Forecasting Taxes: New Evidence from Analysts

Brian Bratten
Gatton College of Business & Economics, University of Kentucky
brian.bratten@uky.edu

Cristi Gleason
Tippie College of Business, The University of Iowa
cristi-gleason@uiowa.edu

Stephannie Larocque
Mendoza College of Business, University of Notre Dame
larocque.1@nd.edu

Lillian F. Mills
McCombs School of Business, The University of Texas at Austin
Lillian.mills@mccombs.utexas.edu

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ABSTRACT

Using recently available pre-tax earnings forecast data from 2003 to 2012, we infer analysts' income tax expense and effective tax rate (ETR) forecasts and provide the first large-sample evidence on their dispersion and accuracy. Even though managers provide annual ETR estimates each interim quarter, management's estimates are not equal in information content and analysts do not merely mimic these estimates, consistent with analysts providing incremental information. Analysts' forecasts are more disperse and less accurate when management's interim ETR estimate includes discrete items, consistent with more uncertainty and greater difficulty in understanding the tax environment when accounting standards require exceptions to the integral method. Even when management provides an estimate free of discrete items, complexity in the tax and operational environment increases dispersion and decreases accuracy. Taken together, our results suggest that management's mandatory estimates are informative to market participants and help mitigate the complexity of the forecasting environment. Accounting requirements for discrete items reduce the information available to market participants.

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1. INTRODUCTION

We examine the attributes of recently available analysts' forecasts of effective tax rates and tax expense, because the tax setting permits new tests of analysts' forecasts when management reports mandatory estimates in a complex environment. Accounting Standards Codification (ASC) 740-270 requires management to provide an estimate of the annual effective tax rate (ETR) in each interim quarterly earnings report. This quarterly estimate of the expected annual ETR is an explicit, mandatory, point forecast that differs from other management guidance that tends to provide voluntary qualitative or range forecasts. However, accounting standards (i.e., ASC 740-270-30-8) also require management to exclude from the annual effective tax rate certain "discrete items," such as settlements with tax authorities, taxes on one-time charges, and return-to-provision reconciliations, and to recognize these items in full when they occur. Thus, the interim ETR estimate is not always a clean prediction of the annual ETR. When management's interim ETR estimate includes discrete items, analysts must disentangle the effects of these items to forecast tax expense for the subsequent quarter. Comparing observations with and without discrete items allows us to assess the information value of management's ETR estimate, and also to assess analysts' ability to understand and forecast taxes, considering the complexity arising from current accounting rules for discrete items as well as the tax environment generally. Such evidence also speaks to the relevance of the accounting standards for interim reporting.

We conduct tests of the dispersion and accuracy of analysts' implied ETR and tax expense forecasts. Forecasting the ETR and future tax expense requires analysts to predict the impact of tax rates and tax planning as well as pre-tax earnings. The volume and complexity of tax laws, different laws across multiple jurisdictions, and the long time required for firms and tax authorities to resolve tax disputes complicate the task. Evidence that market participants fail to correctly price tax-related information underlines the importance of accurately forecasting tax expense (Lev and

Nissim 2004; Thomas and Zhang 2013). Recently available data allow us to infer the tax expense forecast from reported pre-tax and after-tax income forecasts and to construct analysts' implied ETR forecasts. Our sample is comprised of 221,176 forecasts of quarterly pre-tax and after-tax earnings from 2003 through 2012. We include both profit and loss firms in our analysis to enhance our contribution in an area of tax research that is poorly understood.[1]

We predict and find that when management provides an interim ETR estimate that appears free of discrete items (which we label a "clean" estimate), analysts forecasts are less disperse and more accurate. We find that nearly 90 percent of analysts' forecasts deviate from management estimates that include discrete items. Even when management estimates are "clean," 50 percent of analysts' forecasts deviate from management estimates, indicating that analysts do not merely mimic management. We further predict and find that when analysts do not mimic the management estimate, they deviate because they add information and will hence make a more accurate forecast.

We also extend the general forecasting literature by developing proxies for complexity in the tax environment and testing whether these attributes make the specific tax forecasting task more difficult, even in our setting where management already provides a specific forecast of annual effective tax rates. In our primary analyses, we include traditional operational complexity variables such as analyst following, book-to-market, leverage, and market value, and predict lower quality forecasts of more complex firms. We introduce several variables that specifically relate to the complexity of the tax environment, including stock-based compensation expense, R&D expense, foreign operations, losses, prior year permanent book-tax differences, and nonrecurring tax expense. We also introduce two proxies for the complexity of forecasting taxes: changes in the interim ETR estimates reported by management and prior variability in the ETR. When we evaluate

[1] Much ETR-based tax research deletes current loss firms (e.g., Hanlon 2005; Mills and Newberry 2005; Schmidt 2006; Cook, Huston, and Omer 2008) or cumulative five-year loss firms (Dyreng, Hanlon, and Maydew 2010; Rego and Wilson 2012) to avoid dealing with negative ETRs or ETRs greater than one that are more difficult to interpret.

tax rate forecast accuracy, we control for pre-tax forecast accuracy to isolate the incremental impact of complexity on tax forecasts. We predict and find that tax and operational complexity makes it more difficult to forecast both pre-tax earnings and tax expense.

Because there are multiple measures of tax and operational complexity, we also conduct principal components analysis to construct summary measures of complexity. Reducing tax complexity and operational complexity each to three PCA variables also permits us to test the interaction of complexity with the presence of a clean management estimate. We find that complexity has a greater effect on accuracy when management provides a clean estimate, suggesting that analysts utilize other information or analysis when they must deal with discrete items. These results suggest that the discrete items exception to the integral method reduces the relevance of management's interim ETR estimate for predicting future earnings.

We make several contributions to the existing literature. First, using relatively new data, we introduce a method to infer analysts' implied tax expense and provide the first large-sample evidence on the accuracy of analysts' pre-tax earnings and tax expense forecasts. Researchers investigating tax avoidance often attribute ETR changes to tax effects (Mills, Erickson, and Maydew 1998), ignoring the potential material effects of pre-tax earnings changes on ETRs (Guenther, Krull, and Williams 2014). Alternatively, valuation studies of ETRs and tax expense sometimes interpret the relation between tax measures and stock returns as predominately a signal about pre-tax earnings (Thomas and Zhang 2013). This paper sheds light on the extent to which analyst forecast errors arise from the numerator or denominator. In our accuracy tests, the accuracy of the pre-tax earnings forecast is of primary importance in explaining the accuracy of the tax expense forecast. However, we also find that that several proxies for tax complexity are negatively related to the accuracy of pre-tax earnings forecasts and, after controlling for pre-tax earnings accuracy, tax expense forecasts. Thus, tax complexity contributes to analysts' accuracy in forecasting net after-tax earnings and is not fully mitigated by management's ETR estimates.

Second, we show that the presence of discrete items in the interim ETR management estimate increases ETR forecast dispersion and decreases tax expense forecast accuracy. This evidence suggests that the requirement to include some earnings effects in full as a discrete item, rather than incorporating them in the integral method, makes quarterly ETRs less useful for predicting future earnings.

Finally, we contribute to the management forecast literature, by examining management's mandatory ETR estimates. We document the improvement in analysts' forecast accuracy when management forecasts are not complicated by discrete items. We also document that analysts improve on the information provided in management's mandatory estimate.

2. INSTITUTIONAL BACKGROUND AND PRIOR LITERATURE

2.1 Management forecasts of the effective tax rate

Analysts' ETR forecasting task differs from their efforts to forecast other financial statement items, because managers themselves also must forecast and disclose the annual ETR at each interim quarter under ASC 740. Although the disclosure of revenue or earnings forecasts by firm management is voluntary, ASC 740-270 requires that managers disclose a de facto annual ETR forecast each quarter.[2] These interim ETR estimates should be useful to analysts forecasting tax expense and pre-tax earnings. For example, Lululemon (ticker: LULU) reported a 36.1% ETR for the fiscal year ended January 29, 2012. For the first quarter of the fiscal year ended February 3, 2013 LULU reported a 36.5% ETR on June 7, 2012. On June 8, 2012, Credit Suisse's analysts forecasted an ETR of 36.5% for LULU for the remaining three quarters and the fiscal year, and these ETR forecasts were unchanged in its August 10, 2012 report. Credit Suisse's ETR forecasts declined to 29.5% for Q3 and fiscal 2013 after LULU's Q2 results were released on September 7, 2012. LULU's actual six-month ETR as of Q2 was 27.9%, near the eventual annual ETR of 28.8% for fiscal 2013, a decrease

[2] ASC 740-270 requires firms to use the integral method for tax expense, which is the focus of our study. The integral method also applies to cost of goods sold and some operating expenses, such as SG&A.

from the prior year due to transfer pricing agreements.

By comparison, management voluntarily issues earnings guidance for only 20-27% of sample firms, or 45% of firms using a value-based weighting, in the 2000-2003 time period (Anilowski, Feng, and Skinner 2007). Additionally, voluntary guidance is two to five times more likely to be negative or downward guidance (Tucker 2007). In contrast, quarterly ETR increases occur with nearly the same frequency as quarterly decreases in our sample. Although ASC 740 requires a "point" estimate of ETR, earnings guidance takes both qualitative and quantitative forms (Hirst et al. 2008). Quantitative guidance can be expressed as minimum or maximum estimates in addition to the point and range estimates commonly used in empirical finance and accounting research. Even management's range estimates of earnings require researchers to make assumptions, for example using the midpoint, to test hypotheses. In summary, management ETR estimates provide a homogenous setting to examine analysts' forecasts in the presence of mandatory management estimates.[3]

To estimate the ETR, each quarter managers apply the integral method by estimating the total annual income tax expense of the firm based on realized and estimated pre-tax earnings for the entire fiscal year as well as the tax consequences of the transactions expected to generate those earnings. The expected annual ETR represents a weighted average tax rate based on total estimated annual pre-tax earnings. Then quarterly income tax expense is accrued by applying the expected annual ETR to actual year-to-date pre-tax earnings, and subtracting the tax expense accrued in previous quarters. Appendix A illustrates a simple example.

However, analysts cannot necessarily rely on management's interim ETR for their forecasts. Certain "discrete" items must be accrued to tax expense in the quarter they occur, such as the tax effects of transitory gains and losses, settlements with tax authorities, and return-to-provision

[3] Management's quarterly ETR estimates are also free of the confounding problem of selective disclosure in the pre-Reg FD period (Ajinkya and Gift 1984, Hutton 2005).

adjustments (ASC 740-270-30-11 through 13) (Koutney 2014). Discrete items should reduce the usefulness of the interim ETR in forecasting the ETR in subsequent quarters. Thus, the presence or absence of discrete items permits cross-sectional tests of how the relevance of managements' interim estimates impact analysts' forecasts.

2.2 Analysts' forecasts and analysts' processing of tax information

Analysts struggle to incorporate tax effects. Amir and Sougiannis (1999) find that analysts' after-tax EPS forecasts are less accurate when firms have tax loss carryforwards. Several studies document lower after-tax EPS forecast accuracy around tax law changes (Plumlee 2003; Chen, Danielson, and Schoderbek 2003; Hoopes 2013). Shane and Stock (2006) find that analysts fail to anticipate inter-temporal shifting from high- to low-rate tax years. Weber (2009) finds that analysts' after-tax EPS forecast errors are associated with book-tax differences. Kim, Schmidt, and Wentland (2014) find that analysts underestimate the persistence of net earnings generated by or lost due to year-over-year changes in the ETR when predicting earnings. Taken together, these studies suggest that on average analysts make systematic forecasting errors related to income tax.[4] We examine the role of firm attributes, particularly attributes of managements' mandatory tax estimates in explaining cross-sectional differences in analysts' tax forecasts.

A number of studies have examined analysts' response to management's voluntary earnings guidance. Much of this research focuses on managers' strategic response to analysts, including efforts to "walk-down" analysts' forecasts (e.g., Matsumoto 2002, Bergman and Roychowdhury 2008). Analysts revise their forecasts in response to management's voluntary earnings guidance (Waymire 1986; Jennings 1987; Cotter, Tuna, and Wysocki 2006). Williams (1996) and Hutton and Stocken (2010) find that the magnitude of analysts' forecast revisions is positively associated with management's prior estimate accuracy, while Clement and Tse (2003) document a decrease in

[4] See also Abarbanell and Bernard (1992) and Bradshaw and Sloan (2002). However, to the extent that analysts ignore one-time changes, prior research may overstate analysts' failings, especially since actual EPS reported by I/B/E/S ("street earnings") ignore non-recurring tax expense (Koutney 2014).

dispersion following management's confirmatory estimates. Importantly, management estimate accuracy varies with the setting in which it is provided (Bamber and Cheon 1998). Combined these studies suggest that analysts are attentive to managements' voluntary estimates, but raise questions about whether these findings generalize to mandatory ETR estimates disclosed in the 10-Q.[5,6]

Although disaggregated forecasts are not new, their inclusion in databases is relatively recent and allows us to study analysts' ability to forecast the ETR explicitly.[7] Two contemporaneous working papers also use pre-tax forecasts by analysts, but do so to answer different questions.[8] Mauler (2014) and Baik, Choi, Jung, and Martin (2013) both find the issuance of a pre-tax earnings forecast is associated with higher cash ETRs and so conclude that pre-tax forecasts discourage tax avoidance. Consistent with prior research on other disaggregated forecast components (Call, Chen, and Tong 2009; Ertimur, Mayew, and Stubben 2011), Baik et al. also find that analysts who provide pre-tax forecasts to I/B/E/S make more accurate after-tax earnings forecasts. Based on our institutional knowledge, we understand that most analysts make detailed forecasts, but only some analysts and brokerage houses disclose them to I/B/E/S. Thus, we examine the attributes of analysts' disclosed pre-tax forecasts and their implied tax expense forecasts, rather than the effect of analysts' issuance of these forecasts on firms' behavior.

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[5] Prior research has also examined analysts' use of management's interim ETR estimates in forecasting EPS. Bauman and Shaw (2005) find that large ETR decreases are positively associated with analysts' after-tax EPS forecast errors in future quarters. Because Bauman and Shaw do not examine pre-tax earnings forecasts, they cannot disentangle whether analysts' underweighting of the ETR change information arises from mis-estimation of either pre-tax earnings or future tax rates, or both. Our study utilizes disaggregated forecast data to distinguish these joint effects.

[6] We searched through a sample of 1,982 Factiva articles relating to management guidance and identified only 23 articles in which management mentioned an estimate or forecast of tax or the ETR.

[7] I/B/E/S includes pre-tax earnings forecasts beginning in 2002. Yet, for example, analyst research reports from as early as 1986 for Microsoft include disaggregated income statement forecasts such as the ETR.

[8] Several published research studies have examined other non-EPS forecasts, including cash flows (e.g., DeFond and Hung 2003; Hodder, Hopkins, and Wood 2008; Call, Chen, and Tong 2009 and 2013; Givoly, Hayn, and Lehavy 2009) and sales (Ertimur, Mayew, and Stubben 2011), but not pre-tax earnings as in this study.

2.3 Hypothesis development regarding dispersion of analysts' ETR forecasts

Our anecdotal evidence and experience indicate that analysts forecast tax expense by determining a "tax rate" and applying it to their forecast of pre-tax earnings.[9] Thus, we build our theoretical predictions by first considering whether analysts are more likely to cluster around a single tax rate when they receive clear signals from management.

Consistent with prior research (Lehavy, Li, and Merkley 2011; Hodder, Hopkins, and Wood 2008), we expect the complexity of the firm's tax environment increases uncertainty and increases the dispersion of ETR forecasts. Management's quarterly ETR estimates potentially mitigate this uncertainty for analysts. Specifically, when management's estimate is free of discrete items (a "clean" estimate), it arguably provides a clearer signal of the future ETR. Thus, when a clean estimate is available, we expect it to reduce uncertainty and thus reduce dispersion (Imhoff and Lobo 1992; Barron, Kim, Lim, and Stevens 1998; Payne and Robb 2000; Dieter, Malloy, and Scherbina 2002). However, if the tax environment is sufficiently complex or the benefits to more precision are low, analysts may adopt heuristics to cope with the complexity of the tax environment (Amir and Ganzach 1998). The use of heuristics could reduce dispersion, even when management's estimate includes discrete items that require analysts to make adjustments. It is also unclear how the usefulness of management's estimate affects analysts' ability or willingness to gather and process information, which is reflected in forecast dispersion (Herrmann and Thomas 2005). Thus, we believe the association between whether management's ETR estimate includes discrete items and ETR forecast dispersion is an empirical question. This leads to our first set of hypotheses:

H1a: Analysts' ETR forecast dispersion is lower when a clean ETR estimate is available from management.

H1b: Analysts' ETR forecast dispersion is higher when tax complexity increases.

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[9] This tax rate is a form of an effective tax rate, because it is a single rate applied to aggregate pre-tax book income. As such, analysts must take into account an appropriate blend of statutory rates, exemptions and credits across all jurisdictions. Such an aggregate rate differs from the theoretical marginal tax rate that should be used in transaction-level decision making (Graham, Hanlon, Shevlin, and Shroff 2015).

H1c: The association between ETR dispersion and tax complexity differs when a clean ETR estimate is available from management.

2.4 Hypothesis development regarding analysts' forecast accuracy

We next consider how our tax setting permits new insights about the effect of management estimates on forecast accuracy. Although we are not aware of research examining mandatory management forecasts, such as those represented by the ETR estimate, research has examined analysts' responses to voluntary management earnings guidance. Even research on the impact of voluntary management guidance on analysts' forecast accuracy is scarce, however, in part because most voluntary management guidance take the form of qualitative or range estimates and are rarely single-account, financial estimates. The qualitative or range estimates make it difficult for researchers to design tests of analysts' response to the estimates. In one early study, Waymire (1986) finds that voluntary management earnings estimates improve the accuracy of analysts' EPS forecasts, although analysts' forecasts are not more accurate than management's estimates. We are unsure whether this conclusion should be applicable today, because disclosure regulation and analysts' information environment have changed significantly since the time period used in Waymire's study.[10] In the post-Reg FD period, more than 51 percent of analysts revise their forecast within five days of managements' voluntary guidance, but this quick revision suggests the guidance doesn't lead analysts to conduct extensive additional research (Cotter, Tuna, and Wysocki 2006). These findings are instead consistent with analysts' relying on, but not improving on, managements' public disclosures. However, analysts' revisions are related to cross-sectional differences in management's motives in issuing voluntary guidance (Cotter, Tuna, and Wysocki 2006; Kross, Ro, and Suk, 2010), suggesting analysts incorporate information from management guidance with some degree of sophistication rather than naïve acceptance.

[10] Acito (2011) finds that analysts' after-tax EPS forecasts are more accurate than the lower bound of management's range estimates, highlighting the design challenges that researchers face in drawing inferences from voluntary management earnings guidance.

We test whether analysts' ETR forecast accuracy is higher when management's estimate does not include discrete items, which we interpret as management providing a clear signal of the expected future ETR. If analysts process management estimates in a sophisticated manner, we expect no difference in forecast accuracy when management's estimates include discrete items, because analysts will compensate by seeking information to make appropriate adjustments.

We also examine whether analysts gather and process information that increases the accuracy of forecasts. In the tax setting, we can observe whether firms simply mimic management's estimate. We expect that when analysts choose a different ETR than management's estimate, they do so based on newer or superior information. Thus, we expect forecasts that mimic management to be less accurate.

We state the following alternative hypotheses:

H2a: *The accuracy of analysts' quarterly tax rate forecasts is higher when a clean ETR estimate is available from management.*

H2b: *The accuracy of analysts' quarterly tax rate forecasts is lower when analysts mimic management's interim ETR estimate.*

H2c: *The accuracy of analysts' quarterly tax rate forecasts is lower when tax complexity increases.*

H2d: *The association between the accuracy of analysts' quarterly tax rate forecasts and tax complexity differs when a clean ETR estimate is available from management.*

3. RESEARCH DESIGN

3.1 Construction of analysts' implied tax expense and ETR forecasts

Analysts explicitly forecast the ETR and report it or the amount of tax expense in their reports. However, I/B/E/S captures a limited subset of financial statement items forecasted by analysts, so we use I/B/E/S analysts' detailed forecasts to infer analysts' tax expense and ETR forecasts.[11] We compute the implied tax expense forecast and implied ETR forecast as follows:

Tax Expense Forecast = *Pre-Tax Earnings Forecast – After-Tax Earnings Forecast* (1)

We then compute the analyst's implied ETR forecast:

ETR Forecast = *Tax Expense Forecast / Pre-Tax Earnings Forecast* (2)

We similarly construct the actual tax expense and ETR using I/B/E/S reported actuals.

In addition to tax expense, analysts may include other items such as minority interest as a difference between pre-tax and after-tax income. To better understand how well our construction of the implied tax expense forecast captures the tax expense forecast from their reports, we hand collect research reports from Thomson ONE for a random sample of 50 analyst-firm observations for which I/B/E/S reports pre-tax earnings. We found four instances (8%) where the inferred tax expense is not equal to the forecasted tax expense. In all four cases, minority interest is the cause of the discrepancy.[12] Thus, in subsequent tests examining the dispersion and accuracy in analysts' pre-tax earnings, tax expense, and ETR forecasts, we include a control for whether the firm has minority interest.

3.2 Tax and general complexity variables

We are interested in the association between tax forecast properties and complexity, as well as how that association is affected by the presence of a clean ETR estimate from management. Because we infer the ETR from earnings numbers rounded to millions of dollars, rounding differences between analysts and management are inherent in the data. Thus, we conservatively

[11] Using two disaggregated numbers to infer another is common in the literature. Brown and Larocque (2013) infer information about the actual quarterly earnings used in analysts' fiscal-year earnings forecasts, and Call, Chen, and Tong (2013) infer information about analysts' accrual forecasts from analysts' cash flow forecasts.

[12] We then collect an additional 50 research reports with minority interest in Compustat and a pre-tax earnings forecast in I/B/E/S. For this random sample of firms with minority interest, only 24% of the sample had different implied and actual tax expense forecasts. For the sample of firms with minority interest, other differences between the amount of tax expense reported in the analyst's report and the inferred tax expense include discontinued operations, extraordinary income, equity in earnings of affiliates, and dividends on preferred stock of subsidiary. Further examination shows that for a given firm, not all analysts include minority interest in the same place in the forecast, which complicates any I/B/E/S adjustment process.

assume that management's interim ETR estimate is free of discrete or nonrecurring items (i.e., *CLEAN*=1) when the prior-quarter GAAP ETR is within one percentage point of the prior-quarter implied I/B/E/S actual ETR. Similarly, we conservatively assume an analyst's ETR estimate is equal to management's interim ETR estimate (i.e. *MIMIC* =1) when the absolute value of the difference between the analyst forecast and the management estimate is less than one percentage point.[13]

We include complexity in our tests in two ways. First, we include a comprehensive list of tax and general firm-level variables expected to be negatively associated with forecast quality. Second, we conduct a principal components analysis to extract the underlying dimensions of the complexity variables for our hypothesis tests that require interaction terms.

Firm-level complexity variables

We expect tax expense to be more difficult to forecast when analysts see larger changes in ETRs and those ETRs are less stable over time, based on arguments in Comprix, Mills, and Schmidt (2012). Thus, we include the magnitude of changes in ($abs\Delta ETR_{j,q-1,t}$) and variability of (ETR_STD_{t-1}) ETRs as complexity measures. We add the following proxies for complexity from the prior research on income tax. We expect factors that provide tax-planning opportunities also increase forecast complexity: equity compensation ($CompExp_{j,t-1}$) (Hanlon 2003, Austin 2014); permanent differences ($absPermDiff_{j,t-1}$) (Dhaliwal, Gleason, and Mills 2004); quarters during which Congress passed legislation retroactively extending the availability of tax credits such as the R&D Credit ($RetroLegislation_q$) because prior research shows that retroactive tax legislation is complex and reduces analysts' forecast accuracy (Bratten and Hulse 2014, Hoopes 2013); and unused tax loss carryforwards ($TLCF_{j,t-1}$) due to the difficulty of predicting when loss firms will become profitable (Dhaliwal et al. 2013).

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[13] For example, if management's ETR estimate is 35.0%, we assume an analyst's ETR estimate is equal if our inferred analyst ETR forecast is greater than 34.0% and less than 36.0%.

Our other proxies for complexity are common in studies of analyst EPS forecasts. We expect the following proxies to increase firm complexity and thus be negatively associated with forecast quality: whether a firm has foreign operations ($Foreign_{j,t-1}$); a pre-tax loss in the current quarter ($LOSS_{j,q,t}$); and R&D expenditures. ($RDS_{j,t-1}$) (Duru and Reeb 2002; Thomas 2002). Prior research finds forecast accuracy increases in analyst following ($ANF_{j,t}$) and firm size ($lnMV_{j,t-1}$) (Lang and Lundholm 1996; Duru and Reeb 2002). We expect that forecast quality decreases when firms have higher book-to-market ratios ($BM_{j,t-1}$) because investors place less importance on forecast quality for lower growth firms (Frankel, Kothari, and Weber 2006; Dechow and You 2012), higher leverage ($LEV_{j,t-1}$) or more diversification ($Segments_{j,t-1}$) (Thomas 2002), or lower quality or less readable disclosures ($10KSize_{j,t}$) (Lang and Lundholm 1996; Lehavy, Li, and Merkley 2011; Loughran and McDonald 2014).

Principal components analysis of tax and general complexity variables

We expect that some of the complexity variables reflect the same underlying construct and acknowledge the absence of a theory about the differences between individual variables. Thus, including the individual variables separately in the regressions testing our hypotheses or counting them or using an aggregate sum to capture complexity is likely to reduce the power of the tests, make results difficult to interpret (particularly with multiple interactive coefficients), or even cause measurement error and inconsistent regression coefficients (Larcker, Richardson, and Tuna 2007). Therefore, we follow recent research (e.g., Harris, Petrovits, and Yetman 2015; Kubick, Lynch, Mayberry, and Omer 2015) and use a principal component analysis to extract the underlying dimensions of the complexity variables for our hypothesis tests.

3.3 Dispersion and accuracy tests

Firm-level determinants of dispersion

Analysts forecast tax expense by determining a tax rate and applying it to their forecast of pre-tax earnings. Thus, we begin our analysis by examining how analysts determine a tax rate, and whether management estimates influence them to cluster around a single rate, or a narrow band. We are interested in the association between tax complexity variables and the dispersion of analysts' ETR forecasts, and so we include complexity variables germane to the tax setting, as well as controls for firm-level complexity from prior research. Specifically, we estimate a linear regression of the relation between the dispersion of analysts' ETR forecasts and whether management's ETR estimate excludes discrete items as well as tax complexity variables as shown below:

$$DISPetr_{j,q,t} = \gamma_0 + \gamma_1 CLEAN_{,q\text{-}1,t} + A \sum TaxComplexity + B \sum GeneralComplexity + \gamma_2 MI_{j,q,t} + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t} \quad (3)$$

In equation 4, the unit of observation is a firm-quarter. The dependent variable, *DISPetr*, is the tercile ranking of the standard deviation of analysts' forecasts of the implied ETR for analysts following firm *j* in quarter *q* of year *t*, for those firms with at least two analysts providing such forecasts during the quarter following Lys and Sabino (1992). We have three coefficients of interest to our hypotheses. We expect quarters where management's interim ETR estimate excluded discrete items (*CLEAN*=1*)* to result in lower dispersion if uncertainty increases. We expect tax expense to be more difficult to forecast when tax complexity increases. Finally, we expect that the absence of discrete items in management's interim ETR estimate will interact with general and tax environment complexity.

Our tests of ETR forecast dispersion also include a control for minority interest because discrepancies between the analysts' true ETR forecast and that implied by I/B/E/S pre-tax and after-tax earnings may mechanically reduce forecast accuracy. Standard errors are clustered at the firm level. We include industry, year, and quarter fixed effects to control for variation in the average forecast error across industries or time due to unobserved factors.[14]

[14] Our use of year dummies also controls for changes in accounts standards and tax laws. Our inferences are robust to including a proxy for quarters prior to the adoption of FIN 48 in 2007. FIN 48 required firms to

Firm-level determinants of accuracy

As noted previously, ETR forecast accuracy is affected by forecast errors related to both pre-tax earnings and expected tax rates. To disentangle these effects, we test our second set of hypotheses using tax expense forecast errors as the dependent variable, controlling for pre-tax earnings forecast errors. For completeness, we also estimate and report our model of the accuracy of consensus-level pre-tax and ETR forecasts on firm characteristics. We use the model below:

$$
\begin{aligned}
ACC_{j,q,t} &= \gamma_0 + \gamma_1 CLEAN_{,q\text{-}1,t} + \gamma_2 MIMIC_{j,q,t} + A \sum TaxComplexity \\
&\quad + B \sum GeneralComplexity + \gamma_3 MI_{j,q,t} + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t}
\end{aligned}
\tag{4}
$$

As in equation 3, the unit of observation is a firm-quarter. The consensus $ACC_{j,q,t}$ in a given quarter equals the median level of $ACC_{i,j,q,t}$, which is the absolute value of analyst *i*'s forecast of the implied tax expense (pre-tax earnings or ETR) for firm *j* for the upcoming quarter *q* of year *t*, made following the announcement of quarter *q-1* earnings, less the actual implied tax expense (pre-tax earnings or ETR) for quarter *q* according to I/B/E/S, scaled by price at the end of year *t-1* according to CRSP. Pre-tax earnings and implied tax expense are further scaled by the number of shares outstanding at the end of quarter *q* according to Compustat. Each accuracy measure is then multiplied by -1 so that a larger value of the dependent variable indicates greater accuracy.

We expect clean management estimates that exclude discrete items (*CLEAN* = 1) to improve forecast accuracy if analysts have difficulty disentangling the effects of discrete items. We include an indicator variable for whether analysts' forecasts mimic management's estimate. If analysts improve on management's ETR estimate, we expect a negative coefficient on *MIMIC*. We expect tax expense to be more difficult to forecast when tax complexity increases. We also expect that the association between forecast accuracy and tax complexity will differ depending on whether discrete items are present in management's interim ETR estimate.

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disclose details about their uncertain tax positions and that additional detail could help analyst forecast tax expense (Blouin, Gleason, Mills, and Sikes 2007).

Our tests of tax expense forecast accuracy also include a control for pre-tax forecast accuracy. Controlling for pre-tax forecast accuracy isolates the incremental impact of clean management estimates and complexity on the accuracy of tax rate estimates. We continue to control for minority interest in tests of forecast accuracy.[15]

4. SAMPLE SELECTION AND EMPIRICAL RESULTS

4.1 Sample

We derive our sample from the intersection of I/B/E/S, Compustat, and CRSP. The I/B/E/S detail file contains forecasts of earnings per share, net income (NET in I/B/E/S), and pre-tax earnings (PRE in I/B/E/S) for the upcoming fiscal quarter. We begin our sample period in 2003 because pre-tax profit forecasts became more widely available in I/B/E/S after 2002 (Ertimur, Mayew, and Stubben 2011). We limit the sample to those analysts providing EPS, net income, and pre-tax profit forecasts for the same fiscal period (fpedats in I/B/E/S) on the same date (anndats in I/B/E/S) so that we can infer each analyst's implied tax expense and ETR forecast.[16] We use each analyst's latest forecast of the upcoming fiscal quarter *q* made following the issuance of earnings for the prior quarter, *q-1*, and prior to the issuance of earnings for quarter *q*. Our sample thus includes forecasts for fiscal Q2, Q3, and Q4. We include both profit and loss firms in our analysis, and we do not require the ETR to be positive nor below 100% of pre-tax earnings for our main tests to avoid data truncation bias (Henry and Sansing 2014) and to increase the generalizability of our findings. From Compustat, we obtain variables necessary to calculate management's interim ETR as of each quarter and book value and leverage at the end of fiscal year *t-1*. We include only non-ADR firms in the sample to ensure firms follow the same accounting guidance using the integral method to

[15] We control for minority interest in tests of ETR, pre-tax income, and tax expense accuracy. In untabulated analysis, we find similar results when we exclude minority interest from the pre-tax income tests.
[16] Of the 1,712,447 quarterly EPS forecasts provided in I/B/E/S from 2003 to 2012, 619,025 or 36.1% are issued together with a pre-tax and net earnings forecast. In supplemental tests, we develop a selection model and control for the probability of issuing a pre-tax forecast.

compute and report interim tax expense. From CRSP, we obtain share price and market value at the end of fiscal year *t-1*. Our main sample comprises 221,176 analyst-firm-quarters or 54,783 firm-quarters with non-missing I/B/E/S, Compustat, and CRSP data from 2003 to 2012. For our tests of dispersion, we require the firm to be covered by more than one analyst, reducing our sample to 42,214 firms-quarters. Panel A of Table 1 describes the sample selection in more detail.

Panel B of Table 1 describes the firm-quarter consensus (i.e., median) analyst forecast of after-tax earnings, pre-tax earnings, and implied tax expense, and both analysts' implied ETR forecast and management's prior-quarter interim ETR estimate. Although mean actual and pre-tax forecast errors are positive, the median is negative, consistent with firms beating targets. Analysts' implied ETR forecast has a mean (median) of 28.2% (34.5%), which is not significantly different than the mean (median) prior-quarter interim ETR of 27.0% (33.1%) reported by management (untabulated t-test, p-value = 0.32). This suggests that analysts on average merely mimic the management estimate. Consistent with prior research (Comprix, Mills and Schmidt 2012), management's quarterly interim estimate of the annual ETR is higher than the eventual annual ETR. Furthermore, analysts' ETR forecasts are also more upwardly biased (for both median and mean differences) than are management's prior quarter's interim ETR estimate. The lower accuracy of managers' ETR estimates is consistent with the requirement to fully recognize discrete items in the quarter they occur reducing the accuracy of the ETR estimate. The lower accuracy may also be attributable to the longer time horizon relative to the average analyst forecast.[17]

Panel C of Table 1 describes the variables used in our main analysis. The firms in our sample are generally large, with mean (median) market value of $5.9 ($1.1) billion, and have book-to-

[17] In untabulated analysis, we compare the accuracy of pre-tax and tax expense forecasts after scaling forecast errors by the actual amount being forecast, including only observations where the absolute value of tax expense is a meaningful amount (i.e., at or above $100,000) to avoid small-denominator issues. We find that pre-tax earnings forecasts are proportionately closer to actual pre-tax earnings than tax expense forecasts are close to actual tax expense (difference =0.0011). Additionally, the pre-tax earnings forecast error is smaller than the tax-expense forecast error 65.57 percent of the time. This suggests analysts forecast pre-tax earnings with greater accuracy more often than they do tax expense.

market ratios with a mean (median) value of 0.5780 (0.4662). This is unsurprising because analysts generally follow firms that are larger (Bhushan 1989; Lang and Lundholm 1996) and for which they forecast favorable future prospects (McNichols and O'Brien 1997). The sample of firms for which analysts issue implied tax forecasts also have attributes associated with tax complexity. Forty-six percent of firms have foreign operations, and 40 percent of firms have a tax-loss carryforward. On average, firms have permanent differences that lower their ETR by 11 percent relative to the U.S. statutory rate. Management ETR estimates include discrete items nearly one-third of the time, while analysts' *consensus* forecast mimics management 74 percent of the time

At the individual analyst level, Panel D of Table 1 shows that 60,857 (44.3%) of analyst-firm-quarters appear to have discrete items (*CLEAN* = 0). The difference between the proportion of *CLEAN*=1 observations in panels C and D reflects a higher average number of forecasts for firm-quarters with discrete items. As expected, in most of these cases (53,475, or 87.9% of the analyst-firm-quarters with discrete items), analysts did not merely follow management's ETR estimate, presumably to attempt to adjust for the discrete item. Nearly half of the 86,589 analyst forecasts with no discrete items (*CLEAN* = 1) appear to mimic the management estimate, but there are still half of the analysts who do not mimic management even in the absence of discrete items.[18] Thus, in the majority of the observations, analysts are making forecasts different from management, indicating that the tax setting, even in the presence of management estimates, provides a rich opportunity to understand analysts' use of complex information.

Table 2 reports the correlations between our proxies for complexity and accuracy to provide univariate tests of our hypothesis that dispersion increases and accuracy declines as complexity increases. Panel A relates each of our measures of forecast accuracy and dispersion. As expected, dispersion is generally negatively correlated with accuracy, but the absolute magnitudes

[18] In untabulated tests we find that for firms without discrete items, analysts who do not mimic follow firms with lower R&D intensity, but higher levels of foreign operations and also issue forecasts later.

of these correlations are small. All four forecast accuracy measures are correlated with one another. In Panel B, we relate our main dependent variables of interest – dispersion and accuracy of tax forecasts – with our complexity variables. In general, complexity variables are negatively correlated with pre-tax or tax expense forecast accuracy, as expected, with the following exceptions. Firms with higher *CompExp* or nonzero *Foreign* have more accurate pre-tax and tax expense forecasts; firms with higher *PermDiff* have more accurate pre-tax forecasts; and firms with larger R&D expenses have more accurate tax expense forecasts. These results suggest that, rather than complexity impairing forecast accuracy, analysts invest more effort to understand these firms. However, univariate evidence limits our inferences, so we consider multivariate evidence below.

4.2 Tax Complexity and After-tax Earnings Forecast Accuracy

Because it is well known that complexity generally decreases accuracy, it is important to show that our tax-motivated investigation contributes economically relevant knowledge to academics and analysts. Thus, we first examine whether our additional measures of tax complexity meaningfully improve the estimation of after-tax earnings forecast accuracy. Table 3 presents these results. Column 1 includes variables from prior literature that we classify as increasing tax complexity, including *Foreign, Loss, and RDS,* as well as variables known to increase general complexity or otherwise explain accuracy, including *ANF*, *BM*, *LEV*, *lnMB*, *Segments*, and *10KSize.* We initially omit industry, year, and quarter fixed effects to assess the incremental contribution of our firm-level tax complexity measures relative to prior measure of complexity. The variables *Loss, BM, LEV*, and *10KSize* reduce accuracy, consistent with prior evidence that these variables represent complexity. Consistent with prior research, large firms with greater analyst following enjoy more accurate forecasts because firm size and analyst coverage also reflect firms' information environment.

Column 2 adds our individual variables of interest, *CLEAN* and *MIMIC,* as well as our new measures of tax complexity. We see an improvement in the adjusted R^2 of 10 percent (F-Value of the new variables is 64.03; p-value < 0.0001), which we suggest is economically meaningful. Specifically, analysts are less able to accurately forecast after-tax earnings when management does not provide a *CLEAN* forecast of the ETR, when they simply mimic management's ETR estimate, or when the firm has large absolute changes in the quarterly ETR (*absΔETR),* high variance in their quarterly ETRs (*ETR_STD),* and retroactive tax legislation (*RetroLegislation),* such as reinstatement of R&D credits. As expected, in column 3, when we include fixed effects, the explanatory power of the model rises, to 15.1 percent. Having demonstrated that the tax complexity variables improve the estimation of after-tax earnings forecasts, we will test whether these variables affect tax rate forecast dispersion and accuracy.

4.3 Principal Components Analysis of Tax and General Complexity Variables

Panels A and B of Table 4 report results of our principal components analysis for the tax complexity variables. The top three components explain almost half of the covariance among the tax complexity components, have eigenvalues much larger than 1.00, and each of the three have eigenvectors greater than 0.40 for at least two distinct complexity variables, suggesting that these components explain much of the variation across most of the tax complexity variables.[19] The first component has large (greater than 0.40) positive eigenvectors for *CompExp, LOSS*, and *RDS,* the second tax component has large positive eigenvectors for *absΔETR* and *ETR_STD*, and the third component has large positive eigenvectors for *Foreign* and *TLCF*. There are no large (greater than 0.40) negative eigenvectors among the complexity variables in the first three components.

In Panels C and D of Table 4, we repeat this process for our general complexity variables. The top three general complexity components have eigenvalues above 1, explain 69 percent of the

[19] The fourth tax complexity component has an eigenvalue of approximately 1.00 and explains ten percent of the co-variance, but the eigenvectors reveal that it is almost completely a function of *RetroLegislation*, a time-variant indicator variable that only captures 13% of the firm-quarters in our sample. If we include this fourth factor in our subsequent analyses, our main inferences results are unaffected.

covariance, and have large positive eigenvectors indicating that they provide coverage of all six of the general complexity variables.

We include the top three tax principal components and the top three general complexity components when testing our hypotheses. Doing so permits a parsimonious design when we include interaction terms.

4.4 Results Regarding Determinants of Analysts' Dispersion

Table 5 reports tests of the factors associated with forecast dispersion. Panel A reports the associations between the dispersion in ETR forecasts and all of our individual measures of complexity. In column 1, we include only those variables from prior literature that have been shown to be associated with the quality of after-tax earnings forecasts. In column 2 we add the additional measures of tax complexity discussed above, and in column 3 we add *CLEAN,* our variable of interest related to H1a. The new variables we add increase explanatory power from 0.121 (column 1) to 0.183 (column 2). We find that analyst ETR forecast dispersion is lower when management provides a clean interim ETR forecast that is free of discrete items, controlling for firm complexity, consistent with H1a. Lower ETR forecast dispersion for firms with clean forecasts is consistent with univariate evidence than analysts are less likely to mimic management's estimate when the estimate includes discrete items. We do not include *MIMIC* in this test because there would be a mechanical association between *MIMIC* and lower dispersion.

As expected and consistent with H1b, several tax and general complexity are associated with increased dispersion in ETR forecasts. Specifically, we find the magnitude of revisions in management's ETR estimates, variability in managements' ETR estimates, permanent differences, stock compensation, foreign operations, current year losses, retroactive tax legislation, tax loss carryforwards, book to market, and leverage are associated with higher ETR forecast dispersion. Surprisingly, R&D spending and firm size are associated with lower ETR dispersion, perhaps because firms with intellectual property or larger scale have more mobile income (De Simone, Mills, and Stomberg 2014) with sustainable tax savings that reduces analysts' uncertainty.

Panel B of Table 5 reports the associations between the dispersion in ETR forecasts and the principal components of our tax and general complexity measures. Column 1 reports results of a regression that includes only the main effects for the tax and general complexity components. The negative coefficient on *CLEAN* suggests that, controlling for tax and general complexity, analyst ETR forecast dispersion is lower when management provides an interim ETR estimate that is free of discrete items, consistent with H1a. Four of the six complexity PCA measures are positively associated with dispersion, consistent with H1b.

In Column 2, we interact the principal tax and general complexity components with *CLEAN* to formally test H1c, which predicts that the association between tax dispersion and tax complexity differs when an interim estimate is provided without discrete items. We find this to be the case for two of the three tax complexity components. Specifically, the positive coefficients on *CLEAN * TAXPRIN2* and *CLEAN * TAXPRIN3* suggest that forecast dispersion is increasing in complexity for firms with "clean" management estimates. Thus, although the main effect of the presence of a clean estimate from management is to reduce dispersion, when the firm is in a more complex setting, dispersion increases. We conclude analysts appear to gather additional information and differentially incorporate this information across their forecasts when management's estimate is clean. We explore efficacy of these efforts in our next tests examining forecast accuracy.

4.5 Tax expense forecast accuracy

Table 6 reports tests of the factors associated with forecast accuracy. We report the associations of forecast accuracy with individual measures of complexity in Panel A and with the principal components of our complexity measures in Panel B. In column 1, the dependent variable is the accuracy of analyst's implied ETR forecast, while in column 2 (3), the dependent variable is the pre-tax earnings (tax expense) forecast accuracy. As discussed in section 3.3, to disentangle errors in the numerator and denominator of the ETR forecast, we focus on tax expense forecast errors, controlling for pre-tax earnings forecast errors.

Consistent with H2a, we find that clean management estimates that exclude discrete items are associated with higher accuracy of tax expense forecasts, controlling for pre-tax accuracy. Clean estimates are also associated with more accurate pre-tax and ETR forecasts. These results suggest analysts have difficulty interpreting the future impact of discrete items included in management's interim ETR estimates. Accounting requirements for discrete items add noise to the information available to analysts. Consistent with H2b, we find that forecast accuracy is higher when analysts do not merely mimic management, suggesting analysts add value to management information.

Table 6 also shows how complexity affects tax forecast accuracy. Tax complexity is associated with tax expense forecast accuracy, controlling for pre-tax accuracy, consistent with H2c. Tax expense forecasts are less accurate when the firm experiences larger changes in its quarterly ETR (*absΔETR*) or has a more variable ETR (*ETR_STD).*[20] We also observe a negative association between pre-tax and ETR forecast accuracy and the change in and variability of the quarterly ETR. The pre-tax accuracy findings are important because they confirm that ETRs and by extension a firms' tax environment has implications for both tax and pre-tax components of earnings, and that analysts have difficulty predicting those effects.

Firms with high R&D expense intensity (*RDS)* have more accurate tax and pre-tax forecasts. We find this surprising, although the highly-mobile income generated by many high-tech firms could permit more sustained tax benefits (De Simone et al. 2014) that are easier to forecast. Finally, we are surprised to see that *RetroLegislation* diminishes the accuracy of pre-tax earnings forecasts, but not of tax expense (which weakly increases). This suggests analysts' errors when dealing with

[20] In an untabulated analysis, we consider that changes in the interim ETR estimates provided by management may reduce uncertainty faced by analysts about permanent differences, and include an interaction between *abschangeETR* and *absPermDiff*. In this specification for tax expense accuracy, we find that both main effects are significantly negative, and the interaction is significantly positive, consistent with this consideration.

the expiration and reinstatement of R&D credit are concentrated in their forecasts of pre-tax earnings. The uncertainty could relate to the effect of R&D credits on R&D spending and expense, or the effect could be uncertainty regarding macro conditions surrounding Congressional gridlock.

In the tax expense regression, we control for the accuracy of the pre-tax earnings forecast (*ACCpteps)* to isolate tax-related forecast errors from the effect of pre-tax forecast errors on the denominator of ETR. In untabulated tests including only pre-tax forecast accuracy, the R^2 is 48.6%.[21] In spite of this material explanatory power, we still find that the specific tax complexity and general complexity variables are important in explaining tax expense forecast accuracy. Overall, controlling for the complexity of the tax forecasting environment, management's estimate is important in mitigating information asymmetry regarding taxes. When analysts gather and analyze tax information, they provide more accurate tax forecasts to the market.[22] Our general complexity variables affect tax, pre-tax and ETR forecast accuracy in similar ways as they do after-tax accuracy.

Panel B uses summary complexity variables created using principal components analysis. We present only the fully-interacted models for accuracy of tax expense, pretax earnings and ETR. Tax forecast accuracy is higher when management's ETR estimate is free of discrete items, consistent with H2a. Similarly, accuracy of tax expense is lower when analysts merely mimic management, consistent with H2b.

The main effects of the tax and general principal components reflect association for firms that did not issue a clean ETR estimate – that is, management's interim ETR estimate included discrete items. For these firms, *TAXPRIN3* is associated with higher accuracy for tax expense forecasts. Recall that *TAXPRIN3* weights *Foreign* and *TLCF* highly. The positive relation between *TAXPRIN3* and tax forecast accuracy is consistent with the positive association between *TLCF* and

[21] The adjusted R-square when including (excluding) the accuracy of pre-tax income is 0.514 (0.143).
[22] The F-statistic of a test of whether each of the coefficients on the tax complexity variables is equal to zero, is statistically significant for all columns of Table 4 and Table 5.

tax forecast accuracy in Table 6 Panel A. This suggests that rather than making tax forecasting more complex, firms with tax loss carryforwards may be simpler to forecast. In subsequent analyses we examine forecast accuracy for firms with losses in more detail. The main effects for general complexity PCA variables are mixed. Consistent with the positive association we observed for analyst coverage and firm size in Panel A, we observe a positive association between tax forecast accuracy and *GENPRIN1* while the remaining complexity components are associated with lower forecast accuracy consistent with our expectations. As shown in Panel A, tax complexity is also associated with a decrease pre-tax accuracy. This effect carries over to ETR accuracy.

In general we find that clean management estimates are associated with higher tax forecast accuracy and that complexity has a greater impact on forecast accuracy in the presence of discrete items. For firms with clean management estimates, *TAXPRIN1* is associated with more accurate tax forecasts (net coeff= -0.0000 + 0.0001 = 0.0001 F-value =52.52 p-value < 0.001). *TAXPRIN2* is associated with lower forecast accuracy (net coeff = -0.0001 + -0.0002 = -0.0003, F-value = 148.67 p-value = <0.001). The net effect of *TAXPRIN3* (net coeff = 0.0002 + -0.0003 = -0.0001, F-value =2.96, p value =0.09) is weakly significant. In total, the effect of clean management estimates (= *CLEAN* + *CLEAN** *TAXPRIN1* + *CLEAN** *TAXPRIN2* + *CLEAN** *TAXPRIN3*; F-value = 3.93, p-value = 0.048) is higher accuracy. The improvement in forecast accuracy in the presence of clean estimates highlights the loss of information arising from current requirements to account for discrete items in the quarter in which they occur.

5. SUPPLEMENTAL AND ROBUSTNESS TESTS

5.1 Signed forecast errors

To extend our understanding of tax forecasts, we also examine signed forecast errors to consider whether analysts fully use the information in management's interim estimate. We estimate the association between analysts' signed forecast errors and the change in management's interim ETR estimate using the following specification:

$$AFE_{j,q,t} = \alpha_0 + \alpha_1 lagAFEateps_{j,q,t} + \alpha_2 \Delta ETR\_Inc_{j,q\text{-}1,t} + \alpha_3 \Delta ETR\_Dec_{j,q\text{-}1,t} + A\sum TaxComplexity + B\sum GeneralComplexity + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t} \quad (5)$$

In equation 5, the dependent variable captures the signed analysts' forecast error in ETR (*AFEetr*), pre-tax earnings per share (*AFEpteps*), and tax expense per share (*AFEtax*) forecasts for the consensus analyst following firm *j* in quarter *q* of year *t*. Signed forecast errors equal the median consensus forecast less the I/B/E/S actual (or implied actual) amount. Thus, for earnings (tax expense), the forecast error is increasing in the optimism (pessimism) of the consensus analyst forecast relative to *ex post* realized earnings (tax expense). Our tests are two-tailed.

Because our dependent variable is signed forecast errors, and analysts likely process increases in management's interim ETRs differently than decreases (Dhaliwal, Gleason, and Mills 2004, Bauman and Shaw 2005), we separately analyze positive and negative changes. Our interest is in the coefficients α_2 and α_3 for $abs\Delta ETR\_Inc_{j,q\text{-}1,t}$ and $abs\Delta ETR\_Dec_{j,q\text{-}1,t}$. The change in management's ETR estimate is caused by changes in the numerator (tax expense), the denominator (pre-tax earnings), or both. Thus we test whether analysts fail to process any or all of this information, in forming both pre-tax and tax expense forecasts.

Table 7 presents results on signed forecast errors.[23] As in our previous analysis, we examine analysts' forecast errors only from quarters two, three, and four to test how analysts incorporate the signed change in management's interim ETR estimate from the prior quarter of the *same* year into their forecasts for the upcoming quarter. In column 1, results indicate that analysts' ETR forecast error is positively associated with the change in management's interim ETR increases ($abs\Delta ETR\_Inc_{j,q\text{-}1,t}$). In column 2, we see that the pre-tax earnings forecast error is positively related to an increase in management's interim ETR estimate ($abs\Delta ETR\_Inc_{j,q\text{-}1,t}$) and weakly related to

[23] Analysts' signed forecast errors are winsorized at the top and bottom 1% level.

decreases in management's interim ETR estimate ($abs\Delta ETR\_Dec_{j,q-1,t}$). In both cases, errors in incorporating management's ETR estimates lead to over-estimation of pre-tax earnings. Results from column 3 do not indicate incremental signed tax forecast errors, controlling for the pre-tax error.[24] Overall, it appears that analysts have difficulty interpreting the pre-tax implications of management's ETR updates, resulting in optimism in the face of uncertainty, consistent with Easterwood and Nutt (1999).

In the next three columns we control for whether management provides a clean ETR estimate or whether it contains discrete items. To do so, we interact $abs\Delta ETR\_Inc_{j,q-1,t}$ and $abs\Delta ETR\_Dec_{j,q-1,t}$ with indicator variables capturing the presence of discrete items so that the main effects can be interpreted as the effects when a clean ETR estimates are present. We set *Discrete_Pos* (*Discrete_Neg*) equal to 1 for fiscal quarters where the prior-quarter implied I/B/E/S actual ETR is at least 1% above (below) the prior-quarter GAAP ETR, and equals 0 otherwise. We use an indicator variable for whether the forecast includes discrete items instead of *CLEAN* in order to incorporate the sign of the discrete item. Column 4 reveals that when a clean interim ETR estimate is available, there is no association between signed ETR forecast errors and either ETR decreases or ETR increases. Instead, the positive association between forecast errors and ETR decreases we observed in column 1 is driven by the presence of discrete items. When there is both a decrease in management's interim ETR estimate and a discrete item reducing the quarterly ETR, analysts' ETR forecast is positively associated with the decrease in the ETR (untabulated p-value < 0.0001). We also find in column 6 that analysts' tax expense forecasts are negatively associated positive discrete items in management's interim ETR estimates, controlling for the pre-tax forecast error.

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[24] In untabulated analysis, we find that after-tax forecast errors are positively associated with $abs\Delta ETR\_Inc_{j,q-1,t}$ indicating that over-estimation of pre-tax earnings leads to over-estimation of after-tax earnings.

To summarize, controlling for the presence of discrete items, we find no incremental relation between increases or decreases in management's interim ETR estimate and tax expense forecast errors, suggesting that analysts evaluate the *tax* implications of management's ETR estimates efficiently when they are provided with clean ETR estimates. However, when forecasting the ETR, analysts respond optimistically to interim ETR estimate changes when discrete items are present. This extends prior research, which provides mixed evidence that analysts under-react to negative earnings-related news, by finding analysts' response may be a function of the clarity of the information contained in the news.

5.2 Analysts' decision to issue pre-tax earnings forecast

In our main analysis we include only firms who submit pre-tax earnings forecasts to I/B/E/S. Although this design choice allows comparability across our various tests, our findings may not generalize to those analysts who do not submit pre-tax earnings forecasts to I/B/E/S. To address this limitation, we control for the likelihood that a pre-tax earnings forecast is available for the firm in I/B/E/S. Appendix C describes the frequency of pre-tax earnings forecasts and proposes a model to predict whether an analyst issues such a forecast. Based on evidence in Table 8, the appendix concludes that the analyst decision is largely explained by the presence of other disaggregated forecasts, as well as analyst- and firm-specific variables for experience and complexity.

When we re-estimate equations 3 and 4 after including an inverse mills ratio from a firm-level version of equation 6 from Appendix C (i.e., excluding analyst-level variables), we find similar results to our main results reported in Tables 5 and 6.

5.3 Forecast accuracy for Loss Firms (untabulated)

In additional analyses, we separately consider loss firms. Given that most tax research omits loss firms from the test samples because of the difficulty in interpreting ETRs for loss firms, learning about forecasting pre-tax income and taxes in loss samples provides new insights. We continue to find complexity is associated with lower accuracy in general. Pre-tax forecast errors are still the most important determinant of tax expense forecast errors. We also include an additional explanatory variable equal to one if the loss firm recorded a full valuation allowance during the year, following Dhaliwal, Kaplan, Laux, and Weisbrod (2013), and zero otherwise. We expect analysts to more accurately forecast tax expense for firms with a full valuation allowance, because the valuation allowance eliminates the complexity associated with estimating carryforward and carryback effects. Consistent with our expectations, a full valuation allowance is associated with higher forecast accuracy for both tax expense and ETR.

5.4 Inclusion of Q1 forecast errors and analysis by quarter (untabulated)

When we include analysts' Q1 forecasts in our analyses in Tables 5 and 6, using the prior year ETR as the benchmark for the change in management's ETR estimate, our inferences are unchanged. We also re-estimate the results in Tables 5 and 6 by looking at interim quarters (Q2 and Q3) and the final fiscal quarter (Q4) separately. Our main results are not sensitive to this partition.

5.5 Exclusion of observations with negligible ETR estimate changes (untabulated)

We investigate the effect of small or non-existent changes in management's reported ETR estimates by removing those observations where the absolute value of the ETR estimate change, $abs\Delta ETR_{q-1,t}$, is less than 0.001 (i.e., less than one-tenth of a percentage point change in the ETR estimate). Results are qualitatively similar to our main results reported in Tables 5 and 6.

5.6 Specification of accuracy regressions (untabulated)

The effective tax rate is correlated with the level of pre-tax earnings, which complicates our analysis. In our accuracy tests, we focus on tax expense, controlling for the pre-tax forecast. A limitation of this design is that it assumes a linear relation between the errors, which may not be accurate. We test the robustness of our inferences to the linear specification in several ways. First, we find that inferences are unchanged when we also include the level of the pre-tax forecast in the tax expense accuracy regressions. Second, inferences are unchanged when we estimate the pre-tax and tax expense regressions simultaneously.

6. CONCLUSION

Using a sample of quarterly forecasts of pre-tax and after-tax earnings from 2003 to 2012, we introduce a method of inferring analysts' tax expense forecasts and provide large-sample evidence on the accuracy of analysts' forecasts of both pre-tax earnings and tax expense. Tax complexity is incrementally associated with analyst's pre-tax, tax and after-tax forecast accuracy.

Managements' mandatory ETR estimates decrease analyst uncertainty and improve the accuracy of analysts' tax forecasts more when they do not include the effect of discrete items. In fact, "clean" management estimates mitigate the impact of tax complexity on forecast accuracy.

Our study raises questions about accounting standards related to quarterly financial reporting. Specifically, the requirement that discrete items are recorded in full in the quarter in which they occur, increases analysts' uncertainty and decreases forecast accuracy.

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APPENDIX A
ASC 740 Integral Method Example

In fiscal Q1, a firm estimates $200 annual pre-tax earnings and a 30% ETR, for expected annual tax expense of $60. In fiscal Q1, the firm reports $50 of Q1 pre-tax earnings, and so it accrues $15 in quarterly income tax expense. In fiscal Q2, the firm earns $50 of pre-tax earnings. Management projects a fourth quarter windfall that will increase its annual pre-tax earnings to $250 and total tax expense of $80, for an annual ETR estimate of 32%. Based on the 32% revised tax rate and because year-to-date income in Q2 is $100, $32 in taxes must be accrued year-to-date. As $15 was accrued in Q1, an additional $17 is accrued in Q2, which is 34% of pre-tax earnings during Q2.

Beginning with the first-quarter 10-Q, management's expected annual ETR used in determining quarterly income likely represents the best publicly available information about expected tax expense. In the example above, the interim tax expense estimate ($32 in accrued tax expense as of Q2, for a 32% interim ETR) embeds information about innovations in future pre-tax earnings (an anticipated increase in income from $200 to $250 for the year, in this example) and the ensuing expected ETR (32% for the year) on that future income.

In the above example, the pre-tax earnings windfall would naturally increase the ETR if permanent tax benefits are relatively fixed. In such a case, fixed tax benefits shield a smaller proportion of pre-tax earnings, resulting in a higher ETR. Note that if permanent differences *increase* tax expense overall, however, an increase in pre-tax earnings would decrease the ETR. Further, sometimes the new information in Q2 relates not to pre-tax earnings but to the tax expense alone, increasing or decreasing the numerator of ETR. Thus, it is ambiguous whether an ETR increase or decrease alone has implications for higher or lower pre-tax earnings or tax expense, absent other disclosures. This ambiguity motivates our study – because prior research relies heavily on ETR implications, whereas we can separately study pre-tax earnings and tax expense forecasts.

In addition to estimates of future profitability that affect the expected marginal tax rate, management may anticipate changes that affect the application of tax credits, the ability to use tax-loss carryforwards, or valuation allowance estimates causing management to revise its interim ETR estimate. At the same time, discrete events, such as settlements with tax authorities, are exceptions to the integral method and reduce the informativeness of the quarterly ETR for financial statement users, including analysts. When discrete events occur, analysts would need additional guidance from management to understand the implications of discrete items for the expected annual ETR.

APPENDIX B
Variable Definitions

Variable		Definition
$10KSize_{j,t}$	=	The size of the firm's prior year 10K report, in megabytes, from the website http://www3.nd.edu/~mcdonald/10-K_Headers/10-K_Headers.html
$abs\Delta ETR_{j,q\text{-}1,t}$	=	The absolute value of the difference between the interim, year-to-date effective tax rate as of quarter *q-1* of year *t* and the interim, year-to-date effective tax rate for the prior quarter, quarter *q-2*
$absPermDiff_{j,q,t\text{-}1}$	=	The absolute value of the difference between the firm's year *t-1* GAAP ETR and 35%.
$ACCateps_{j,q,t}$	=	Median of the absolute value of each analyst's forecast of after-tax earnings for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less actual after-tax earnings for quarter *q* according to I/B/E/S, scaled by price at the end of year *t-1* and multiplied by -1
$ACCetr_{j,q,t}$	=	Median of the absolute value of each analyst's implied forecast of the effective tax rate for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less the implied actual GAAP effective tax rate for quarter *q* according to I/B/E/S, and multiplied by -1
$ACCpteps_{j,q,t}$	=	Median of the absolute value of each analyst's forecast of pre-tax earnings per share for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less actual pre-tax earnings per share for quarter *q* according to I/B/E/S, scaled by price at the end of year *t-1* and multiplied by -1
$ACCtax_{j,q,t}$	=	Median of the absolute value of each analyst's implied forecast of tax expense for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less the implied actual tax expense for quarter *q* according to I/B/E/S, scaled by price at the end of year *t-1* and multiplied by -1
$AFEateps_{j,q,t}$	=	Median of each analyst's forecast of after-tax earnings for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less actual after-tax earnings for quarter *q* according to I/B/E/S, scaled by price at the end of year *t-1*
$AFEetr_{j,q,t}$	=	Median of each analyst's implied forecast of the effective tax rate for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less the implied actual GAAP effective tax rate for quarter *q* according to I/B/E/S
$AFEpteps_{j,q,t}$	=	Median of each analyst's forecast of pre-tax earnings per share for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less actual pre-tax earnings per share for quarter *q* according to I/B/E/S, scaled by price at the end of year *t-1*
$AFEtax_{j,q,t}$	=	Median of each analyst's implied forecast of tax expense for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, less the implied actual tax expense for quarter

		q according to I/B/E/S
$ANF_{j,t}$	=	The number of I/B/E/S analysts issuing EPS forecasts for firm *j* during year *t*
$BM_{j,t-1}$	=	Book value of firm *j* as of the end of fiscal year *t-1*, from Compustat, divided by market value as of the end of fiscal year *t-1*, obtained from CRSP
$BSIZE_{i,t}$	=	The number of analysts appearing in I/B/E/S during year *t* for the brokerage house by which analyst *i* is employed, scaled relative to the level of $BSIZE_{i,t}$ for all analysts following firm *j* in year *t*
$CompExp_{j,t-1}$	=	The decile rank of firm *j*'s year *t-1* stock compensation expense (STKCO in Compustat) plus implied option expense (XINTOPT in Compustat divided by 0.65), if any, scaled by total assets (AT in Compustat)
$CDISPetr_{j,q,t}$ ($DISPetr_{j,q,t}$)	=	(Tercile ranking of the) standard deviation of analysts' implied forecasts of the effective tax rate for firm *j* for the upcoming quarter *q* in fiscal year *t*, made following the announcement of fiscal quarter *q-1* earnings, for all firm-quarters with more than one analyst providing pre-tax forecasts
CLEAN	=	An indicator variable that equals 1 for those fiscal quarters where the prior-quarter GAAP ETR (based on TXTQ divided by PIQ in Compustat) is within 1% (on either side) of the prior-quarter I/B/E/S actual ETR, and equals 0 for those fiscal quarters where the prior-quarter GAAP ETR is at least 1% different from the prior-quarter I/B/E/S actual ETR
Discrete_Pos	=	An indicator variable that equals 1 for those fiscal quarters where the prior-quarter implied I/B/E/S actual ETR is at least 1% above the prior-quarter GAAP ETR (based on TXTQ divided by PIQ in Compustat), and equals 0 otherwise
Discrete_Pos	=	An indicator variable that equals 1 for those fiscal quarters where the prior-quarter implied I/B/E/S actual ETR is at least 1% below the prior-quarter GAAP ETR (based on TXTQ divided by PIQ in Compustat), and equals 0 otherwise
$ETR\_STD_{j,t-1}$	=	The standard deviation of the interim, year-to-date effective tax rate during year *t-1*
$\Delta ETR_{q-1,t}$	=	The difference between the interim, year-to-date effective tax rate as of quarter *q-1* of year *t* and the interim, year-to-date effective tax rate for the prior quarter, quarter *q-2*
$\Delta ETR\_Dec_{q-1,t}$	=	The difference between the interim, year-to-date effective tax rate as of quarter *q-1* of year *t* and the interim, year-to-date effective tax rate for the prior quarter, when $ETR\Delta_{q-1,t} < 0$, and zero otherwise
$\Delta ETR\_Inc_{q-1,t}$	=	The difference between the interim, year-to-date effective tax rate as of quarter *q-1* of year *t* and the interim, year-to-date effective tax rate for the prior quarter, when $ETR\Delta_{q-1,t} >= 0$, and zero otherwise
$FEXP_{i,j,t}$	=	The number of consecutive years for which analyst *i* appears in I/B/E/S following firm *j* as of year *t*, scaled relative to the level of $FEXP_{i,j,t}$ for all analysts following firm *j* in year *t*
$Foreign_{j,t-1}$	=	An indicator variable that equals 1 if the firm has non-zero pre-tax foreign income (Compustat item 'PIFO') in year *t-1*, and 0 otherwise
$FREQ_{i,j,t}$	=	The number of EPS forecasts that analyst *i* issues for firm *j* during year *t*, scaled relative to the level of $FREQ_{i,j,t}$ for all analysts following firm *j* in year *t*
$GEXP_{i,t}$	=	The number of consecutive years for which analyst *i* appears in I/B/E/S following any firm as of year *t*, scaled relative to the level of $GEXP_{i,t}$ for all

		analysts following firm *j* in year *t*
$Horizon_{i,j,q,t}$	=	The number of days between the date analyst *i*'s forecast for firm *j* in quarter *q* is announced and the quarter *q* earnings reporting date, divided by 365, scaled relative to the level of $Horizon_{i,j,q,t}$ for all analysts' forecasts of firm *j* in year *t*
Implied ETR	=	Implied tax expense / Pre-tax earnings, from I/B/E/S
Implied Tax Expense	=	Pre-tax earnings – After-tax earnings, from I/B/E/S
$LOSS_{j,q,t}$	=	Indicator variable that equals one if there is a pre-tax loss in the current period, and equals zero otherwise
$MI_{j,q,t}$	=	Indicator variable that equals one if there is non-zero minority interest during quarter *q*, and equals zero otherwise
MIMIC	=	Indicator variable that equals one when at least half of the analysts in a quarter issue implied ETR forecasts that are within 1% of management's prior-quarter interim ETR estimate, and zero otherwise
$MV_{j,t-1}$	=	Market value as of the end of year *t-1*, according to CRSP
$LEV_{j,t-1}$	=	Leverage as of the end of year *t-1*, calculated as long-term debt (Compustat item DLTT) scaled by total assets (Compustat item AT)
$NCOS_{i,t}$	=	The number of firms followed by analyst *i* in I/B/E/S during year *t*, scaled relative to the level of $NCOS_{i,t}$ for all analysts following firm *j* in year *t*
$PermDiff_{j,t-1}$	=	The difference between the firm's year *t-1* GAAP ETR and 35%.
$PTIssue_{i,j,q,t}$	=	Indicator variable that equals one if analyst *i* issued a pre-tax forecast of quarterly earnings for firm *j* during quarter *q*, and equals zero otherwise
$RDS_{j,t-1}$	=	R&D spending (Compustat item XRD) divided by sales (Compustat item SALE) for firm *j* during year *t-1.* The variable is set to one if R&D spending exceeds sales.
$RetroLegislation_q$	=	Indicator variable set to one in quarters during which Congress passed legislation retroactively extending the availability of tax credits such as the R&D Credit (i.e., for quarters ending in the 90 days following October 4, 2004, December 20, 2006, October 3, 2008, and December 17, 2010), and zero otherwise.
$SalesIssue_{i,j,q,t}$	=	Indicator variable that equals one if analyst *i* issued a sales forecast of quarterly earnings for firm *j* during quarter *q*, and equals zero otherwise
$Segments_{j,t-1}$	=	The number of 4-digit SIC segments according to Compustat
$Slack_{j,t-1}$	=	Indicator variable that equals one if ETR in Q1 of year *t-1* exceeds ETR in Q4 of year *t-1*, and zero otherwise
$TLCF_{j,t}$	=	An indicator variable that equals 1 if the firm has non-zero tax loss carryforwards (Compustat item 'TLCF') in year *t-1*, and 0 otherwise

APPENDIX C
Controlling for Analyst's Choice to Issue a Pre-tax Earnings Forecast

Our institutional experience and conversations with analysts indicate that most analysts construct their net earnings forecasts using a detailed line-item model, but these items were not collected by large data providers until recently. Brokerage houses and individual analysts continue to differ in whether they report such detail to I/B/E/S. We find the disclosure of pre-tax earnings forecasts is not independent from the disclosure of sales forecasts, and frequently a disclosure of either detail includes both. Thus, issuing the pre-tax earnings forecast (and by construction, tax expense and the ETR) does not appear to be primarily a tax-driven decision. Our dispersion and accuracy tests are robust to controls for potential self-selection.

Table 8, panel A describes the frequency of sales, pre-tax, and after-tax earnings forecasts for analysts that provide an EPS forecast for at least one firm during the sample period.[1] From 2003 to 2012, 30 percent of the 466,795 analyst-firm-quarters with an EPS forecast also include a sales forecast.[2] After-tax (33%) and pre-tax (35%) earnings forecasts are only slightly more common, consistent with anecdotal evidence that for many analysts the decision to provide pre-tax forecasts reflects the decision to provide detailed, disaggregated forecasts, rather than a singular emphasis on tax expense. The correlation between the decision to disclose sales and pre-tax forecasts suggests that research that treats disaggregated forecast components as independent decisions may be mis-specified.

We next construct a prediction model, based in part on Ertimur, Mayew, and Stubben's (2011) model of an analyst's decision to supply disaggregated forecasts to I/B/E/S:[3]

$$\begin{aligned}\Pr(PTIssue_{i,j,t}) = {} & \alpha_0 + \alpha_1 SalesIssue_{i,j,t} + \alpha_2 PTIssue_{i,j,t-1} + \alpha_3 BSIZE_{i,t} + \alpha_4 FEXP_{i,j,t} + \alpha_5 FREQ_{i,j,t} \\ & + \alpha_6 GEXP_{i,t} + \alpha_7 Horizon_{i,j,t} + \alpha_8 NCOS_{i,t} + \alpha_9 abs\Delta ETR_{j,q-1,t} + \alpha_{10} CompExp_{j,t-1} \\ & + \alpha_{11} ETR\_STD_{j,t-1} + \alpha_{12} Foreign_{j,t-1} + \alpha_{13} LOSS_{qt} + \alpha_{14} absPermDiff_{j,t-1} + \alpha_{15} RDS_{j,t-1} \\ & + \alpha_{16} RetroLegislation_{q} + \alpha_{17} TLCF_{j,t-1} + \alpha_{18} ANF_{j,t} + \alpha_{19} BM_{j,t-1} + \alpha_{20} LEV_{j,t-1} \\ & + \alpha_{21} lnMV_{j,t-1} + \alpha_{22} Segments_{j,t-1} + \alpha_{23} 10KSize_{j,t-1} + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t}\end{aligned} \tag{6}$$

The above model explains the propensity of an analyst *i* issuing a pre-tax earnings forecast ($PTIssue_{i,j,t}$) for firm *j* in quarter *q* of year *t*. In untabulated tests, we include the inverse Mills ratio from this estimation in our models of forecast dispersion and accuracy to assess robustness.

Explanatory variables in the model include the analysts' other forecasted items issued to I/B/E/S, analyst-level variables, and firm complexity variables. We expect analysts are more likely to issue a pre-tax earnings forecast if they did so in the past ($PTIssue_{i,j,t-1}$) or if they concurrently issue a sales forecast ($SalesIssue_{i,j,t}$). Analyst-level variables include proxies for the analyst's access to resources and ability (Mikhail, Walther, and Willis 1997; Clement 1999; Clement and Tse 2003), which should increase the likelihood of a pre-tax earnings forecast. Broker size, measured as the number of analysts in the brokerage house ($BSIZE_{i,t}$) proxies for resources. The number of consecutive years the analyst issues a forecast for that firm to I/B/E/S ($FEXP_{i,j,t}$), the number of EPS forecasts the analyst issues for the firm that year ($FREQ_{i,j,t}$), and the number of consecutive years

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[1] I/B/E/S provides both EPS (i.e., earnings per share) and after-tax (i.e., earnings in millions of dollars) forecasts. Since EPS is most commonly forecast by analysts, we begin with all analysts issuing EPS forecasts.
[2] Ertimur, Mayhew and Stubben (2011) find that 39 percent of analyst-firm combinations reported sales forecasts from 1995 to 2006. The (untabulated) percent of analyst-firm combinations that report sales forecasts increased during our sample period from 19% in 2003 to 43% in 2012.
[3] This model includes both analyst-level and firm-level variables. Baik, Choi, Jung, and Morton (2013) form a model of pre-tax earnings forecast issuance that includes similar analyst-level variables.

the analyst issues a forecast of any firm to I/B/E/S ($FEXP_{i,j,t}$), for analyst *i*, firm *j*, and year *t* each proxy for analyst ability. We expect the likelihood I/B/E/S reports a pre-tax earnings forecast *decreases* when the following factors increase: information uncertainty, measured as the number of days between the forecast and the earnings release ($Horizon_{i,j,t}$), and analysts' workload, measured as the number of firms the analyst follows ($NCOS_{i,t}$). Following Clement and Tse (2005), we scale each of the analyst-level control variables relative to the characteristics of all other analysts following the same firm in the same year, so that each analyst-level variable falls between 0 and 1.

Table 8, panel B reports the result of estimating the likelihood an analyst issues a pre-tax forecast. Column 1 includes proxies for analyst attributes, tax-specific complexity and firm-level attributes. In columns 2 and 3 we add an indicator variable for whether the analyst issued a pre-tax forecast for the same firm at any time in the prior year and whether the analyst issued a sales forecast for the same firm in the current period, respectively.[4] We learn from the pseudo R^2 and predictive power in column 2 that the decision to issue a pre-tax forecast is sticky. Column 3 shows that analysts who provide a sales forecast are significantly more likely to provide other disaggregated forecasts, even after controlling for prior period decisions.[5] However, after controlling for prior pre-tax and concurrent sales forecasts, analyst attributes, tax complexity, and general firm attributes incrementally explain analysts' decisions to report pre-tax forecasts to I/B/E/S. For some forms of complexity, it appears analysts must be responding to market demands for information in the face of complexity.

[4] Column 1 is the most free of selection bias, because issuing a sales forecast or initiation of pre-tax forecasts in some prior year are themselves choices.

[5] In untabulated tests, we include the sales forecast indicator but omit the lagged pre-tax forecast. The explanatory power of the sales forecast is even greater than that of the lagged pre-tax forecast, with a Pseudo R^2 of 0.634, compared to 0.585 in Column 2, providing further evidence that the decision to provide a pre-tax earnings forecast to I/B/E/S is dependent in large part on decisions to provide other types of disaggregated forecasts.

TABLE 1
Sample Selection and Descriptive Statistics

This table contains details regarding sample selection and descriptive statistics. Panel A outlines the sample selection. Panel B provides descriptive statistics on the consensus (i.e., median) analyst forecast and actual value of after-tax earnings, pre-tax earnings, implied tax expense, and the implied effective tax rate, as well as management's interim ETR estimate as of the prior quarter. Panel C compares individual analysts' forecasts of the implied effective tax rate with management's ETR estimates, and is limited to the sample of analyst-firm-years for which we can estimate the *Slack* variable. Panel D provides descriptive statistics on the variables used in this study for the 54,783 firm-quarters with non-missing Compustat and CRSP data in the sample. Unsigned forecast errors (i.e., accuracy) for after-tax earnings, pre-tax earnings, and implied tax expense are scaled by price, and are multiplied by -1 so that the variable is increasing in accuracy with respect to *ex post* realized earnings. Variable definitions are in Appendix B.

Panel A: Sample Selection

	Firm-Years	Firm-Quarters	Analyst-firm-years	Analyst-firm-quarters
Observations with I/B/E/S pre-tax and after-tax forecasts available for upcoming quarter	28,981	70,448	150,508	275,729
Observations with non-missing Compustat and CRSP data (for Tables 1c, 2, 3, 4, 6, and 7)	21,513	54,783	129,818	221,176
Observations with >1 analyst following (for Table 5)	17,475	42,214		

TABLE 1 (continued)

Panel B: Consensus Analyst Forecasts of Quarterly After-Tax Earnings, Pre-Tax Earnings, Implied Tax Expense, and Implied Effective Tax Rate

	Mean	Std. Dev.	P25	Median	P75
After-Tax Earnings Forecast ($/share)	0.6058	15.8638	0.1221	0.3292	0.6094
After-Tax Earnings Actual ($/share)	0.6090	16.4475	0.1256	0.3440	0.6445
After-Tax Earnings Forecast Error (scaled by price)	0.0001	0.0120	-0.0025	-0.0006	0.0007
Pre-Tax Earnings Forecast ($/share)	0.9400	26.4772	0.1770	0.4868	0.9123
Pre-Tax Earnings Actual ($/share)	0.9106	24.3014	0.1712	0.4962	0.9453
Pre-Tax Earnings Forecast Error (scaled by price)	0.0003	0.0148	-0.0032	-0.0005	0.0017
Implied Tax Expense Forecast ($/share)	0.3349	10.7121	0.0410	0.1546	0.3045
Implied Tax Expense Actual ($/share)	0.3016	7.9373	0.0309	0.1497	0.3082
Implied Tax Expense Forecast Error (scaled by price)	0.0003	0.0060	-0.0010	0.0000	0.0012
Implied Effective Tax Rate Forecast (%)	0.2816	2.7510	0.2578	0.3445	0.3802
Implied Effective Tax Rate Forecast Error (%)	0.0297	0.3148	-0.0101	0.0029	0.0355
Prior Quarter Interim ETR (%)	0.2698	0.2971	0.2155	0.3308	0.3782
Actual Effective Tax Rate (%)	0.2512	14.0791	0.2104	0.3299	0.3800

TABLE 1 (continued)

Panel C: Descriptive Statistics for firm-quarter observations

	Mean	Std. Dev.	P25	Median	P75
$ACCateps_{j,q,t}$	-0.0047	0.0111	-0.0045	-0.0017	-0.0006
$ACCetr_{j,q,t}$	-0.1172	0.2936	-0.0788	-0.0224	-0.0056
$ACCtax_{j,q,t}$	-0.0028	0.0053	-0.0029	-0.0011	-0.0003
$ACCpteps_{j,q,t}$	-0.0064	0.0133	-0.0065	-0.0026	-0.0009
$CDISPetr_{j,q,t}$	0.2928	13.6256	0.0036	0.0122	0.0502
$absETR\Delta_{j,q-1,t}$	0.0800	0.1898	0.0025	0.0120	0.0505
$ANF_{j,t}$	13	9	6	11	18
$BM_{j,t-1}$	0.5780	0.5778	0.2887	0.4662	0.7187
$CLEAN_{j,q-1,t}$	0.6755	0.4682	0	1	1
$CompExp_{j,t-1}$	0.0150	0.0300	0.0021	0.0058	0.0156
$ETR\_STD_{i,t-1}$	0.0789	0.2806	0.0043	0.0137	0.0525
$Foreign_{j,t-1}$	0.4573	0.4982	0	0	0
$LEV_{j,t-1}$	0.1631	0.1688	0.0068	0.1164	0.2659
$LOSS_{j,q,t}$	0.1752	0.3801	0	0	0
$MIMIC$	0.7416	0.4377	1	1	1
$MV_{j,t-1}$ ($ millions)	5,898	20,782	395	1,067	3,328
$PermDiff_{t-1}$	-0.1115	0.3659	-0.1790	-0.0292	0.0240
$RDS_{j,t-1}$	0.0566	0.1502	0	0	0.0429
$RetroLegislation_{q}$	0.1265	0.3324	0	0	0
$Segments_{j,t-1}$	1.4238	0.9113	1	1	1
$10KSize_{j,t-1}$ (Mb)	3.1692	5.5379	1.0852	1.7069	2.9851
$TLCF_{j,t-1}$	0.4030	0.4905	0	0	1

TABLE 1 (continued)

Panel D – Attributes for Clean and Mimicking Forecasts

Frequency that Individual Analyst ETR Forecasts Mimic Management's ETR Estimate Compared to Frequency of Discrete or Transitory Tax Items (n=184,412)

	CLEAN = 0		*CLEAN* = 1		Full Sample	
	No. of Obs.	Frequency	No. of Obs.	Frequency	No. of Obs.	Frequency
MIMIC = 1	7,382	0.050	45,289	0.307	52,671	0.357
MIMIC = 0	53,475	0.363	41,280	0.280	94,755	0.643
	60,857		86,589		147,426	

TABLE 2
Correlations

This table displays correlations among the variables used in this study, with Pearson (Spearman) correlations presented above (below) the diagonal. Panel A presents correlations among the dependent variables used in this study, while Panel B displays correlations among accuracy, dispersion, and complexity measures. Variable definitions are in Appendix B.

Panel A: Correlations among accuracy, dispersion, and signed forecast errors measures

	DISPetr	*ACCateps*	*ACCpteps*	*ACCtax*	*ACCetr*	*AFEpteps*	*AFEtax*	*AFEetr*
DISPetr		-0.008 *	-0.011 **	-0.016 ***	-0.026 ***	-0.001	-0.004	-0.006
ACCateps	-0.213 ***		0.900 ***	0.582 ***	0.189 ***	-0.605 ***	-0.185 ***	-0.068 ***
ACCpteps	-0.224 ***	0.798 ***		0.697 ***	0.170 ***	-0.615 ***	-0.236 ***	-0.015 ***
ACCtax$_j$	-0.277 ***	0.496 ***	0.643 ***		0.417 ***	-0.345 ***	-0.252 ***	-0.072 ***
ACCetr	-0.462 ***	0.283 ***	0.300 ***	0.566 ***		-0.098 ***	-0.109 ***	-0.309 ***
AFEpteps	-0.022 ***	0.148 ***	0.132 ***	-0.002	-0.117 ***		0.614 ***	0.056 ***
AFEtax	-0.005	0.038 ***	0.095 ***	-0.041 ***	-0.210 ***	0.711 ***		0.096 ***
AFEetr	0.024 ***	-0.052 ***	0.035 ***	-0.053 ***	-0.234 ***	0.162 ***	0.419 ***	

TABLE 2 (continued)

Panel B: Correlations among accuracy, dispersion and complexity measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) *ACCpteps*		0.679***	-0.011**	-0.089***	-0.055***	0.043***	-0.065***	0.083***	-0.217***	-0.095***	0.021***	0.008**	-0.052***	0.001	0.144***	-0.200***	-0.058***	0.196***	0.024***	0.014***
(2) *ACCtax*	0.643***		-0.016***	-0.105***	-0.098***	0.082***	-0.081***	0.068***	-0.151***	-0.136***	0.002	0.092***	-0.039***	0.019***	0.133***	-0.218***	-0.084***	0.166***	-0.002	-0.001
(3) *DISPetr*	-0.224***	-0.277***		0.035***	-0.007	-0.003	0.010**	0.003	0.024***	0.013***	0.012**	0.004	-0.002	-0.003	0.001	0.002	0.007	-0.006	-0.005	-0.002
(4) *absETRΔ*	-0.152***	-0.220***	0.332***		-0.184***	0.037***	0.237***	0.237***	0.085***	0.174***	-0.197***	0.027***	-0.041***	0.079***	-0.039***	0.078***	0.035***	-0.080***	-0.000	-0.005
(5) *CLEAN*	0.083***	0.121***	-0.316***	-0.272***		0.018***	-0.085***	-0.138***	-0.010**	-0.279***	0.068***	0.025***	0.007*	-0.084***	-0.113***	-0.096***	-0.109***	-0.120***	-0.015***	-0.144***
(6) *CompExp*	0.097***	0.200***	-0.020***	0.006	0.038***		0.032***	0.071***	0.184***	-0.123***	-0.112***	0.433***	0.006	0.089***	0.045***	-0.160***	-0.207***	-0.117***	-0.095***	-0.099***
(7) *ETR_STD*	-0.193***	-0.262***	0.340***	0.512***	-0.234***	0.033***		0.065***	0.066***	0.089***	-0.241***	0.021***	0.003	0.049***	-0.024***	0.064***	0.019***	-0.058***	-0.000	-0.007
(8) *Foreign*	0.078***	0.023***	0.085***	0.209***	-0.138***	0.253***	0.247***		-0.075***	0.077***	-0.027***	0.052***	-0.011***	0.259***	0.159***	-0.080***	-0.056***	0.240***	0.084***	0.050***
(9) *LOSS*	-0.220***	-0.019***	0.132***	0.022***	-0.010**	0.165***	0.041***	-0.075***		0.043***	-0.131***	0.372***	0.012***	0.068***	-0.110***	0.063***	0.005	-0.213***	-0.068***	-0.048***
(10) *MIMIC*	-0.143***	-0.191***	0.405***	0.337***	-0.279***	-0.075***	0.258***	0.077***	0.048***		-0.076***	-0.032***	0.003	0.037***	-0.095***	0.100***	0.067***	-0.069***	0.021***	0.045***
(11) *PermDiff*	0.057***	-0.079***	-0.184***	-0.113***	0.138***	-0.093***	-0.212***	-0.095***	-0.201***	-0.149***		-0.157***	0.000	-0.065***	0.023***	0.004	-0.009**	0.068***	0.032***	0.003
(12) *RDS*	0.058***	0.161***	0.092***	0.106***	-0.049***	0.568***	0.150***	0.403***	0.163***	0.051***	-0.272***		0.009**	0.138***	0.028***	-0.142***	-0.149***	-0.091***	-0.094***	-0.065***
(13) *RetroLegislation*	-0.008**	-0.036***	0.026***	-0.060***	0.007*	0.005	-0.002	-0.011***	0.012***	-0.013***	0.009**	-0.003		-0.003	-0.011**	-0.024***	-0.001	-0.005	-0.032***	-0.072***
(14) *TLCF*	-0.038***	-0.003	0.070***	0.109***	-0.084***	0.212***	0.156***	0.259***	0.068***	0.059***	-0.097***	0.228***	-0.003		0.024***	-0.015***	0.058***	0.003	0.013***	0.004
(15) *ANF*	0.249***	0.197***	0.059***	-0.040***	-0.118***	0.089***	-0.060***	0.137***	-0.107***	-0.055***	-0.012***	0.050***	-0.007*	0.037***		-0.129***	0.056***	0.717***	0.023***	0.182***
(16) *BM*	-0.314***	-0.336***	0.172***	0.163***	-0.118***	-0.429***	0.192***	-0.123***	0.045***	0.154***	0.018***	-0.303***	-0.032***	-0.054***	-0.230***		0.026***	-0.240***	0.038***	0.063***
(17) *LEV*	-0.059***	-0.110***	0.054***	0.039***	-0.112***	-0.331***	0.042***	-0.036***	-0.044***	0.075***	0.024***	-0.269***	-0.002	0.045***	0.126***	0.082***		0.131***	0.087***	0.084***
(18) *lnMV*	0.304***	0.187***	-0.043***	-0.028***	-0.123***	-0.102***	-0.073***	0.233***	-0.224***	-0.023***	0.018***	-0.025***	-0.006	0.014***	0.725***	-0.287***	0.218***		0.181***	0.281***
(19) *Segments*	0.008*	-0.038***	-0.044***	0.020***	0.003	-0.077***	0.016***	0.069***	-0.073***	0.002	0.060***	-0.006	0.040***	0.027***	0.013***	0.030***	0.120***	0.132***		-0.079***
(20) *10KSize*	-0.042***	-0.065***	0.149***	0.107***	-0.218***	-0.246***	0.118***	0.041***	-0.023***	0.141***	-0.082***	-0.117***	-0.053***	0.016***	0.181***	0.129***	0.195***	0.307***	-0.083***	

TABLE 3
Accuracy of After-Tax EPS Forecasts

This table presents the results of estimating versions of the following specification for the full sample of firms:

$$ACCateps_{j,q,t} = \gamma_0 + \gamma_1 CLEAN_{,q\text{-}1,t} + \gamma_2 MIMIC_{j,q,t} + A\sum TaxComplexity + B\sum GeneralComplexity + \gamma_3 MI_{j,q,t} + Industry_j + Year_t + \varepsilon_{j,q,t}$$

T-statistics are in parentheses and are based upon standard errors clustered at the firm level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on one-tailed tests where there is a predicted sign and based on two-tailed tests otherwise. Variable definitions are in Appendix B.

TABLE 3 (continued)

	Predicted Sign	Dependent variable = *ACCateps* (1)	(2)	(3)
Intercept	?	-0.0075***	-0.0072***	-0.0075***
		(-9.92)	(-9.01)	(-5.92)
CLEAN	+		0.0006***	0.0004***
			(4.13)	(3.08)
MIMIC	-		-0.0009***	-0.0008***
			(-9.59)	(-8.54)
<u>Tax Complexity</u>				
absΔETR	-		-0.0020***	-0.0020***
			(-5.02)	(-5.12)
ETR_STD	-		-0.0009***	-0.0007***
			(-2.82)	(-2.38)
absPermDiff	-		-0.0003	-0.0003
			(-1.08)	(-1.08)
CompExp	-		0.0133	0.0024
			(4.45)	(1.00)
Foreign	-	0.0003	0.0006	-0.0001
		(2.17)	(3.94)	(-0.64)
LOSS	-	-0.0077***	-0.0074***	-0.0067***
		(-18.61)	(-18.35)	(-18.49)
TLCF	-		-0.0000	-0.0002
			(-0.18)	(-1.25)
RDS	-	0.0030	0.0021	0.0019
		(4.43)	(3.25)	(3.02)
RetroLegislation	-		-0.0019***	-0.0012***
			(-9.10)	(-6.15)
<u>General Complexity</u>				
ANF	+	0.0000***	0.0000**	-0.0000
		(2.95)	(1.94)	(-0.07)
BM	-	-0.0025***	-0.0023***	-0.0017***
		(-4.34)	(-4.09)	(-3.51)
LEV	-	-0.0041***	-0.0033***	-0.0035***
		(-8.20)	(-6.53)	(-7.06)
lnMV	+	0.0007***	0.0007***	0.0010***
		(8.88)	(8.77)	(11.72)
Segments	-	0.0001	0.0001	0.0001
		(1.65)	(2.20)	(1.21)
10KSize	-	-0.0303***	-0.0256	-0.0339***
		(-3.39)	(-3.16)	(-3.86)
Industry, Year, Quarter Effects		No	No	Yes
Number of firm-quarters		54,783	54,783	54,783
Adj. R^2		0.105	0.115	0.151

TABLE 4
Principal Component Analysis

This table provides principal component analysis for the tax complexity and general complexity variables used in this study. Panel A provides eigenvalues of the correlation matrix for the nine identified principal components for the tax complexity variables while Panel B provides eigenvectors for each tax complexity variable. Panel C provides eigenvalues of the correlation matrix for the nine identified principal components for the general complexity variables while Panel D provides eigenvectors for each general complexity variable. Variable definitions are in the Appendix.

Panel A: Eigenvalues of the correlation matrix for tax complexity variables

	Eigenvalue	Difference	Proportion	Cumulative
TAXPRIN1	1.8885	0.5305	0.2098	0.2098
TAXPRIN2	1.3580	0.1541	0.1509	0.3607
TAXPRIN3	1.2039	0.2018	0.1338	0.4945
TAXPRIN4	1.0021	0.1660	0.1113	0.6058
TAXPRIN5	0.8361	0.0492	0.0929	0.6987
TAXPRIN6	0.7868	0.0502	0.0874	0.7862
TAXPRIN7	0.7366	0.0527	0.0818	0.8680
TAXPRIN8	0.6839	0.1800	0.0760	0.9440
TAXPRIN9	0.5039		0.0560	1.0000

Panel B: Eigenvectors for each tax complexity variable

	TAXPRIN1	TAXPRIN2	TAXPRIN3	TAXPRIN4	TAXPRIN5	TAXPRIN6	TAXPRIN7	TAXPRIN8	TAXPRIN9
absΔETR	0.2641	**0.4809**	-0.1794	-0.0797	0.1790	0.6516	-0.3749	0.1718	0.0855
CompExp	**0.4436**	-0.3151	0.1046	-0.0394	-0.5440	0.2091	0.0204	0.3299	-0.4924
ETR_STD	0.3548	**0.4838**	-0.2903	0.1045	-0.1390	-0.0889	0.7514	0.0997	0.0637
Foreign	0.1683	0.3126	**0.6329**	0.0403	-0.1979	0.1363	0.0503	-0.6380	-0.0660
LOSS	**0.4122**	-0.2822	-0.2331	-0.0280	0.6037	0.0504	0.1579	-0.0386	-0.3930
absPermDiff	-0.3605	-0.2803	0.3094	-0.0618	0.2070	0.5952	0.5108	0.1653	0.0812
RDS	**0.5174**	-0.3765	0.0459	-0.0355	-0.0627	0.0220	0.0238	-0.0574	0.7608
RetroLegislation	-0.0008	-0.0858	-0.0198	0.9855	0.0204	0.1228	-0.0733	0.0137	0.0007
TLCF	0.2694	0.1740	**0.5652**	0.0503	0.4493	-0.3263	-0.0122	0.5147	-0.0433

TABLE 4 (continued)

Panel C: Eigenvalues of the correlation matrix for general complexity variables

	Eigenvalue	Difference	Proportion	Cumulative
GENPRIN1	1.9370	0.8273	0.3228	0.3228
GENPRIN2	1.1097	0.0269	0.1850	0.5078
GENPRIN3	1.0829	0.1769	0.1805	0.6883
GENPRIN4	0.9060	0.1792	0.1510	0.8393
GENPRIN5	0.7268	0.4892	0.1211	0.9604
GENPRIN6	0.2376		0.0396	1.000

Panel D: Eigenvectors for each general complexity variable

	GENPRIN1	GENPRIN2	GENPRIN3	GENPRIN4	GENPRIN5	GENPRIN6
ANF	**0.6110**	-0.1106	0.0311	0.1656	0.4479	0.6208
BM	-0.2241	**0.6177**	0.3179	0.4789	0.4645	-0.1483
LEV	0.1624	**0.5925**	-0.0643	-0.7712	0.1455	0.0496
lnMV	**0.6636**	-0.0264	-0.0751	0.0929	0.0765	-0.7340
Segments	0.1236	**0.4466**	**-0.6889**	0.3652	-0.3843	0.1724
10KSize	0.3073	0.2346	**0.6431**	0.0801	-0.6394	0.1471

TABLE 5
Determinants of Analyst Quarterly Implied ETR Forecast Dispersion

This table associates dispersion in analysts' quarterly implied ETR forecasts with tax and general complexity factors as well as *CLEAN*, an indicator variable that equals one when managers' interim ETR estimate from the previous quarter is free of discrete items, and equals zero otherwise. We estimate versions of the following specification:

$$DISPetr_{j,q,t} = \gamma_0 + \gamma_1 CLEAN_{,q\text{-}1,t} + A\sum TaxComplexity + B\sum GeneralComplexity + \gamma_2 MI_{j,q,t} + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t}$$

Panel A presents the results of estimating the above equation using a comprehensive list of tax and general complexity variables while Panel B uses principal components for the tax and general complexity variables. T-statistics are in parentheses and are based upon standard errors clustered at the firm level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on one-tailed tests where there is a predicted sign and based on two-tailed tests otherwise. Variable definitions are in Appendix B.

TABLE 5 (continued)

		Dependent variable		
Panel A		*DISPetr*	*DISPetr*	*DISPetr*
	Predicted Sign	(1)	(2)	(3)
Intercept	?	1.2455***	1.0852***	1.3893***
		(11.12)	(10.08)	(13.73)
CLEAN	-			-0.3137***
				(-24.96)
Tax Complexity				
absΔETR	+		0.5075***	0.3854***
			(20.40)	(16.09)
ETR_STD	+		0.0656***	0.0555**
			(2.44)	(2.24)
absPermDiff	+		0.1693***	0.1562***
			(8.72)	(8.35)
CompExp	+		1.1873***	0.9746***
			(4.62)	(3.91)
Foreign	+	0.1757***	0.1375***	0.1140***
		(8.88)	(7.37)	(6.43)
LOSS	+	0.3585***	0.3157***	0.3101***
		(16.88)	(15.37)	(15.63)
TLCF	+		0.0522***	0.0440***
			(3.28)	(2.90)
RDS	+	-0.2240	-0.3368	-0.3294
		(-3.16)	(-4.90)	(-4.96)
RetroLegislation	+		0.0195**	0.0207**
			(1.70)	(1.82)
General Complexity				
ANF	-	0.0170	0.0156	0.0149
		(13.09)	(12.63)	(12.68)
BM	+	0.0575**	0.0485**	0.0286*
		(2.24)	(2.06)	(1.44)
LEV	+	0.3490***	0.2975***	0.2400***
		(6.18)	(5.59)	(4.78)
LnMV	-	-0.1016***	-0.0812***	-0.0828***
		(-11.31)	(-9.47)	(-10.22)
Segments	+	-0.0023	-0.0006	-0.0027
		(-0.24)	(-0.07)	(-0.32)
10KSize	+	2.1389**	1.4798*	0.8747
		(1.88)	(1.33)	(0.83)
Controls				
MI	?	0.2218***	0.2216***	0.1366***
		(11.63)	(12.35)	(7.94)
Industry, Year, Quarter Effects		Yes	Yes	Yes
Number of firm-quarters		42,214	42,214	42,214
Adj. R^2		0.121	0.150	0.183

TABLE 5 (continued)

Panel B	Dependent variable	
	DISPetr	*DISPetr*
	(2)	(3)
Intercept	1.2142***	1.2483***
	(14.27)	(14.85)
CLEAN -	-0.3359***	-0.3560***
	(-25.89)	(-27.17)
TAXPRIN1	0.1038***	0.1083***
	(15.07)	(10.01)
TAXPRIN2	0.0463***	-0.0154
	(5.90)	(-1.48)
TAXPRIN3	-0.0115	-0.0389***
	(-1.39)	(-3.72)
GENPRIN1	0.0001	-0.0015
	(0.01)	(-0.19)
GENPRIN2	0.0402***	0.0284**
	(3.77)	(2.13)
GENPRIN3	0.0247***	0.0222***
	(3.30)	(2.77)
*CLEAN * TAXPRIN1*		0.0061
		(0.52)
*CLEAN * TAXPRIN2*		0.0999***
		(7.26)
*CLEAN * TAXPRIN3*		0.0331***
		(2.84)
*CLEAN * GENPRIN1*		0.0036
		(0.41)
*CLEAN * GENPRIN2*		0.0211
		(1.45)
*CLEAN * GENPRIN3*		0.0076
		(0.85)
MI	0.0527	0.1220***
	(0.52)	(6.85)
Industry, Year, Quarter Effects	Yes	Yes
Number of firm-quarters	42,214	42,214
Adj. R^2	0.160	0.165

TABLE 6
Determinants of Consensus Analyst Quarterly Pre-Tax Earnings, Implied Tax Expense, and Implied ETR Forecast Accuracy

This table associates accuracy in analysts' quarterly implied ETR forecasts with tax and general complexity factors as well as *CLEAN*, an indicator variable that equals one when managers' interim ETR estimate from the previous quarter is free of discrete items, and equals zero otherwise and *MIMIC*, an indicator variable that equals one when the consensus analyst implied ETR forecast is within 1 percentage point of management's prior quarter's interim ETR estimate, and zero otherwise. We estimate versions of the following specification:

$$ACC_{j,q,t} = \gamma_0 + \gamma_1 CLEAN_{,q\text{-}1,t} + \gamma_2 MIMIC_{j,q,t} + A\sum TaxComplexity + B\sum GeneralComplexity + \gamma_3 MI_{j,q,t} + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t}$$

Panel A presents the results of estimating the above equation using a comprehensive list of tax and general complexity variables while Panel B uses principal components for the tax and general complexity variables. In both panels, Columns 1, 2, and 3 present the respective results of estimating the above specifications for accuracy in the implied effective tax rate, pre-tax earnings, and implied tax expense for consensus-level analyst forecasts. We add a control for the accuracy of pre-tax forecasts (*ACCpteps*) in Column 3. T-statistics are in parentheses and are based upon standard errors clustered at the firm level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on one-tailed tests where there is a predicted sign and based on two-tailed tests otherwise. Variable definitions are in Appendix B.

TABLE 6 (continued)

Panel A	Predicted Sign	Dependent variable *ACCtax* (1)	*ACCpteps* (2)	*ACCetr* (3)
Intercept	?	-0.0011***	-0.0102***	-0.1397***
		(-2.99)	(-6.46)	(-4.97)
CLEAN	+	0.0004***	0.0006***	0.0326***
		(7.19)	(3.67)	(8.10)
MIMIC	-	-0.0005***	-0.0011***	-0.0508***
		(-13.22)	(-9.01)	(-20.85)
Tax Complexity				
absΔETR	-	-0.0008***	-0.0030***	-0.1223***
		(-6.50)	(-6.26)	(-11.82)
ETR_STD	-	-0.0004***	-0.0010***	-0.0204**
		(-2.83)	(-2.88)	(-1.90)
AbsPermDiff	-	0.0001	0.0001	-0.0360***
		(0.79)	(0.33)	(-4.23)
CompExp	-	0.0011	0.0034	0.0235
		(1.80)	(1.21)	(0.47)
Foreign	-	-0.0001***	-0.0000	-0.0165***
		(-2.33)	(-0.11)	(-3.53)
LOSS	-	-0.0004***	-0.0072***	-0.1435***
		(-3.46)	(-17.33)	(-18.48)
TLCF	-	0.0001	-0.0001	-0.0058*
		(2.10)	(-0.48)	(-1.48)
RDS	-	0.0023	0.0036	0.1314
		(11.08)	(4.97)	(9.18)
RetroLegislation	-	0.0001	-0.0014**	-0.0062*
		(1.74)	(-6.07)	(-1.47)
General Complexity				
ANF	+	0.0000	-0.0000	0.0005**
		(1.63)	(-0.08)	(2.02)
BM	-	-0.0004***	-0.0024***	-0.0109**
		(-3.61)	(-3.59)	(-1.87)
LEV	-	-0.0008***	-0.0041***	-0.0480***
		(-4.37)	(-6.69)	(-3.44)
lnMV	+	0.0001***	0.0014***	0.0150***
		(4.49)	(12.44)	(7.85)
Segments	-	-0.0000*	0.0000	-0.0025
		(-1.40)	(0.54)	(-1.20)
10KSize	-	-0.0102***	-0.0446***	-0.1965
		(-2.81)	(-4.09)	(-0.63)
Controls				
ACCpteps		0.2567***		
		(35.60)		
MI		-0.0002***	-0.0007***	-0.0160***
		(-3.80)	(-3.53)	(-3.22)
Industry, Year, Quarter Effects		Yes	Yes	Yes
Number of firm-quarters		54,783	54,783	54,783
Adj. R^2		0.514	0.153	0.106

TABLE 6 (continued)

Panel B		Dependent variable		
		ACCtax	*ACCpteps*	*ACCetr*
		(1)	(2)	(3)
Intercept		-0.0005*	-0.0035**	-0.0836***
		(-1.85)	(-2.85)	(-3.39)
CLEAN	+	0.0004***	0.0009***	0.0398***
		(8.44)	(5.40)	(9.54)
MIMIC	-	-0.0005***	-0.0013***	-0.0595***
		(-14.75)	(-10.04)	(-23.31)
TAXPRIN1		-0.0000	-0.0009***	-0.0365***
		(-0.35)	(-6.40)	(-9.25)
TAXPRIN2		-0.0001	0.0006***	0.0055
		(-1.55)	(4.40)	(1.32)
TAXPRIN3		0.0002***	0.0011***	0.0251***
		(5.41)	(6.48)	(6.16)
GENPRIN1		0.0003***	0.0018***	0.0303***
		(6.98)	(13.65)	(10.44)
GENPRIN2		-0.0003***	-0.0016***	-0.0218***
		(-3.64)	(-3.58)	(-2.96)
GENPRIN3		-0.0001**	-0.0007***	-0.0046
		(-2.36)	(-4.21)	(-1.36)
*CLEAN * TAXPRIN1*		0.0001***	-0.0003*	0.0134***
		(3.16)	(-1.88)	(3.37)
*CLEAN * TAXPRIN2*		-0.0002***	-0.0005***	-0.0228***
		(-3.71)	(-3.14)	(-4.92)
*CLEAN * TAXPRIN3*		-0.0003***	-0.0006***	-0.0176***
		(-5.98)	(-3.41)	(-4.15)
*CLEAN * GENPRIN1*		-0.0001**	-0.0002	-0.0147***
		(-3.23)	(-1.42)	(-5.00)
*CLEAN * GENPRIN2*		0.0000	-0.0001	0.0081
		(0.26)	(-0.33)	(1.17)
*CLEAN * GENPRIN3*		-0.0000	-0.0002	0.0021
		(-0.36)	(-1.42)	(0.64)
ACCpteps		0.2590***		
		(36.03)		
MI		-0.0003***	-0.0007***	0.0200***
		(-4.03)	(-3.09)	(-3.86)
Industry, Year, Quarter Effects		Yes	Yes	Yes
Number of firm-quarters				
Adj. R^2		0.513	0.132	0.091

TABLE 7
Consensus Analyst Quarterly Pre-Tax Earnings, Implied Tax Expense, and Implied ETR Forecast Errors and Information in the Interim ETR Estimate

This table presents the results of estimating the following specification:

$AFE_{j,q,t} = \alpha_0 + \alpha_1 lagAFEateps_{j,q,t} + \alpha_2 \Delta ETR\_Inc_{j,q\text{-}1,t} + \alpha_3 \Delta ETR\_Dec_{j,q\text{-}1,t} + A \sum TaxComplexity$
$+ B \sum GeneralComplexity + \gamma_3 MI_{j,q,t} + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t}$

Columns 1 and 4, 2 and 5, and 3 and 6 present the respective results of estimating the above specification for signed forecast errors in implied effective tax rate, pre-tax earnings, and implied tax expense forecasts. We add controls for the pre-tax forecast error (*AFEpteps*) in Columns 3 and 6. T-statistics are in parentheses and are based upon standard errors clustered at the firm level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on two-tailed tests. Variable definitions are in Appendix B.

TABLE 7 (continued)

	Dependent variable					
	AFEetr	*AFEpteps*	*AFEtax*	*AFEetr*	*AFEpteps*	*AFEtax*
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0182	-0.0001	0.0005	0.0185	-0.0000	0.0005*
	(0.75)	(-0.08)	(1.60)	(0.77)	(-0.02)	(1.68)
lagAFEateps	0.0987	0.3668***	-0.0292	0.0882	0.3667***	-0.0292***
	(0.31)	(13.27)	(-3.43)	(0.28)	(13.28)	(-3.44)
AFEpteps			0.2523**			0.2523***
			(27.25)			(27.27)
absΔETR_Inc	0.0012	0.0014**	-0.0001	0.0002	0.0012	-0.0006
	(0.07)	(2.22)	(-0.52)	(0.01)	(1.13)	(-1.58)
absΔETR_Dec	0.0470***	0.0014*	0.0001	0.0245	0.0012	0.0005
	(2.69)	(1.66)	(0.54)	(0.79)	(0.80)	(1.26)
*absΔETR_Inc * Discrete_Pos*				-0.0146	-0.0006	0.0008
				(-0.43)	(-0.42)	(1.44)
*absΔETR_Inc * Discrete_Neg*				0.0122	0.0013	0.0009
				(0.38)	(0.98)	(1.59)
*absΔETR_Dec * Discrete_Pos*				0.0011	0.0007	0.0001
				(0.03)	(0.37)	(0.19)
*absΔETR_Dec * Discrete_Neg*				0.0756*	-0.0001	-0.0010
				(1.66)	(-0.03)	(-1.47)
Discrete_Pos				0.0021	-0.0003	-0.0002***
				(0.44)	(-0.27)	(-3.42)
Discrete_Neg				-0.0011	-0.0003	-0.0000
				(-0.23)	(-1.47)	(-0.11)
MI	0.0106**	0.0003	0.0001	0.0101**	0.0003*	0.0001
	(2.50)	(1.36)	(0.80)	(2.28)	(1.69)	(1.51)
Tax complexity controls	Yes	Yes	Yes	Yes	Yes	Yes
General complexity controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year, Quarter Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of firm-quarters	48,100	48,100	48,100	48,100	48,100	48,100
Adj. R^2	0.005	0.095	0.387	0.006	0.095	0.387

TABLE 8
Determinants of Issuance of Pre-Tax Earnings Forecasts to I/B/E/S

This table provides analysis of individual analysts' issuance of pre-tax earnings forecasts to I/B/E/S. Panel A of this table contains analysis of the items forecast in I/B/E/S, across all analyst forecasts of quarterly earnings issued during 2003 to 2012. Column 1 of Panel A provides information on the type of quarterly forecasts provided to I/B/E/S during the year for analysts who issue EPS forecasts to I/B/E/S, while column 2 (3) provides this information for analysts who issue EPS and sales forecasts (EPS and pre-tax forecasts) to I/B/E/S.

Panel B presents the results of estimating variations of the following specification:

$$\Pr(PTIssue_{i,j,t}) = \alpha_0 + \alpha_1 SalesIssue_{i,j,t} + \alpha_2 PTIssue_{i,j,t-1} + \alpha_3 BSIZE_{i,t} + \alpha_4 FEXP_{i,j,t} + \alpha_5 FREQ_{i,j,t} + \alpha_6 GEXP_{i,t} + \alpha_7 Horizon_{i,j,t} + \alpha_8 NCOS_{i,t} + \alpha_9 abs\Delta ETR_{j,q-1,t} + \alpha_{10} CompExp_{j,t-1} + \alpha_{11} ETR\_STD_{j,t-1} + \alpha_{12} Foreign_{j,t-1} + \alpha_{13} LOSS_{qt} + \alpha_{14} absPermDiff_{j,t-1} + \alpha_{15} RDS_{j,t-1} + \alpha_{16} RetroLegislation_q + \alpha_{17} TLCF_{j,t-1} + \alpha_{18} ANF_{j,t} + \alpha_{19} BM_{j,t-1} + \alpha_{20} LEV_{j,t-1} + \alpha_{21} lnMV_{j,t-1} + \alpha_{22} Segments_{j,t-1} + \alpha_{23} 10KSize_{j,t-1} + \text{Industry}_j + \text{Year}_t + \varepsilon_{j,q,t}$$

In Panel B, the intercept is not shown. Standard errors are in parentheses and are clustered at the firm level. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively, based on two-tailed tests. Variable definitions are in Appendix B.

Panel A: Analysis of Items Forecast in I/B/E/S

Type of Forecast:	Analysts Issuing EPS Forecasts (1)	Analysts Issuing EPS and Sales Forecasts (2)	Analysts Issuing EPS and Pre-Tax Forecasts (3)
(1) EPS	1.00	1.00	1.00
(2) Sales	0.35	1.00	0.88
(2) Pre-Tax Earnings	0.30	0.75	1.00
(3) After-Tax Earnings	0.33	0.82	0.98

TABLE 8 (continued)

Panel B: Probit model of likelihood that pre-tax forecast is issued

	(1)		(2)		(3)	
SalesIssue					1.9532***	(0.0066)
PTIssue$_{t-1}$			1.7741***	(0.0056)	1.7035***	(0.0068)
BSIZE	-0.0408***	(0.0089)	-0.0353***	(0.0101)	-0.0464***	(0.0121)
FEXP	-0.0159**	(0.0072)	0.0368***	(0.0082)	0.0769***	(0.0098)
FREQ	0.1112***	(0.0078)	0.1144***	(0.0089)	0.0951***	(0.0106)
GEXP	0.0114	(0.0080)	0.0295***	(0.0091)	0.0533***	(0.0109)
Horizon	0.0683***	(0.0099)	0.0652***	(0.0112)	0.0481***	(0.0134)
NCOS	0.0788***	(0.0079)	0.0750***	(0.0089)	-0.0231**	(0.0107)
absΔETR	0.0112***	(0.0066)	0.0033	(0.0075)	-0.0069	(0.0090)
CompExp	2.5054***	(0.1313)	2.1867***	(0.1457)	0.6612***	(0.1731)
ETR_STD	0.0421***	(0.0082)	0.0462***	(0.0092)	0.0315***	(0.0106)
Foreign	-0.0062**	(0.0058)	-0.0313***	(0.0067)	-0.0396***	(0.0079)
LOSS	-1.5487***	(0.0057)	-1.9233***	(0.0066)	-1.1730***	(0.0081)
absPermDiff	0.0189**	(0.0083)	0.0347***	(0.0093)	0.0078	(0.0111)
RDS	1.003***	(0.0200)	1.0700***	(0.0225)	0.7665***	(0.0263)
RetroLegislation	0.2027***	(0.0082)	0.2696***	(0.0094)	0.1803***	(0.0113)
TLCF	0.0120***	(0.0047)	0.0145***	(0.0054)	0.0049	(0.0065)
ANF	0.0081***	(0.0004)	0.0034***	(0.0004)	0.0002	(0.0005)
BM	0.0630***	(0.0065)	0.1144***	(0.0073)	0.0715	(0.0086)
LEV	-0.0583***	(0.0159)	0.0545***	(0.0180)	0.0099	(0.0214)
lnMV	-0.1095***	(0.0025)	-0.0744***	(0.0028)	-0.0677***	(0.0034)
Segments	-0.0134***	(0.0026)	-0.0103***	(0.0030)	0.0035	(0.0037)
10KSize	-1.0140***	(0.3849)	0.3794	(0.4414)	0.4154	(0.5238)
Industry, Qtr, Year Effects	Yes		Yes		Yes	
Number of analyst-firm-quarters	464,718		464,718		464,718	
Pseudo R^2	0.345		0.585		0.752	
% Concordant	80.4		89.9		95.5	