return on net financing assets, the difference in competing models' forecasts, and industry sector classification. Finally, we examine whether the superiority of the *UNINFREQ* model is driven by extraordinary items or, alternatively, whether, a model that disaggregates special items yields superior forecast accuracy over the *OPFIN* model for forecasting year ahead income before extraordinary items (instead of *ROE*). We find evidence consistent with the special item disaggregation providing superior forecasts, suggesting that the results are not driven by extraordinary items.

This study presents timely evidence relevant to the Boards' Financial Statement Presentation Project. The Boards assert that disaggregating the financial statements into operating and financing activities will improve users' forecasts of future profitability although those claims have been largely untested. Our findings suggest that users will not benefit from the proposed disaggregation when using parsimonious forecasting models. In addition, retracting the requirement for U.S. firms to identify unusual and/or infrequent items has the potential to reduce the accuracy of forecasts of future profitability. We also show that supplementing the proposed disaggregation with a requirement for firms to identify unusual and/or infrequent items does not rectify the limited predictive ability of the Boards' proposed operating/financing disaggregation. Our results do not support the Boards' proposed disaggregation of the financial statements into operating and financing activities.

This study also contributes to the extant literature considering how disaggregation of earnings improves forecasts of future profitability. Prior research shows that identifying unusual and/or infrequent items improves forecasts of future profitability (e.g., Fairfield et al. 1996). This study extends prior research by demonstrating that identifying unusual and/or infrequent items leads to more accurate predictions of future profitability relative to disaggregating financial statements based on firms' operating and financing activities. This study's findings question the merits of the theoretical claims that suggest disaggregating financial statements into operating and financing activities improves forecasts of future profitability (Feltham and Ohlson 1995).

The rest of the paper is organized as follows. In the next section, we provide a summary of the relevant literature concerning the effects of financial statement presentation and the Boards' proposed disaggregation. Section III explains our sample selection process and discusses the empirical models used. Section IV presents the study's main results. Section V provides further analyses involving the robustness of our findings. In Section VI, we discuss conclusions and the implications of our study.

II. RELATED LITERATURE

Effects of Financial Statement Presentation

Prior research emphasizes that earnings are comprised of components that are heterogeneous in terms of both persistence and predictive content (Lipe 1986; Sloan 1996). For example, Lipe (1986) demonstrates that various components of earnings have differential predictive content. Consistent with these findings, Fairfield et al. (1996) and others document a relation between the predictive content of income statement items and how they are classified on the income statement.

Related experimental-based research suggests that financial statement presentation influences how financial information is used. Even after controlling for information content, various studies directly illustrate the effects of financial statement presentation on users' judgments. For example, Hopkins (1996) shows that how an item is classified affects analysts' valuation judgments. Further, Hirst and Hopkins (1998) and

Maines and McDaniel (2000) demonstrate that the presentation format of comprehensive income affects investors' acquisition and evaluation of information. Finally, Hewitt (2009) finds that when earnings consist of differentially persistent components, disaggregating earnings improves the forecast accuracy of both analysts and nonprofessional investors. Collectively, these studies highlight the importance of accounting standards that require firms to disaggregate earnings in order to aid users' forecasts of future profitability.

The Boards' Proposals Involving Disaggregation

FASB states in Concepts Statement No. 1 that "(t)he primary focus of financial reporting is information about an enterprise's performance provided by measures of earnings and its components" (FASB 1978, 13). Consistent with this objective, the Boards' Financial Statement Presentation discussion paper states that "(a)n entity should disaggregate information in its financial statements in a manner that makes it useful in assessing the amount, timing, and uncertainty of its future cash flows" (FASB 2008, 10).[2] Further, the Boards suggest in their discussion paper that "forecasts of income" (i.e., future profitability) are useful outcome measures for evaluating the effectiveness of disaggregating financial statement information.

With this 'disaggregation' objective in mind, the Boards' current proposals require that firms disaggregate the statement of comprehensive income and the statement of financial position into operating (labeled "business" in the Discussion Paper) and financing activities, similar to the classifications used by firms to present the statement of cash flows in accordance with SFAS No. 95 (FASB 1987). According to the Boards'

[2] FASB believes that users interested in future cash flows are primarily interested "in information about [a firm's] earnings rather than information directly about its cash flows" (FASB 1978, 13).

proposals, each firm would present subtotals on its financial statements summarizing its operating and financing activities. The Boards' rationale for this proposal is that firms' should separately disclose how they create value and how they fund their operations.

The Boards' proposals could be very costly to preparers and users. All firms will be required to adapt their reporting systems to incorporate the Boards' proposals although research suggests that this disaggregation will only affect the information content of some firms' earnings (Hopwood, Newbold and Silhan 1982; Hirshleifer and Teoh 2003). Investors and other users could also incur costs as a result of the Boards' proposals. For example, the AICPA (2009) claims that users might face more complex financial statements as a result of the proposed changes. When users face more complex information, prior research shows that they are less likely to assimilate this information into their forecasts to the detriment of their forecast accuracy (Plumlee 2003; Hewitt 2009). Aside from the need to adapt to the new presentation format of the income statement, users may also incur costs if the Boards' proposals exclude useful information that was previously available to users. Collectively, the potential costs likely to be borne by preparers and users arguably warrant an empirical investigation of the incremental information content of each disaggregation when forecasting future profitability.

While the Boards do not cite evidence in support of their proposals, their discussion paper reflects similar tenets underlying related analytic accounting research and financial statement analysis texts. Building from the Ohlson (1995) residual income valuation model, Feltham and Ohlson (1995) demonstrate the implications of a valuation model separately accounting for operating and financing activities. Feltham and Ohlson (1995) distinguish operating profitability from the profitability of financing activities for firm valuation where operating activities relate to the production of goods and services and financing activities relate to the raising or disposition of cash used for operations. The motivation for the distinction between operating and financing activities is that operating activities are likely to drive firm value while financing activities are zero net present value activities (Modigliani and Miller 1958).

Feltham and Ohlson (1995) also argue that accounting principles systematically undervalue operating income, while appropriately measuring financing income. Accordingly, Feltham and Ohlson (1995) propose a valuation model where operating profitability is weighted more heavily than financing profitability. The disaggregation of financial statements into operating and financing activities has been accepted as a fundamental tenet in financial statement analysis research (e.g., Nissim and Penman 2001; Fairfield and Yohn 2001; Soliman 2008; Fairfield et al. 2009), and financial statement analysis texts recommend the operating/financing disaggregation for profitability forecasting and firm valuation (e.g., Penman 2009; Lundholm and Sloan 2009).

While there is popular appeal for the need to disaggregate the firm's financial statements into operating and financing activities, there is little empirical evidence to support the usefulness of this disaggregation. Recent research has examined the information content of the disaggregation in a valuation context, and the research presents mixed evidence at best. Beaver (2002) notes that various analytic assumptions of the Feltham and Ohlson (1995) model (e.g., linearity properties and the consistency of the coefficients) have been undermined by empirical investigations. Callen and Segal (2005) find limited support for the Feltham and Ohlson (1995) disaggregated valuation model over the Ohlson (1995) aggregated model, and also find that the Feltham and Ohlson (1995) model fails to outperform the Ohlson (1995) model and a naïve valuation model in year-ahead price predictions. In addition, there is no evidence on the usefulness of the operating and financing disaggregation for forecasting profitability.

Given the Boards' stated goal of providing financial information that is useful for forecasting future profitability, we argue that the lack of empirical evidence on the implications of disaggregating the firm's financial statements into operating and financing activities is an important and relevant void in the literature. The Boards' apparent reliance on the untested notion that disaggregating operating and financing activities is useful for predicting future profitability suggests a critical need for such an empirical investigation before the efficacy of the financial statement presentation proposal can be assessed. Our study seeks to provide direct empirical evidence on the Boards' proposal.

Prior Research Concerning Unusual and/or Infrequent Items

In accordance with U.S. GAAP (FASB 1973, 6), if an income item is both unusual in nature and not expected to recur in the foreseeable future, then it is classified as an extraordinary item. Current U.S. GAAP requires extraordinary items to be presented separately below income from continuing operations on the income statement. Income items that are unusual in nature or not expected to recur, but not both, (hereafter referred to as special items) are currently required to be presented separately on the income statement above income from continuing operations.

Prior research supports the notion that extraordinary items and special items are less likely to recur in the future. Fairfield et al. (1996) suggest that extraordinary items should be assigned zero weight for forecasting *ROE* and that special items should not be weighted when forecasting *ROE* before special items and only assigned a small positive weight when forecasting *ROE*. Dechow and Ge (2005) arrive at a similar conclusion by suggesting that the differential persistence of accruals and operating cash flows is driven by special items. To the extent that firms do not opportunistically report special items, Fairfield et al. (2009) also provide evidence in favor of distinguishing special items from other income items on the income statement.

Analysts also appear to find the classification of extraordinary items and special items to be informative for forecasting future profitability. For example, Bradshaw and Sloan (2002) note that analysts track 'street' earnings, which exclude unusual and/or infrequent items. This observation suggests that analysts perceive unusual and/or infrequent items to be less likely to recur in future periods. Collectively, these studies support the separate presentation of unusual and/or infrequent items on the income statement.

Despite this research, the FASB's Financial Statement Presentation proposal eliminates the current U.S. GAAP requirement that firms separately present unusual and/or infrequent items on the income statement, instead requiring firms to disclose this information in the notes to the financial statements (i.e., as part of the proposed reconciliation schedule requirement).[3] Many constituents support FASB's proposal. For example, PwC (2009) agree that unusual and/or infrequent items should be presented in

[3] In our analyses, we only consider disaggregations that are required on the face of the financial statements and do not consider the implications of footnote disclosures of disaggregations. We refer to research suggesting that footnote information is less value relevant than information reported in the financial statements (e.g., Davis-Friday, Folami, Liu and Mittelstaedt 1999). This lower value relevance could be attributed to investors not acquiring footnote information or to investors placing less weight on the information (Maines and McDaniel 2000). This issue is left for further research to consider.

the notes to the financial statements. While FASB proposes changing the location of the disclosure of unusual and/or infrequent items, IASB proposes an even stronger stance and opposes any disclosure of these items (FASB 2008; IASB 2008).

With respect to the proposed location of unusual and/or infrequent items, recent research provides evidence against the Boards' proposal. Riedl and Srinivasan (2009) suggest that managers use the location of special items to communicate to users the persistence of the income item. They argue that managers place special items with lower persistence on the face of the income statement more so than in the notes to the financial statements. Further, the authors suggest that managers make this choice for informational, and not opportunistic, reasons. This research provides further evidence suggesting that the identification of unusual and/or infrequent items on the face of the income statement is particularly informative for forecasting future profitability. Therefore, to the extent that special items and extraordinary items have different implications for forecasting future profitability, the Boards' proposal to not require firms to present these items on the face of the income statement will arguably reduce the information content of the income statement.

Summary

There appears to be widespread acceptance of the Boards' proposals for firms to disaggregate financial statements into operating and financing activities despite the lack of empirical evidence as to the usefulness of doing so for forecasting future profitability. Equally, despite considerable research suggesting the benefits of identifying unusual and/or infrequent items for forecasting, constituents of the standard-setting process appear to support retracting the requirement for firms to identify these items on the face of the income statement. Given the Boards' proposals, this study directly examines the incremental usefulness of the *OPFIN* and *UNINFREQ* disaggregations for forecasting future profitability by comparing the out-of-sample forecast errors for these two models. We also compare the out-of-sample forecast errors of these models to a model that combines the *OPFIN* and *UNINFREQ* disagggregations. These analyses provide evidence concerning the empirical merits of the Boards' proposals.

III. RESEARCH DESIGN

Model Estimation

We are interested in the incremental usefulness of the *OPFIN* and *UNINFREQ* disaggregations relative to a naïve *ROE* model and relative to each other. For each model, we calculate in-sample coefficient estimates from regressions with the disaggregated components of interest as the explanatory variables and ROE_t as the dependent variable for 10-year periods. We then use the in-sample coefficient estimates derived from each of these models to provide out-of-sample firm-specific estimates of ROE_{t+1}.

The regression used to calculate the coefficient estimates for the naïve *ROE* model is presented below:

$$ROE_{i,t} = \alpha_0 + \alpha_1 . ROE_{i,t-1} + \varepsilon_{i,t}.$$

The *OPFIN* model decomposes *ROE* into components based on operating and financing activities. Penman (2009) presents the following disaggregation of *ROE* according to operating and financing activities:

$$ROE = RNOA - (NFA \,/\, BVE)\,(RNOA - RNFA)$$

where *RNOA* is the return on net operating assets, *NFA* is net financial assets, *BVE* is the average book value of equity, and *RNFA* is the return on net financial assets. Consistent with the disaggregated model presented in Nissim and Penman (2001), this expression of *ROE* can be rearranged as follows:

$$ROE = RNOA - (NFA / BVE)(RNOA) + (NFA / BVE)(RNFA)$$

$$ROE = (NOA / BVE)(RNOA) + (NFA / BVE)(RNFA). \quad (1)$$

The *OPFIN* model substitutes ROE_{t-1}.on the right-hand side of the regression used in the naïve *ROE* model to calculate in-sample coefficient estimates with the decomposition of *ROE* as presented in equation (1):[4]

$$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}.$$

The *UNINFREQ* model substitutes ROE_{t-1}.on the right-hand side of the regression used in the naïve *ROE* model to calculate in-sample coefficient estimates with a decomposition of *ROE* into *ROE* before unusual and/or infrequent items (*ROEBUNIN*) and unusual and/or infrequent items (*UNINFREQ*):

$$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}.$$

Our final model (*COMBINED*) combines the *OPFIN* and *UNINFREQ* models as follows:

$$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABUNIN_{i,t-1})$$
$$+ \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})(UNINFREQ_{i,t-1} / NOA_{i,t-1})$$
$$+ \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$$

[4] We also analyzed a model that reflects the *OPFIN* disaggregation but also includes *RNOA* and *RNFA* as additional explanatory variables. The results for the model with these additional explanatory variables are similar to those reported for the *OPFIN* model.

where *RNOABUNIN* is the return on net operating assets before unusual and/or infrequent items. We present the models tested and summarize the definitions of the variables used in this study in Table 1.

[INSERT TABLE 1 HERE]

Sample Selection

Our in-sample coefficient estimates are derived from a sample consisting of 85,657 firm-year observations available on Compustat for the years 1973 through 2006. Consistent with Fairfield et al. (2009), we exclude financial firms with SIC codes between 6000 and 6999 due to the arbitrary separation of these firms' operating and financing activities. Due to size, we restrict our sample to firms with greater than $10 million, $1 million, and $5 million in *NOA*, *BVE*, and *NFA*, respectively, in year *t*-1. To ensure that our in-sample coefficient estimates are not unduly influenced by outliers, we also restrict our sample to firms with an absolute value of *RNOA* and *RNFA* less than one for year *t*-1, and an absolute value of *ROE* less than one for years *t* and *t*-1. We only include firms with available data to calculate the variables in the in-sample regressions. Finally, we truncate the independent and dependent variables of our in-sample estimation regressions at the 1st and 99th percentiles.

We apply our in-sample screening procedures to the right-hand side variables of our out-of-sample forecasting tests. To avoid a look-ahead bias, we do not apply any screens to *ROE* in year *t*+1 (i.e., the year that we observe the accuracy of the models to forecast future profitability). These screening procedures result in our out-of-sample forecasting tests being based on 79,683 firm-year observations.

IV. RESULTS

Descriptive Statistics

Table 2 reports the descriptive statistics and the correlations for the variables used in this study. Panel A presents the descriptive statistics for firm-year observations in the in-sample estimation procedure. The means and medians of the variables presented in Table 2, Panel A are consistent with prior research. We observe that most firm-year observations in our sample have larger *NOA* relative to *NFA*. Further, *NFA* is negative for the majority of observations in our sample suggesting that net financial liabilities are larger than net financial assets. Consistent with Fairfield et al. (1996) and Fairfield et al. (2009), we observe that most firm-year observations have unusual and/or infrequent items (extraordinary items and special items) equal to zero and that the mean value for both extraordinary items and special items is negative.

With respect to the ratios investigated in our study, the mean (median) *ROE* for the sample in year *t* is 8.7% (11.5%). Consistent with unusual and/or infrequent items being negative on average, the mean (median) *ROEBUNIN* for the sample is higher than *ROE*, i.e., 10.8% (12.1%). The mean (median) of the *RNOA* and *RNFA* is 14.8% (13.2%) and 8.8% (8.8%), respectively. Our profitability metrics are consistent with the metrics underlying the samples of Fairfield et al. (2003) and Fairfield et al. (2009).

In Table 2, Panel B we present the Spearman (Pearson) correlations below (above) the diagonal of the correlation matrix. We observe that special items are significantly correlated with extraordinary items. Further, extraordinary and special items are significantly positively (negatively) correlated with NFA_{t-1} (NOA_{t-1}).

The correlations related to the ratios are consistent with those documented in prior research. For example, the correlation matrix suggests that firms with larger (smaller) $BVE_{t\text{-}1}$ and $NOA_{t\text{-}1}$ ($NFA_{t\text{-}1}$) have larger ROE_t. Panel B also suggests that ROE_t is strongly positively correlated with our prior year measures of *RNOA* (i.e., $RNOA_{t\text{-}1}$, $RNOABUNIN_{t\text{-}1}$) and *ROE* (i.e., $RNOA_{t\text{-}1}$, $RNOABUNIN_{t\text{-}1}$). Consistent with Fairfield et al. (1996), ROE_t is also significantly positively correlated with special items and negatively correlated with $RNFA_{t\text{-}1}$.

[INSERT TABLE 2 HERE]

Comparative Ability of Models to Forecast Future Profitability

Table 3 presents our in-sample estimation of the coefficients for the naïve *ROE*, *OPFIN*, *UNINFREQ*, and *COMBINED* models. We model *ROE* as a linear function of either lagged *ROE* or components of lagged *ROE*. To control for possible inter-temporal instabilities of the forecasting models, we estimate the in-sample regression coefficients using rolling 10-year regressions. For example, to forecast profitability in 2007, the regression models use ten years of data from 1997 to 2006. All models are estimated using the same sample of firms.

Table 3 reports the mean coefficient estimates and the associated *t*-statistics calculated in accordance with Fama and MacBeth (1973). These *t*-statistics are also adjusted for serial correlation (Bernard 1995). In each year, we calculate the average coefficient for all firms. We report the mean of the annual coefficients for each model. Finally, we calculate the average adjusted-R^2 of the annual regression models estimated. Although we report and discuss the cross-sectional means and *t*-statistics of the regression coefficients, we provide no statistical tests of comparisons of the models. Instead, we evaluate the predictive ability of the models in out-of-sample tests.

In the naïve *ROE* model, the mean coefficient for lagged *ROE* is 0.5864. This coefficient is similar to the coefficient reported by Fairfield et al. (1996). The average adjusted-R^2 from this model is 24.32%. Our in-sample results show that when lagged *ROE* is disaggregated according to operating and financing activities that the coefficients on operating activities (0.4141) and financing activities (0.3932) are similar. These results suggest that the *OPFIN* disaggregation does not appear to identify differentially persistent components of firms' profitability. Relative to the naïve *ROE* model, the *OPFIN* model increases the average adjusted-R^2 to 26.21%.

In contrast to the *OPFIN* model, Table 3 shows that the *UNINFREQ* model captures the different implications that lagged *ROEBUNIN* (0.6904) and *UNINFREQ* (0.1906) have for forecasts of future profitability. This disaggregation appears to identify components of firms' earnings that are differentially persistent for *ROE*. Further, this disaggregation increases the average adjusted-R^2 to 27.43%. Combining the *OPFIN* and *UNINFREQ* disaggregations (i.e., the *COMBINED* model) appears not to successfully differentiate the implications of the earnings components for forecasts of future profitability, i.e., operating (0.4099), financing (0.3894), and unusual and/or infrequent items (0.4323). Equally, combining these disaggregations does not increase the average adjusted-R^2 as much as each of the disaggregations in isolation (i.e., overall average adjusted-R^2 of 26.12%).

[INSERT TABLE 3 HERE]

Table 4 reports the out-of-sample tests of the models. For each year *t*+1 , we use the estimates from the rolling regression models using data from the preceding 10 years (*t*-10 to *t*-1). For example, the 2007 forecasts use the coefficient estimates from the in-sample estimation period 1997-2006. Improvement in accuracy is measured through a matched-pair comparison of the absolute value of prediction errors from the two competing models.

The mean (median) improvement in accuracy is computed annually and the reported grand mean (median) improvement is the mean (median) of the 25 yearly mean (median) improvements in predictive accuracy. Improvement in forecast accuracy implies that the first-mentioned model produces superior forecasts of future profitability by that percent of average book value of equity.[5] We also report the number of years that the median values are positively or negatively significantly different from zero (at the 10% significance level) across the sample period of 25 years. Tests of means are based on Fama and MacBeth (1973) *t*-statistics computed from the annual mean forecast improvements. Tests of medians are based on Wilcoxon Signed Ranks tests of the annual median forecast improvement. Panel A reports the results of regressions on the continuous variables while Panel B reports the results of regressions on the ranked variables.

Our first two analyses examine whether the *OPFIN* and *UNINFREQ* models improve forecasts of future profitability relative to the naïve *ROE* prediction model. Table 4 illustrates that the *OPFIN* model provides little to no improvement in forecasts of future profitability. While the mean improvement in Panel A is significant, the median

[5] For example, the median improvement in accuracy of 0.00165 for the *UNINFREQ* model vs. the naïve *ROE* model implies that the *UNINFREQ* model improves forecast accuracy of future profitability by 0.165% of average book value of equity relative to the naïve *ROE* model.

improvement on the continuous variable model and the mean and median improvements in the rank regression model are insignificant. In addition, the *OPFIN* disaggregation leads to significant improvements in the median forecasts of future profitability in only seven (nine) years of the 25-year sample period and leads to significantly worse median forecasts of future profitability in nine (seven) years of the 25-year sample period using the continuous (rank) specification. The results suggest that disaggregating financial statements into operating and financing activities does not appear to improve forecasts of future profitability over a naive aggregate forecasting model.

Table 4 also shows that the *UNINFREQ* model improves forecasts of future profitability by 0.415% of average book value of equity relative to the naïve *ROE* model. This mean improvement is over twice as large as the relative improvement generated from the *OPFIN* model, and the *UNINFREQ* model significantly improves profitability forecasts over the naive model using means and medians and both the continuous and rank specifications. In addition, the *UNINFREQ* disaggregation leads to significant improvements in the median forecasts of future profitability in 24 (25) years of the 25-year sample period using the continuous (rank) specification.

The direct comparison of the *OPFIN* and *UNINFREQ* disaggregations reveals that the *UNINFREQ* disaggregation yields significantly more accurate forecasts of future profitability than the *OPFIN* model using means and medians and for both the continuous and rank specifications. In addition, the *UNINFREQ* model yields significantly more accurate forecasts in 23 (20) years of the 25-year sample period relative to the *OPFIN* disaggregation. The mean (median) improvement in forecast accuracy stemming from the *UNINFREQ* model relative to the *OPFIN* model is 0.249% (0.145%).

Interestingly, Table 4 shows that combining the *OPFIN* and *UNINFREQ* disaggregations (i.e., the *COMBINED* model) does not lead to significantly more accurate forecasts of future profitability relative to the *UNINFREQ* disaggregation alone. Instead, we find that the *UNINFREQ* disaggregation yields significantly more accurate forecasts for the means and medians and using both the continuous and rank specifications. The *UNINFREQ* model yields more accurate forecasts than the *COMBINED* model in 23 (19) years of the 25-year sample period. We observe 0.262% (0.143%) mean (median) greater accuracy from the *UNINFREQ* model relative to the *COMBINED* model.

[INSERT TABLE 4 HERE]

V. ROBUSTNESS TESTS

Our primary analyses suggest that the *UNINFREQ* disaggregation leads to significantly superior forecasts of future profitability relative to the naïve *ROE* model, *OPFIN* model, and a model combining the *OPFIN* and *UNINFREQ* disaggregations. Tables 5 through 9 consider the robustness of this study's key findings. First, we consider whether our results are robust to different levels of leverage (Table 5). We then investigate whether our findings are sensitive to observed differences in *RNOA* and *RNFA* (Table 6). We also examine whether the difference in the forecasts produced by the competing models drives the relative forecast accuracy (Table 7). We are also interested in whether our results are isolated to particular industry sector classifications (Table 8). Finally, we examine whether the superior ability of the *UNINFREQ* model is driven by extraordinary items or whether the *UNINFREQ* model is also superior when only special items are segregated and profitability before extraordinary items is forecasted (Table 9).

Leverage

Table 5 investigates the robustness of the study's findings to different levels of leverage. We separate firm-year observations annually into one of six categories based on leverage. These categories represent firms with positive net financial assets and quintiles of firms with leverage. We define leverage as *NFA* scaled by book value of equity. "Quintile 1" ("Quintile 5") represents firm-years with leverage of the lowest (highest) absolute magnitude. The reported means and medians are for paired differences between the absolute forecast errors.

Relative to the naïve *ROE* model, the *OPFIN* model produces significant mean and median improvements in forecast accuracy only for firms with relatively low leverage (i.e., leverage Quintile 1). In contrast, the *UNINFREQ* model consistently produces significant mean and median improvement in forecasts of future profitability relative to the naïve *ROE* model across all categories of leverage. In all leverage categories, the mean improvement is at least 0.35% of average book value of equity.

When directly comparing the median difference in forecast accuracy for the *UNINFREQ* model relative to the *OPFIN* model, we observe that the *UNINFREQ* model outperforms the *OPFIN* model for all leverage categories. Only in Quintile 1, does the *UNINFREQ* model not significantly improve the mean forecast accuracy relative to the *OPFIN* model. The findings comparing the *UNINFREQ* and *COMBINED* models demonstrate the superiority of the *UNINFREQ* model for every leverage category. Collectively, these findings suggest that the superiority of the *UNINFREQ* disaggregation relative to the *OPFIN* and *COMBINED* disaggregations for forecasting future profitability is robust to leverage.

[INSERT TABLE 5 HERE]

RNOA vs. RNFA

Table 6 investigates the robustness of the study's findings to the absolute value of the difference between *RNOA* and *RNFA*. We separate firm-year observations annually into quintiles based on the absolute value of the difference between *RNOA* and *RNFA*. "Quintile 1" ("Quintile 5") represents firm-years with absolute values of (*RNOA* – *RNFA*) of the lowest (highest) absolute magnitude. Our expectation is that the *OPFIN* is most likely to perform well relative to the other models in situations where there are large differences between *RNOA* and *RNFA*. The reported means and medians are for paired differences between the absolute forecast errors.

Table 6 provides some evidence that the *OPFIN* model performs better relative to the naïve *ROE* model in conditions where there are large differences between *RNOA* and *RNFA*. However, Quintile 4 is the only quintile where the *OPFIN* model produces mean and median forecasts of future profitability that are significantly more accurate than the naïve *ROE* model. The *UNINFREQ* model leads to significant mean and median improvements in forecasts of future profitability relative to the naïve *ROE* model in the three highest quintiles of *RNOA* and *RNFA* differences. In all quintiles, the mean improvement is at least 0.20% of average book value of equity. Further, we observe that the mean and median improvement in forecast accuracy of the *UNINFREQ* model relative to the naïve *ROE* model is generally monotonically increasing in the absolute value of the difference between *RNOA* and *RNFA*. This finding suggests that the *UNINFREQ* disaggregation is useful in conditions in which relatively large differences between *RNOA* and *RNFA* are expected.

When directly comparing the mean and median improvement in the forecasting performance of the *UNINFREQ* model relative to the *OPFIN* model, we observe that the *UNINFREQ* model outperforms the *OPFIN* model for all quintiles. Further, we observe that the *UNINFREQ* model significantly outperforms the *COMBINED* model for all quintiles based on both means and median improvements. Collectively, these findings suggest that the relative superiority of the *UNINFREQ* disaggregation for forecasting future profitability is robust to the absolute value of the difference between *RNOA* and *RNFA*.

[INSERT TABLE 6 HERE]

Difference Between the Models' Forecasts

Table 7 investigates the robustness of the study's findings to the absolute value of the difference between the competing models' forecasts. We separate firm-year observations annually into quintiles based on the absolute value of the difference between the competing models' forecasts. "Quintile 1" ("Quintile 5") represents firm-years with absolute values of the difference between the models' forecasts of the lowest (highest) absolute magnitude. We use this analysis to test whether our results are driven by a select group of firms for which there is a dramatic difference in forecast between the models. The reported means and medians are for paired differences between the absolute forecast errors.

Table 7 provides evidence that the *OPFIN* model only outperforms the naïve *ROE* model for the largest quintile of differences between the two models' forecasts. In Quintile 5, the mean and median forecast is significantly more accurate for the *OPFIN* model while in Quintiles 1 and 2, the mean and median forecast is significantly less accurate for the *OPFIN* model relative to the naïve *ROE* model. This evidence suggests that only when large differences between the forecasts generated by these two models exist does the *OPFIN* model dominate the naïve *ROE* model. In comparison, the *UNINFREQ* model leads to significant mean and median improvements in forecasts of future profitability relative to the naïve *ROE* model in Quintiles 3, 4, and 5. There is no evidence of the *UNINFREQ* model yielding significantly less accurate forecasts than the naïve *ROE* model.

When we directly compare the *OPFIN* and *UNINFREQ* models, we observe that the *UNINFREQ* model outperforms the *OPFIN* model for all quintiles. Further, the findings comparing the *UNINFREQ* and *COMBINED* models demonstrate the superiority of the *UNINFREQ* model in each of the quintiles. Collectively, these findings suggest that the superiority of the *UNINFREQ* disaggregation relative to the other models for forecasting future profitability is robust to the absolute difference in magnitude between the forecasts that it generates relative to those of the competing models.

[INSERT TABLE 7 HERE]

Industry Sector Classification

Table 8 examines the robustness of the study's findings to industry sector classification. We classify firm-year observations according to two-digit GICS sector codes. We exclude firms in the financial sector (GICS Sector #40) due to the arbitrary separation of these firms' operating and financing activities. We use this analysis to test whether our results are isolated to particular industry sectors and whether different models dominate for different industry sectors. In-sample regression models are estimated by sector and by year, and the estimated coefficients from the rolling regressions are used to predict one-year-ahead ROE. The reported means and medians are for paired differences between the absolute forecast errors.

Table 8 provides evidence that the *OPFIN* model outperforms the naïve *ROE* model in the materials, industrials, and consumer staples industry sectors. The *OPFIN* model appears to perform best in the consumer staples industry sector where the mean (median) improvement in forecast accuracy over the naïve *ROE* model is 0.543% (0.133%). The *UNINFREQ* model leads to significant mean and median improvements in forecasts of future profitability relative to the naïve *ROE* model in all industry sectors with the only exception being the energy industry sector. There is no evidence of the *UNINFREQ* model performing worse than the naïve *ROE* model. The *UNINFREQ* model achieves greater than 0.4% mean improvement in forecast accuracy in five of the industry sectors (i.e., materials, consumer staples, health care, information technology, telecommunication services).

When we compare the *OPFIN* and *UNINFREQ* models, we observe that the *UNINFREQ* model achieves significant mean and median improvement in forecast accuracy relative to the *OPFIN* model in five industry sectors (i.e., energy, consumer discretionary, health care, information technology, utilities). There is no evidence of the *UNINFREQ* model performing significantly worse than the *OPFIN* model in any industry sector. The findings comparing the *UNINFREQ* and *COMBINED* models are inferentially identical to the results of the *UNINFREQ* versus *OPFIN* comparison. Collectively, these findings suggest that the relative superiority of the *UNINFREQ* disaggregation for forecasting future profitability holds across most industry sector classifications and that in no case does the *OPFIN* disaggregation lead to improvements in forecasts of future profitability in a particular industry.

[INSERT TABLE 8 HERE]

Forecasting Profitability Before Extraordinary Items

We note that the *UNINFREQ* model disaggregates both unusual *and* infrequent (i.e., extraordinary) items and unusual *or* infrequent (special) items from net income. This is consistent with the Boards' proposal that neither special items nor extraordinary items be required to be segregated in the financial statements. However, in our final analysis, we examine whether the superiority of the *UNINFREQ* model is driven by the disaggregation of extraordinary items or whether disaggregating special items is useful in forecasting profitability before extraordinary items. We believe that this analysis could provide useful insights as to the usefulness of disaggregating special items and extraordinary items for forecasting future profitability.

In this analysis, we forecast year ahead *ROE* before extraordinary items (*ROEBXI*). The models examined are identical to those in the previous analyses except that income before extraordinary items is included in the models instead of net income, and special items are disaggregated from other income before extraordinary items. Table 9 reports the comparison of the out-of-sample forecast accuracy of the different models. The reported means and medians are for paired differences between the absolute forecast errors for forecasts of *ROEBXI*.

The results are consistent with the results of forecasts of bottom-line profitability. The *OPFIN* model fails to lead to improved forecast accuracy relative to the naïve model while the *UNINFREQ* model (which disaggregates special items) leads to significantly improved mean and median forecast accuracy relative to the naïve model. The *UNINFREQ* model yields significantly more accurate median forecasts than the naïve model in 24 of the 25 years examined. The *UNINFREQ* model also yields significantly greater mean and median forecast accuracy than the *OPFIN* model and yields significantly more accurate median forecasts than the *OPFIN* model in 24 of the 25 years. Finally, the results demonstrate that the *UNINFREQ* model yields significantly greater mean and median forecast accuracy than the *COMBINED* model. These results suggest that the superiority of the *UNINFREQ* model in the main analyses is not driven by the segregation of extraordinary items and that a model that disaggregates both extraordinary items and special items yields significantly more accurate forecasts than a model that disaggregates operating and financing activities.

[INSERT TABLE 9 HERE]

VI. CONCLUSIONS

Prior academic research (Nissim and Penman 2001; Feltham and Ohlson 1995) and financial statement analysis texts (Penman 2009; Lundholm and Sloan 2009) suggest that disaggregating financial statements into operating and financing activities will improve the usefulness of the financial statements for forecasting profitability and for valuation. This conclusion is based on the notion that operating and financing activities have different implications for future profitability. Consistent with this notion, the standard-setting Boards have recently proposed requiring firms to disaggregate the financial statements into operating and financing activities (FASB 2008).

The Boards' proposals represent a significant departure from the existing requirement for U.S. firms to identify unusual and/or infrequent items when presenting income statements (FASB 1973). The proposed changes are likely to impose costs on preparers in adapting financial reporting systems to accommodate the new requirements and to increase the complexity of the financial statement information faced by users. Given the significance of the changes proposed by the Boards, this study examines the empirical merits of the Boards' proposals with respect to the comparative usefulness of disaggregating financial statements into operating and financing activities versus disaggregating unusual and/or infrequent income items.

Based on the Boards' proposals we compare the forecast improvements generated by decomposing lagged *ROE* into (1) its operating and financing components (*OPFIN*), (2) *ROE* before unusual and/or infrequent items, and unusual and/or infrequent items (*UNINFREQ*), and (3) a combination of these two disaggregations (*COMBINED*). For each model, we use the in-sample coefficient estimates generated from 10-year rolling regressions to predict one-year-ahead return-on-equity in the out-of-sample period.

While we find that the *UNINFREQ* disaggregation consistently outperforms the naïve *ROE* prediction model, we find little to no evidence of an incremental benefit of the *OPFIN* disaggregation relative to the naïve *ROE* prediction model. A direct comparison of the *OPFIN* and *UNINFREQ* disaggregations finds that the *UNINFREQ* disaggregation produces significantly more accurate forecasts of future profitability in all but two of the 25-year sample period relative to the *OPFIN* disaggregation. We also find that the *UNINFREQ* disaggregation produces significantly more accurate forecasts of future profitability relative to a model combining the *OPFIN* and *UNINFREQ* disaggregations.

This study contributes to the extant literature considering how disaggregation of income improves forecasts of future profitability (e.g., Fairfield et al. 1996). The study extends prior research by demonstrating that identifying unusual and/or infrequent items leads to more accurate predictions of future profitability relative to disaggregating financial statements based on firms' operating and financing activities. This study also provides direct evidence on the usefulness of disaggregating financial statements into operating and financing activities for the purposes of forecasting future profitability (Nissim and Penman 2001). Our findings question the merits of the theoretical claims that suggest that disaggregating financial statements into operating and financing activities improves forecasts of future profitability (Feltham and Ohlson 1995).

We believe that this study presents timely evidence relevant to the Boards' Financial Statement Presentation Project. While the Boards assert that disaggregating financial statements into operating and financing activities will improve users' forecasts of future profitability, we find little to no evidence to support their claims. Our findings suggest that retracting the requirement for U.S. firms to identify unusual and/or infrequent items reduces the accuracy of forecasts of future profitability. We also provide evidence suggesting that supplementing the proposed disaggregation with a requirement for firms to identify unusual and/or infrequent items will not rectify the limited predictive ability of the Boards' proposed disaggregation. Collectively, our results suggest that the Boards reconsider their proposals to require firms to disaggregate financial statements into operating and financing activities and to retract the requirement that firms identify unusual and /or infrequent items on the face of the income statement.

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TABLE 1
Variable Definitions and Summary of Models

Panel A: Variable definitions

Variable Name	Description	Computation
BV_t	Common shareholders' equity	
CHE_t	Cash and short-term investments	
DLC_t	Debt in current liabilities	
$DLTT_t$	Long-term debt	
$IDIT_t$	Interest and related income	
$INTC_t$	Interest capitalized	
MII_t	Minority interest income	
NI_t	Net income	
$NOPIO_t$	Nonoperating income (expense) before interest income	
$OIADP_t$	Operating income after depreciation	
$PSTK_t$	Preferred stock	
SPI_t	Special items	
$TXDB_t$	Deferred taxes	
TXP_t	Income taxes payable	
$XINT_t$	Interest and related expense	
XI_t	Extraordinary items	
BVE_t	Average common shareholders' equity	$(BV_t + BV_{t-1})/2$
NFA_t	Net financial assets	$CHE_t - (DLTT_t + DLC_t) - PSTK_t$
NFI_t	Net financial income	$IDIT_t - XINT_t - INTC_t$
NOA_t	Net operating assets	$BV_t - NFA_t + TXP_t + TXDB_t$
NOI_t	Net operating income	$OIADP_t + NOPIO_t - INTC_t - MII_t$
$UNINFREQ_t$	Unusual or infrequent items	$SPI_t + XI_t$
$RNFA_t$	Return on net financial assets	$NFI_t / [(NFA_t + NFA_{t-1})/2]$
$RNOA_t$	Return on net operating assets	$NOI_t / [(NOA_t + NOA_{t-1})/2]$
$RNOABSPI_t$	*RNOA* before special items	$(NOI_t - SPI_t)/[(NOA_t + NOA_{t-1})/2]$
$RNOABUNIN_t$	*RNOA* before unusual or infrequent items	$(NOI_t - SPI_t - XI_t)/[(NOA_t + NOA_{t-1})/2]$
$RNOABXI_t$	*RNOA* before extraordinary items	$(NOI_t - XI_t)/[(NOA_t + NOA_{t-1})/2]$
ROE_t	Return on equity	NI_t / BVE_t
$ROEBUNIN_t$	*ROE* before unusual or infrequent items	$(NI_t - SPI_t - XI_t) / BVE_t$
$ROEBSPI_t$	*ROE* before special items	$(NI_t - SPI_t) / BVE_t$
$ROEBXI_t$	*ROE* before extraordinary items	$(NI_t - XI_t) / BVE_t$

Panel B: Summary of Models

Model	Equation
Naïve *ROE*	$ROE_{i,t} = \alpha_0 + \alpha_1.ROE_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})\,(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})\,(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})\,(RNOABUNIN_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})\,(UNINFREQ_{i,t-1} / NOA_{i,t-1})$ $+ \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})\,(RNFA_{i,t-1}) + \varepsilon_{i,t}$

TABLE 2
Descriptive Statistics and Correlation Matrix

Panel A: Descriptive statistics (for variables used to estimate in-sample regression coefficients)

	Mean	Median	Std. Dev	First Quartile	Third Quartile	Min	Max
BVE_{t-1}	467.653	113.881	1,045.499	38.295	401.240	4.413	11,935.500
NFA_{t-1}	-349.362	-45.966	918.390	-254.453	-9.808	-9,060.000	571.586
NOA_{t-1}	927.720	187.704	2,115.666	59.458	748.750	11.847	22,952.000
SPI_{t-1}	-4.293	0.000	25.221	0.000	0.000	-359.032	66.976
XI_{t-1}	-0.177	0.000	2.471	0.000	0.000	-40.934	13.000
$RNFA_{t-1}$	0.088	0.088	0.066	0.062	0.117	-0.228	0.398
$RNOA_{t-1}$	0.148	0.132	0.124	0.083	0.201	-0.333	0.695
$RNOABUNIN_{t-1}$	0.155	0.136	0.125	0.087	0.209	-0.315	0.739
ROE_{t-1}	0.098	0.118	0.127	0.051	0.167	-0.600	0.480
ROE_{t}	0.087	0.115	0.150	0.043	0.166	-0.700	0.498
$ROEBUNIN_{t-1}$	0.108	0.121	0.112	0.060	0.169	-0.459	0.477

Panel B: Correlation matrix (for variables used to estimate in-sample regression coefficients)

	BVE_{t-1}	NFA_{t-1}	NOA_{t-1}	$RNFA_{t-1}$	$RNOA_{t-1}$	$RNOABUNIN_{t-1}$	ROE_{t}	ROE_{t-1}	$ROEBUNIN_{t-1}$	SPI_{t-1}	XI_{t-1}
BVE_{t-1}		-0.73	0.94	***0.00***	0.01	***0.01***	0.08	0.09	0.10	-0.25	-0.07
NFA_{t-1}	-0.59		-0.91	-0.02	0.10	0.10	-0.05	-0.06	-0.07	0.21	0.08
NOA_{t-1}	0.94	-0.78		0.01	-0.04	-0.04	0.07	0.09	0.10	-0.23	-0.08
$RNFA_{t-1}$	-0.10	-0.21	0.01		-0.10	-0.11	-0.04	-0.03	-0.04	0.01	***0.00***
$RNOA_{t-1}$	0.06	0.21	-0.02	-0.02		0.95	0.45	0.69	0.72	0.05	0.01
$RNOABUNIN_{t-1}$	0.08	0.22	-0.01	-0.04	0.94		0.41	0.54	0.70	-0.08	-0.04
ROE_{t}	0.11	-0.06	0.12	-0.03	0.56	0.52		0.51	0.52	0.03	***0.01***
ROE_{t-1}	0.12	-0.05	0.13	-0.02	0.79	0.68	0.62		0.88	0.17	0.09
$ROEBUNIN_{t-1}$	0.16	-0.07	0.17	-0.03	0.81	0.79	0.63	0.91		-0.04	***-0.01***
SPI_{t-1}	-0.10	0.04	-0.08	0.05	0.08	-0.09	0.08	0.23	***0.00***		0.06
XI_{t-1}	-0.13	0.09	-0.12	0.03	***-0.01***	-0.08	***0.00***	0.07	-0.04	0.05	

See Table 1, Panel A for variable definitions. Data are firm-year observations from 1973 to 2006. Number of observations is 85,657. In Table 2, Panel B, Spearman (Pearson) correlations are presented below (above) the diagonal. All correlations are significant at the 1% significance level unless in bold and italics.

TABLE 3
In-sample Estimation of Models

Naïve *ROE*	$ROE_{i,t} = \alpha_0 + \alpha_1.ROE_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})\,(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})\,(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})\,(RNOABUNIN_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})\,(UNINFREQ_{i,t-1} / NOA_{i,t-1}) + \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})\,(RNFA_{i,t-1}) + \varepsilon_{i,t}$

Model	α_0	α_1	α_2	α_3	**Adj. R-Squared**
Naïve *ROE*					
Mean	0.0269 ***	0.5864 ***			24.32%
t-Statistic	4.90	25.58			
OPFIN					
Mean	0.0101	0.4141 ***	0.3932 ***		26.21%
t-Statistic	0.74	10.43	6.11		
UNINFREQ					
Mean	0.0124	0.6904 ***	0.1906 ***		27.43%
t-Statistic	1.33	182.79	6.89		
COMBINED					
Mean	0.0115	0.4099 ***	0.4323 ***	0.3894 ***	26.12%
t-Statistic	0.90	11.35	6.50	6.40	

t-statistics are computed using the Fama-MacBeth (Fama and MacBeth 1973) approach and adjusted for serial correlation in yearly coefficients (Bernard 1995). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 4
Out-of-sample Improvement in Forecast Accuracy of Models Forecasting Future Profitability

In-sample coefficient estimation regressions

Naïve *ROE*	$ROE_{i,t} = \alpha_0 + \alpha_1.ROE_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABUNIN_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})(UNINFREQ_{i,t-1} / NOA_{i,t-1}) + \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$

Panel A: Regressions on Continuous Variables

	Mean Improvement		Median Improvement		Number of
	Value	*p*-Value	Value	*p*-Value	years
OPFIN vs. Naïve *ROE*	0.00167 ***	0.0092	-0.00034	0.2075	7 / 9
UNINFREQ vs. Naïve *ROE*	0.00415 ***	0.0000	0.00165 ***	0.0000	24 / 0
UNINFREQ vs. *OPFIN*	0.00249 ***	0.0000	0.00145 ***	0.0000	23 / 0
UNINFREQ vs. *COMBINED*	0.00262 ***	0.0000	0.00143 ***	0.0000	23 / 0

Panel B: Rank Regressions

	Mean Improvement		Median Improvement		Number of
	Value	*p*-Value	Value	*p*-Value	years
OPFIN vs. Naïve *ROE*	6.65130	0.1224	-0.50245	0.5038	9 / 7
UNINFREQ vs. Naïve *ROE*	22.32323 ***	0.0000	11.60865 ***	0.0000	25 / 0
UNINFREQ vs. *OPFIN*	15.67607 ***	0.0000	10.16511 **	0.0180	20 / 4
UNINFREQ vs. *COMBINED*	26.16723 ***	0.0000	14.47008 **	0.0127	19 / 2

Improvement in accuracy is measured through a matched-pair comparison of the absolute value of prediction errors from the two competing models. The mean (median) improvement in accuracy is computed annually and the reported grand mean (median) improvement is the mean (median) of the 25 yearly mean (median) improvements in predictive accuracy. Positive (negative) values imply that the first mentioned model is more (less) accurate than the second model. Number of years is the number of years out of 25 that the yearly median improvement is significantly positive / negative (at the 10% significance level). Tests of means are based on Fama-MacBeth *t*-statistics computed from the annual mean forecast improvements. Tests of medians are based on Wilcoxon Signed Ranks tests of the annual median forecast improvement. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5
Out-of-sample Improvement in Forecast Accuracy of Models Forecasting Future Profitability by Quintiles Based on Leverage

In-sample coefficient estimation regressions

Naïve *ROE*	$ROE_{i,t} = \alpha_0 + \alpha_1.ROE_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABUNIN_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})(UNINFREQ_{i,t-1} / NOA_{i,t-1}) + \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$

		OPFIN vs. Naïve ***ROE***	***UNINFREQ*** vs. Naïve ***ROE***	***UNINFREQ*** vs. ***OPFIN***	***UNINFREQ*** vs. ***COMBINED***
Positive	Mean	0.00125 **	0.00432 ***	0.00308 ***	0.00307 ***
	Median	0.00129	0.00250 ***	0.00127 ***	0.00131 ***
Quintile 1	Mean	0.00389 ***	0.00431 ***	0.00041	0.00081 *
	Median	0.00075 *	0.00167 ***	0.00062 ***	0.00074 ***
Quintile 2	Mean	0.00312 ***	0.00419 ***	0.00107 **	0.00104 **
	Median	0.00009	0.00147 ***	0.00092 ***	0.00107 ***
Quintile 3	Mean	0.00306 ***	0.00495 ***	0.00189 ***	0.00212 ***
	Median	-0.00064	0.00114 ***	0.00142 ***	0.00137 ***
Quintile 4	Mean	-0.00026	0.00352 ***	0.00378 ***	0.00378 ***
	Median	-0.00335 ***	0.00092 ***	0.00327 ***	0.00298 ***
Quintile 5	Mean	-0.00047	0.00380 ***	0.00427 ***	0.00460 ***
	Median	-0.00190 ***	0.00150 ***	0.00310 ***	0.00258 ***

Leverage is calculated as NFA_t / BV_t. "Positive" identifies firm-years with leverage greater than or equal to zero. "Quintile 1" ("Quintile 5") represents firm-years with negative leverage of the lowest (highest) absolute magnitude. The reported means and medians are for paired differences between the absolute forecast errors. The mean (median) improvement in accuracy is computed annually and the reported grand mean (median) improvement is the mean (median) of the 25 yearly mean (median) improvements in predictive accuracy. Positive (negative) values imply that the first mentioned model is more (less) accurate than the second model. Tests of means are based on Fama-MacBeth *t*-statistics computed from the annual mean forecast improvements. Tests of medians are based on Wilcoxon Signed Ranks tests of the annual median forecast improvement. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6
Out-of-sample Improvement in Forecast Accuracy of Models Forecasting Future Profitability by Quintiles Based on *RNOA* vs. *RNFA*

In-sample coefficient estimation regressions

Naïve *ROE*	$ROE_{i,t} = \alpha_0 + \alpha_1.ROE_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABUNIN_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})(UNINFREQ_{i,t-1} / NOA_{i,t-1}) + \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$

		OPFIN* vs. Naïve *ROE	***UNINFREQ* vs. Naïve *ROE***	***UNINFREQ* vs. *OPFIN***	***UNINFREQ* vs. *COMBINED***
Quintile 1	Mean	0.00152	0.00272 ***	0.00120 **	0.00141 ***
	Median	-0.00273 ***	-0.00031 *	0.00230 ***	0.00203 ***
Quintile 2	Mean	0.00064	0.00241 ***	0.00176 ***	0.00182 ***
	Median	-0.00214 ***	0.00051	0.00210 ***	0.00176 ***
Quintile 3	Mean	0.00306 ***	0.00398 ***	0.00092 ***	0.00111 ***
	Median	0.00017	0.00182 ***	0.00105 ***	0.00118 ***
Quintile 4	Mean	0.00281 ***	0.00531 ***	0.00250 ***	0.00270 ***
	Median	0.00210 ***	0.00356 ***	0.00081 ***	0.00084 ***
Quintile 5	Mean	0.00030	0.00635 ***	0.00605 ***	0.00604 ***
	Median	0.00050 *	0.00402 ***	0.00234 ***	0.00191 ***

The difference in *RNOA* and *RNFA* is calculated as the absolute value of (*RNOA* – *RNFA*). The reported means and medians are for paired differences between the absolute forecast errors. "Quintile 1" ("Quintile 5") represents firm-years with absolute values of (*RNOA* – *RNFA*) of the lowest (highest) absolute magnitude. The mean (median) improvement in accuracy is computed annually and the reported grand mean (median) improvement is the mean (median) of the 25 yearly mean (median) improvements in predictive accuracy. Positive (negative) values imply that the first mentioned model is more (less) accurate than the second model. Tests of means are based on Fama-MacBeth *t*-statistics computed from the annual mean forecast improvements. Tests of medians are based on Wilcoxon Signed Ranks tests of the annual median forecast improvement. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 7
Out-of-sample Improvement in Forecast Accuracy of Models Forecasting Future Profitability by Quintiles Based on the Difference Between the Models' Forecasts

In-sample coefficient estimation regressions

Naïve *ROE*	$ROE_{i,t} = \alpha_0 + \alpha_1.ROE_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABUNIN_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})(UNINFREQ_{i,t-1} / NOA_{i,t-1}) + \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$

		OPFIN vs. Naïve ***ROE***	***UNINFREQ*** vs. Naïve ***ROE***	***UNINFREQ*** vs. ***OPFIN***	***UNINFREQ*** vs. ***COMBINED***
Quintile 1	Mean	-0.00020 ***	0.00003	0.00010 ***	0.00007 ***
	Median	-0.00034 ***	0.00003	0.00013 ***	0.00011 ***
Quintile 2	Mean	-0.00046 ***	0.00028 **	0.00058 ***	0.00046 ***
	Median	-0.00496 *	0.00255	0.00392 ***	0.00405 ***
Quintile 3	Mean	-0.00051	0.00116 ***	0.00140 ***	0.00121 ***
	Median	-0.00065	0.00611 ***	0.00844 ***	0.00827 ***
Quintile 4	Mean	-0.00037	0.00303 ***	0.00333 ***	0.00330 ***
	Median	-0.00488	0.01244 ***	0.01628 ***	0.01657 ***
Quintile 5	Mean	0.00987 ***	0.01626 ***	0.00701 ***	0.00805 ***
	Median	0.02525 **	0.03096 ***	0.03632 ***	0.03774 ***

The difference in the models' forecasts is calculated as the absolute value of the difference between the two models' forecasts. The reported means and medians are for paired differences between the absolute forecast errors. "Quintile 1" ("Quintile 5") represents firm-years with absolute values of the difference between the two models' forecasts of the lowest (highest) absolute magnitude. The mean (median) improvement in accuracy is computed annually and the reported grand mean (median) improvement is the mean (median) of the 25 yearly mean (median) improvements in predictive accuracy. Positive (negative) values imply that the first mentioned model is more (less) accurate than the second model. Tests of means are based on Fama-MacBeth *t*-statistics computed from the annual mean forecast improvements. Tests of medians are based on Wilcoxon Signed Ranks tests of the annual median forecast improvement. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8
Out-of-sample Improvement in Forecast Accuracy of Models Forecasting Future Profitability by GICS Industry Sector

In-sample coefficient estimation regressions

Naïve *ROE*	$ROE_{i,t} = \alpha_0 + \alpha_1.ROE_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOA_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROE_{i,t} = \alpha_0 + \alpha_1.ROEBUNIN_{i,t-1} + \alpha_2.(UNINFREQ_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROE_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABUNIN_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})(UNINFREQ_{i,t-1} / NOA_{i,t-1}) + \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$

GICS Sector (Two-digit GICS #)	*N*		*OPFIN* vs. Naïve *ROE*	*UNINFREQ* vs. Naïve *ROE*	*UNINFREQ* vs. *OPFIN*	*UNINFREQ* vs. *COMBINED*
10. Energy	1,692	Mean	-0.00156	0.00170	0.00326 ***	0.00331 ***
		Median	-0.00227 ***	0.00126	0.00259 ***	0.00264 ***
15. Materials	2,616	Mean	0.00395 ***	0.00437 ***	0.00043	0.00083
		Median	0.00239 ***	0.00130 ***	0.00038 *	0.00018
20. Industrials	4,798	Mean	0.00423 ***	0.00340 ***	-0.00083	-0.00041
		Median	0.00265 ***	0.00192 ***	-0.00001	-0.00006
25. Consumer Discretionary	5,554	Mean	0.00174 **	0.00399 ***	0.00225 ***	0.00237 ***
		Median	0.00011	0.00187 ***	0.00123 ***	0.00138 ***
30. Consumer Staples	1,905	Mean	0.00543 ***	0.00560 ***	0.00017	0.00069
		Median	0.00133 ***	0.00180 ***	0.00072 ***	0.00076 ***
35. Health Care	1,347	Mean	0.00340 ***	0.00531 ***	0.00192 **	0.00225 ***
		Median	0.00101 *	0.00242 ***	0.00187 ***	0.00182 ***
45. Information Technology	2,280	Mean	0.00208 *	0.00437 ***	0.00229 ***	0.00231 ***
		Median	0.00051	0.00128 ***	0.00265 ***	0.00213 ***
50. Telecommunication Services	813	Mean	0.00703 **	0.00973 ***	0.00270	0.00451
		Median	-0.00014	0.00148 ***	0.00101 *	0.00117 *
55. Utilities	2,906	Mean	-0.00113	0.00160 ***	0.00273 ***	0.00294 ***
		Median	-0.00132 ***	0.00043 ***	0.00154 ***	0.00193 ***

Improvement in accuracy is measured through a matched-pair comparison of the absolute value of prediction errors from the two competing models. The in-sample regression models are estimated by sector and by year. *N* represents the average number of annual observations for that industry across the sample period. The mean (median) improvement in accuracy is computed annually and the reported grand mean (median) improvement is the mean (median) of the 25 yearly mean (median) improvements in predictive accuracy. Tests of means are based on Fama-MacBeth *t*-statistics computed from the annual mean forecast improvements. Tests of medians are based on Wilcoxon Signed Ranks tests of the annual median forecast improvement. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 9
Out-of-sample Improvement in Forecast Accuracy of Models Forecasting Future Profitability Before Extraordinary Items

In-sample coefficient estimation regressions

Naïve *ROE*	$ROEBXI_{i,t} = \alpha_0 + \alpha_1.ROEBXI_{i,t-1} + \varepsilon_{i,t}$
OPFIN	$ROEBXI_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABXI_{i,t-1}) + \alpha_2.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$
UNINFREQ	$ROEBXI_{i,t} = \alpha_0 + \alpha_1.ROEBSPI_{i,t-1} + \alpha_2.(SPI_{i,t-1} / BVE_{i,t-1}) + \varepsilon_{i,t}$
COMBINED	$ROEBXI_{i,t} = \alpha_0 + \alpha_1.(NOA_{i,t-1} / BVE_{i,t-1})(RNOABSPI_{i,t-1}) + \alpha_2.(NOA_{i,t-1} / BVE_{i,t-1})(SPI_{i,t-1} / NOA_{i,t-1})$ $+ \alpha_3.(NFA_{i,t-1} / BVE_{i,t-1})(RNFA_{i,t-1}) + \varepsilon_{i,t}$

	Mean Improvement		**Median Improvement**		**Number of**
	Value	***p*-Value**	**Value**	***p*-Value**	**years**
OPFIN vs. Naïve *ROE*	-0.00080	0.1654	-0.00146 ***	0.0001	3 / 15
UNINFREQ vs. Naïve *ROE*	0.00311 ***	0.0000	0.00086 ***	0.0000	24 / 0
UNINFREQ vs. *OPFIN*	0.00391 ***	0.0000	0.00169 ***	0.0000	24 / 0
UNINFREQ vs. *COMBINED*	0.00397 ***	0.0000	0.00176 ***	0.0000	25 / 0

Improvement in accuracy is measured through a matched-pair comparison of the absolute value of prediction errors from the two competing models. The mean (median) improvement in accuracy is computed annually and the reported grand mean (median) improvement is the mean (median) of the 25 yearly mean (median) improvements in predictive accuracy. Tests of means are based on Fama-MacBeth *t*-statistics computed from the annual mean forecast improvements. Tests of medians are based on Wilcoxon Signed Ranks tests of the annual median forecast improvement. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.