Examining which tax rates investors use for equity valuation

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ABSTRACT:

Little empirical evidence exists about the tax rates investors use to forecast future payoffs in valuation models. The limited guidance available suggests investors should use the marginal tax rate (MTR), but it is unclear whether investors follow this guidance. We therefore examine the value relevance of simulated MTRs along with tax rates that are less costly to obtain. Across a battery of tests, we find that a simplified, trichotomous MTR explains firm value better than simulated MTRs, prior-year effective tax rates (ETR), prior three-year average ETRs, or prior-year industry-average ETRs. We find some evidence that the value relevance of other tax rates increases when (1) those rates reflect firm-specific tax benefits not captured by the trichotomous MTR or (2) investors have access to lower cost information that facilitates more complex tax modelling. This study advances the valuation of tax literature and informs management and standard setters of investors' use of tax information.

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1. INTRODUCTION

We examine which income tax rates investors use to forecast future after-tax payoffs for equity valuation. When valuing firms' equity, investors require a tax rate to forecast the after-tax payoffs (i.e., free cash flows, residual income) of valuation models. Thus, tax rates are critical to equity valuation. However, little empirical evidence exists about the tax rate investors use when forecasting the future payoffs of valuation models. The limited practical guidance available suggests that the marginal tax rate (MTR), which captures the present value of all taxes paid on an additional dollar of income earned today (e.g., Blouin, Core, and Guay 2010; Shevlin 1990), is the rate investors should use when forecasting future payoffs. However, simulating MTRs requires a complex algorithm that uses multiple years of taxable income forecasts as well as information about net operating loss carryforwards, income tax credits, and the alternative minimum tax. Because this information is often difficult to discern from publicly available financial statements (e.g., Hutchens 2015; Raedy, Seidman and Shackelford 2012), it is costly for the average investor to simulate an MTR.

We propose that, on average, investors incorporate taxes into forecasts of future payoffs using heuristic tax rates that are simpler to obtain and process than complex simulated MTRs. Heuristics are strategies that allow individuals to make decisions while using limited information and simpler methods that are within their processing abilities (e.g. Einhorn 1976; Gigerenzer and Gaissmaier 2011; Tversky and Kahneman 1974). Prior literature provides evidence that individuals use heuristics to address complex tasks (Payne 1976, 1982). Our prediction that investors use heuristic tax rates mirrors evidence from Graham, Hanlon, Shevlin, and Shroff (2017) that corporate managers often use simple tax rates and not simulated MTRs when making corporate investment and financing decisions.

We examine investors' use of simulated MTRs (Blouin et al. 2010) and four alternative heuristic tax rates (a trichotomous MTR, the prior-year GAAP effective tax rate (ETR), a firm average ETR, and an industry-average ETR). We refer to these alternative rates as heuristics because investors likely forecast future after-tax payoffs more quickly and/or at a lower cost using these tax rates, relative to a simulated MTR or other complex method. (Gigerenzer and Gaissmaier 2011). Additionally, each of the heuristics has unique strengths and weaknesses, making it unclear which is preferable to the average investor. First, Graham (1996) shows that a trichotomous MTR based on the sign of current-year income and the existence of tax loss carryforwards is a reasonable substitute for simulated MTRs. Further, the trichotomous MTR has fewer information gathering and processing costs and thus is potentially more accessible to investors. Next, the firm's prior-year GAAP ETR and prior three-year average GAAP ETR are salient to investors and easy to obtain because firms disclose the information needed to calculate these rates in their 10-K. These rates are also reasonable substitutes for the MTR when a firm has significant permanent book-tax differences. Finally, industry-average ETRs are a reasonable substitute for MTRs because firms in the same industry face similar tax planning opportunities and constraints. Thus, industry-average ETRs may reflect forward-looking information to the extent that some firms have yet to adopt industry-specific tax strategies.

To test our research question of which tax rates investors use to forecast future payoffs, we use the residual income model to derive annual regressions of 12-month raw returns as a function of pre-tax earnings surprise, tax surprise, and controls. For each tax rate, we calculate a distinct measure of tax surprise and then estimate separate regressions for each tax surprise measure. The explanatory power of each tax surprise model reveals how well the included tax rate reflects the tax rate investors use in equity valuation. Because equity values should incorporate expectations about the future, the tax surprise model with the highest adjusted R^2 should reflect the rate investors use, on average, to forecast future after-tax payoffs. By focusing on relative explanatory power, our methodology parallels Francis, Schipper, and Vincent (2003), who examine the relative explanatory power of various earnings measures for returns "to provide evidence about aggregate investor behavior" (126).

We find that the adjusted R^2 of the trichotomous MTR surprise model is significantly larger than the adjusted R^2 of all other tax surprise models, both on average and in 15 of the 18 years in the sample.

These findings suggest that investors recognize the theoretical appeal of marginal tax rates but rely on simplified estimations when making equity valuation decisions. These results are consistent with recent survey evidence in Graham et al. (2017) and experimental evidence in Amberger, Eberhartinger, and Kasper (2016) that individuals use heuristics when considering the tax effects of various investment options.

To supplement the explanatory power tests, we undertake two additional tests. First, we examine whether the trichotomous MTR is more value relevant for firms with net operating loss carryforwards (NOL). One appeal of the trichotomous MTR is that it provides a simple modification to the statutory tax rate that incorporates the effect of NOL deductions (Graham 1996; Shevlin 1990). We find evidence that the trichotomous MTR is even more value relevant for firms with an NOL carryforward than for the average firm in our sample. This evidence is consistent with investors considering tax losses when forecasting future after-tax payoffs. Second, we form equally-weighted hedge portfolios using the predicted values from each tax surprise model and take long (short) positions in stocks within the top (bottom) four deciles of the distribution of predicted values. We scale these tax surprise hedge returns by returns from perfect foresight returns-based hedge portfolios to generate a ratio that represents the percentage of all information in returns that is captured by each of the tax surprise models. We find hedge portfolios formed using the predicted values of the trichotomous MTR surprise model earn larger returns and explain a greater percentage of perfect foresight returns than hedge portfolios formed using predicted values from any of the other rates we test. These findings corroborate our results from the explanatory power tests and provide further evidence that investors favor a heuristic tax rate over a simulated MTR in equity valuation.

Although a trichotomous MTR is a simple, low-cost, heuristic tax rate for investors to obtain, the cost-benefit trade-off of using this rate likely varies with firm characteristics. Using a trichotomous MTR can lead to biased valuations when it is not a reasonable substitute for simulated MTRs. For example, the trichotomous MTR omits firm- and industry-specific tax information. Therefore, we conduct subsample tests to examine whether the value relevance of other tax rates increases when those rates better reflect firm-specific tax information not captured by the trichotomous MTR. We focus on firms that (1) have significant foreign income, (2) are likely eligible to receive U.S. R&D tax credits, or (3) operate in an enhanced information environment.

Governments tax the income of multinational firms at different rates depending on the source country of the income. Though most lower-taxed foreign earnings eventually face incremental U.S. tax, many U.S. multinationals defer this tax for several years. Because the trichotomous MTR is derived based on U.S. statutory tax rates and the presence of estimated tax loss carryforwards, it ignores this deferral; therefore, investors who use this rate when valuing multinational firms could overestimate the net present value of future tax costs. We find that the simulated MTR and industry-average ETRs are more value relevant for firms in the top quintile of foreign operations than for the average firm in our sample. This result is consistent with the trichotomous MTR being less informative about future taxes for multinational firms with extensive foreign operations.

Second, tax credits offer dollar-for-dollar reductions in tax expense such that using the trichotomous MTR to forecast future net income of firms with significant tax credits likely overstates expected tax costs. We focus on the U.S. credit for increasing research activities and identify eligible firms following Gupta, Hwang and Schmidt (2011). We find evidence that the simulated MTR and the industry-average ETR are more value relevant for firms eligible for R&D tax credits than for the average firm in our sample.

Finally, Liu and Thomas (2000) show that the returns-earnings association improves when investors have access to richer information sets that include information about future earnings from analysts. These enhanced information sets allow investors access to aggregated firm- and industry-specific information that could facilitate more complex tax modelling. Consistent with this notion, we find that the industry-average ETR is more value relevant for firms that operate in an enhanced information environment relative to the average firm in our sample. Overall, the results of our subsample tests are consistent with investors using tax rates other than the trichotomous MTR when those rates better reflect firm-specific tax information not captured by the trichotomous MTR.

Our study makes two important contributions. First, we advance the literature that analyzes how stakeholders incorporate taxes into investment decisions (Ayers, Jiang, and Laplante 2009; Chen and Schoderbek 2000; Hanlon, Laplante, and Shevlin 2005; Plumlee 2003; Schmidt 2006; Thomas and Zhang 2014). Finding that the trichotomous MTR has the most explanatory power for returns reveals that investors – stakeholders outside the firm – use a simplified version of the theoretically correct tax rate to forecast payoffs. These results are consistent with survey evidence from Graham et al. (2017) that corporate managers – stakeholders inside the firm – often rely on simplified tax rates when making investment decisions. Further, finding that, on average, investors primarily use the trichotomous MTR contrasts prior literature that implicitly assumes investors use a firm's prior-year tax expense to set expectations about future taxes. Therefore, these results have implications for future research examining the valuation of taxes.

Second, our study informs standard setters and managers about the tax information that is salient to investors. Our finding that investors rely heavily on the trichotomous MTR suggests they might ignore or underweight firm-specific information when making valuation decisions. However, finding that other tax rates become more value relevant when they better reflect firm-specific tax information not captured by the trichotomous MTR suggests firm-specific tax information is important to investors in certain circumstances. These results could be useful to the FASB as they consider modifications to required income tax disclosures. For example, requiring more disclosure of jurisdiction-specific income tax expense would likely enhance investors' ability to forecast future payoffs for multinational firms. Managers may also want to focus their discussion of the ETR on persistent differences between the ETR and the trichotomous MTR to allow better assimilation of firm-specific information into price.

2. RELATED LITERATURE AND SUMMARY OF TAX RATES

2.1. Overview

Income taxes are a material and recurring expense for most U.S. corporations and are therefore a critical component of firm value. From 1996 through 2013 (our sample period), the average (median) profitable Compustat firm reported income tax expense equal to 25.4% (32.3%) of pre-tax income, 3.6% (2.7%) of sales, and 2.8% (2.4%) of market capitalization. In comparison, research expenditures are 5.3% (1.8%) of sales and 3.5% (1.4%) of market capitalization.[1] These statistics reveal not only that income taxes are of sufficient magnitude to warrant investors' consideration in equity valuation but that they are perhaps one of the most significant expenses for investors to consider.

When valuing firms' equity, investors require a tax rate to forecast the after-tax payoffs (i.e., free cash flows, residual income) of valuation models.[2] Thus, tax rates are critical to equity valuation. Consistent with this notion, Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997; 1998) identify income taxes as a firm "fundamental" that explains equity prices and future earnings, providing initial evidence that income taxes are value relevant.

However, studies demonstrate that even sophisticated investors have difficulty processing the implications of income taxes for future payoffs. One potential reason is that firms disclose a significant amount of tax information in footnotes, which can hamper investors' ability to acquire information because it increases cognitive costs (e.g., Maines and McDaniel 2000). Consistent with this notion, Chen and Schoderbek (2000) find that analysts failed to properly adjust their earnings forecasts to include the effect of the statutory tax rate change from the 1993 Omnibus Budget Reconciliation Act on the deferred tax accounts even though the information required to estimate the effect was available. Similarly, Plumlee

[1] We base tax expense statistics on 91,603 Compustat observations from 1996 to 2013 with positive pre-tax income (PI), sales (SALE) and market capitalization (PRCC_F*CSHO), and non-missing total tax expense (TXT). We base the R&D expense statistics on 38,110 observations with non-missing R&D (XRD) that also meet the previous sample criteria and. We do not set missing XRD to zero to avoid biasing statistics downward. We winsorize all ratios by year (FYEAR) at one and 99 percent.

[2] Alternatively, investors may incorporate tax-adjusted discount rates into their valuations (i.e. use a higher pre-tax rate of return to discount pre-tax payoffs). Under either method, investors must choose a tax rate.

(2003) examines tax law changes from the Tax Reform Act of 1986 and finds that analysts incorporated the effect of less complicated changes into their earnings forecasts but did not incorporate the effect of more complicated changes. Weber (2009) and Kim, Schmidt, and Wentland (2015) find that analysts struggle to properly incorporate tax information into earnings forecasts even in the absence of tax law changes.

Further, there is conflicting evidence on the association between tax expense and stock returns. Hanlon et al. (2005) document a positive association between estimated taxable income and stock returns, consistent with the notion that taxable income is an alternative measure of firm performance. Further, they find that estimated taxable income has incremental power in explaining stock returns relative to pre-tax income. Building on the idea that income tax expense can serve as a proxy for economic profitability, Ayers et al. (2009) find that investors rely more (less) on taxable income as an alternative performance measure when earnings quality is low (tax planning is high). However, Thomas and Zhang (2014) show that tax expense is informative about future profitability only in model specifications that do not otherwise control for estimated future performance. In samples where earnings surprises are small and in specifications that include controls for expected future profitability, Thomas and Zhang (2014) find that investors value income tax expense as a cost that represents value lost to tax authorities (i.e., there is a negative association between tax expense and returns).

These results collectively suggest that the average investor faces substantial information gathering and processing costs to incorporate income tax expense into valuation models. Our research question addresses which tax rates investors use to forecast future payoffs. We propose that investors use heuristic tax rates to incorporate taxes into forecasts of future payoffs instead of using a more complex decision process to understand the firm- and industry-specific drivers and characteristics of firms' tax expense. This conjecture follows from the psychology literature that demonstrates people rely on simple decision mechanisms to help them process complex information; that is, "people choose shortcuts to save effort" (Gigerenzer and Gaissmaier (2011, 457). Our results are also consistent with concurrent work that analyzes other stakeholders' use of tax heuristics. Amberger et al. (2016) find in an experimental setting that participants apply heuristics based on the salience of statutory tax rates when tasked with making financing decisions under time pressure. Similarly, Graham et al. (2017) find that when evaluating investing, financing, and operating decisions, corporate managers use heuristic tax rates despite the availability of relevant firm-specific tax information that could lead to more optimal decisions. We compliment and extend this line of literature by examining investors' use of heuristic tax rates. We test which of five tax rates – simulated MTRs and four heuristic rates – are most associated with returns. We use these results to infer which tax rates investors use to calculate the future payoffs of valuation models and whether investors favor heuristic tax rates over simulated MTRs in equity valuation. Next, we discuss each of the tax rates we examine.

2.2. Tax Rates

The theoretical value of common equity is the present value of expected future after-tax payoffs (e.g., residual income, free cash flows) to common shareholders. Investors therefore must choose a tax rate to incorporate into their payoff forecasts. Academic valuation experts typically guide investors towards using the marginal tax rate when forecasting payoffs. For example, in "Damodaran on Valuation," finance professor Aswath Damodaran notes, "[c]omputing the tax effect is usually a simple exercise of multiplying the expected pre-tax operating income by the tax rate (Damodaran 2006). The only real estimation question we face is what tax rate to use – marginal or effective." Damodaran further expands on this rate choice on his website and highlights situations in which the rates most likely differ. In particular, he notes the difficulty that arises in selecting the appropriate tax rate when valuing multinational firms, firms with tax credits, and firms with NOL carryforwards. In "Financial Statement Analysis and Security Valuation," author Stephen Penman suggests investors use marginal tax rates, which he defines as "… the highest rate at which income is taxed…" but then further clarifies that, "… the marginal tax rate is *almost always* the maximum statutory tax rate for federal and state taxes combined" (Penman 2013, 305-306)(*emphasis added*).[3] Thus, even informed investors may struggle to understand which tax rate is most appropriate to include in valuation models.

We examine which of five tax rates investors use in equity valuation: (1) the Blouin et al. (2010) simulated marginal tax rate (*BCG_MTR*); (2) a trichotomous marginal tax rate in the spirit of Graham (1996) (*Tri_MTR*); (3) the firm's prior-year ETR (*PY_ETR*); (4) the average of the firm's three prior annual ETRs (*FirmAvg_ETR*); and (5) the prior-year industry-average ETR (*IndAvg_ETR*). We acknowledge that this set of rates is not exhaustive.[4] However, we believe these rates represent and are highly correlated with those used by investors. For example, investors might use a longer-run firm-average ETR that would be highly correlated with our three-year measure.

2.2.1. Marginal Tax Rates

The marginal tax rate is the present value of current and expected future taxes paid on an additional dollar of income earned today (Graham 1996). Thus, estimating the MTR requires an understanding of how an additional dollar of income will affect income taxes in the current year and future years. Several complexities of the U.S. tax code, including the treatment of NOLs, the availability of tax credits, and the Alternative Minimum Tax, make it computationally intensive to estimate a firm-specific MTR (Graham 1996). Graham et al. (2017) find that even corporate managers, who have more complete information regarding the timing and character of expected future cash flows than investors do, often do not use the MTR when evaluating incremental decisions.

The MTR is even more difficult for those outside the firm to estimate. Estimating MTRs involves quantifying all NOL and tax credit carryforwards available as of the end of year *t* and then simulating

[3] Penman (2013) articulates the difference between marginal and effective tax rates and discourages investors from using the GAAP ETR.

[4] Another possible heuristic rate is the top U.S. statutory tax rate, which Graham (1996) concludes is a reasonable proxy for simulated MTRs. The statutory rate is also likely salient to investors (and easily obtained) because SEC registrants reconcile their ETR to the statutory tax rate in their tax footnotes. However, the top U.S. statutory tax rate equals 35% during our entire sample period. Therefore, we exclude the U.S. statutory tax rate from our analysis because the statutory rate does not vary over time. However, as discussed in more detail below, we view *Tri_MTR* as a modified statutory tax rate because it incorporates the effect of net operating losses into the statutory tax rate.

future taxable income from year *t* through the end of the carryforward period for all tax attributes. Most academic research papers that estimate MTRs assume taxable income follows a random walk with a drift and simulate realizations of taxable income using a normally distributed, zero-mean random variable (Graham 1996, Shevlin 1990). The present value of incremental taxes due on an additional dollar of taxable income is then determined after considering NOLs, tax credits, and the effect of the Alternative Minimum Tax. Other simulations use different taxable income forecasts. For example, Blouin et al. (2010) "use a non-parametric approach to estimate future taxable income" (195). The non-parametric approach requires simulations of the entire distribution of future taxable income and generates estimated distributions with less bias than those generated using a random-walk procedure. We use the Blouin et al. (2010) simulated marginal tax rates, available through 2012 on WRDS, as one potential tax rate investors can use in equity valuation (*BCG_MTR*).

Graham (1996) acknowledges the potential complexity in estimating MTRs and finds that a trichotomous rate based on the sign of estimated taxable income and the existence of tax loss carryforwards is a reasonable alternative. The second tax rate we examine, *Tri_MTR*, is equal to (1) the top statutory rate if a firm has both positive pre-tax income and no tax loss carryforwards, (2) one-half of the top statutory tax rate if a firm has either positive pre-tax income or no tax loss carryforwards, and (3) zero otherwise. This rate can therefore be considered a hybrid between the MTR and the statutory tax rate; it essentially modifies the top U.S. statutory rate to incorporate the effect of tax loss carryforwards, which are a critical input to simulated MTRs.

2.2.2. Effective Tax Rates

The firm's prior-year ETR is another alternative to the MTR. Because corporations must present information about both their current and prior-year taxes in the annual report and frequently discuss differences between the two, the prior-year ETR is salient to investors. Additionally, U.S. GAAP and SEC disclosure rules require firms to present two prior years of tax expense and pre-tax income on the face of the income statement, allowing investors to easily calculate prior-year ETRs without relying on footnote disclosures. The prior-year ETR also has the advantage of providing recent information about firm-specific characteristics – such as significant permanent book-tax differences or significant foreign income taxed at rates different from the U.S. rate – that contribute to a firm's ability and willingness to avoid tax.

Investors' cost to obtain a firm's prior-year ETR (*PY_ETR*) is low, but improper use may bias estimated future tax payoffs. Periodic settlements with taxing authorities, significant one-time corporate transactions, and earnings management through the tax accrual (Dhaliwal, Gleason and Mills 2004) are all items that add noise to the annual ETR as a proxy for future tax payoffs, and firms' tax disclosures may be insufficient to allow investors to isolate the persistent components of tax expense. Raedy et al. (2012) collect detailed tax footnote data and document that 90% of the rate reconciliations in their sample include a line entitled "Other," "Miscellaneous," or a similarly vague description that gives no information about the underlying transactions. Raedy et al. (2012) state, "During the process of collecting, interpreting, and categorizing the information, we were repeatedly struck by the difficulty in understanding these data" (9). Similarly, Hutchens (2015) estimates that only 24% of firms in her sample discuss year-over-year changes in the ETR, making it difficult for investors to distinguish between transitory and persistent changes.

Multi-year or multi-firm averages can mitigate problems arising from noise in firm-year measures and from opacity in tax disclosures. Investors can average tax rates over multiple periods to arrive at a firm-average ETR (e.g., Dyreng, Hanlon, and Maydew 2008), which will reduce the effect of deviations from normal trends and can therefore be a more reasonable alternative to the MTR than single-year measures. However, to the extent that annual deviations contain information rather than noise, taking an average masks this information. Keeping with the spirit of a heuristic tax rate, which is relatively easy to obtain, we use only the information included in a single annual report and calculate *FirmAvg_ETR* over a three-year window.[5] Specifically, *FirmAvg_ETR* is the average ETR from *t*–3 through *t*–1; we define the ETR as (TXT/PI).

Industry-average tax rates are also relevant to the extent firms in the same industry have comparable income tax avoidance opportunities and are similarly affected by changes in tax legislation (e.g., Balakrishnan, Blouin, and Guay 2012). Prior studies show that analysts and investors frequently use industry-average performance to set expectations about and evaluate firm-specific performance (Lev 1989). Industry-average tax rates can therefore provide information about potential changes or trends that are not yet reflected in a particular firm's tax expense. However, an industry rate is more difficult for investors to calculate because it requires cumulating information across multiple companies and knowing at what level to define an industry.[6] We include *IndAvg_ETR* to capture the average ratio of tax expense to pre-tax income in a given industry and calculate *IndAvg_ETR* as the firm's industry-average *ETR* in year *t*–1, where we define industry using the Fama-French 30 industry classification.

To summarize, we propose that investors weigh the relative costs and benefits of various tax rates when impounding taxes into firm value. Although the MTR is the most theoretically sound choice, it can be costly to estimate. Therefore, we anticipate that investors rely on other heuristic tax rates that allow them to ignore some information and thus impound taxes into firm value more quickly and with lower cost than they could with a simulated MTR. Because each of the rates discussed above has unique strengths and weaknesses that vary based on firm-specific circumstances, it is not clear, *ex ante*, which are

[5] We aim to test which rate best summarizes the tax information market participants use in year *t*. SEC Regulation S-X, Rule 3.02 requires registrants to file audited statements of income for each of the three fiscal years preceding the date of the most recent audited balance sheet being filed. Rule 4-08(h) requires various information related to income tax expense to be disclosed in the income statement or in the footnotes for each statement required to be filed. Thus, the most recent annual information available at the beginning of the concurrent return window for year *t* is the annual report containing tax information for years *t*–1, *t*–2, and *t*–3.

[6] To serve as a reasonable proxy for the MTR, the industry-average ETR must effectively combine firms with similar opportunities for income tax avoidance. Common industry definitions include one-, two-, or three-digit SIC codes, as well as other groupings based on 4-digit codes such as those provided by Fama and French. Researchers also use GCIS and NAICS codes. For example, Lev (1989) classifies industry using two-digit SIC codes while Balakrishnan et al. (2012) and Dyreng et al. (2008) use the Fama and French 30 classification.

associated with firm value. Thus, we make no predictions about which rate(s) investors use and instead examine this question empirically.

3. RESEARCH METHOD

3.1. Regression Specification

We use the residual income model as the foundation for our empirical design. The residual income model suggests that investors' primary objective in equity valuation is forecasting future after-tax payoffs (e.g., net earnings).[7] To reflect how investors' forecasts affect valuations in a regression framework, we provide a brief discussion that describes how accounting numbers link to stock returns. In a "perfect" fair value accounting system, price (market value) will equal the book value of equity, and a change in price (ΔP_t) will equal the change in book value (ΔB_t). However, U.S. GAAP includes a mixture of historical cost and fair value accounting such that the book value of equity measures price with error. Thus, returns equal the change in book value plus the change in the market premium over book value ($(P_t - B_t) - (P_{t-1} - B_{t-1})$):

$$P_t = B_t + (P_t - B_t) \tag{1}$$
$$(P_t - P_{t-1}) = \Delta B_t + ((P_t - B_t) - (P_{t-1} - B_{t-1})) \tag{2}$$

At the end of each period, accountants must update the beginning-of-period book value using the clean surplus relation. Substituting $\Delta B_t = Earnings_t - d_t$ into equation (2) and rearranging, we arrive at:

$$(P_t - P_{t-1} + d_t) = Earnings_t + ((P_t - B_t) - (P_{t-1} - B_{t-1})) \tag{3}$$

Equation (3) shows that the unscaled stock return equals earnings plus the change in the market premium over book value. If we divide equation (3) through by the price at the beginning of the period (P_{t-1}) and allow information about current growth (i.e., $P_t - B_t$) to fall into the residual, we have a return regression that links accounting information and valuation:

$$(P_t - P_{t-1} + d_t)[P_{t-1}]^{-1} = Ret_t = \Gamma_0 + \Gamma_1 Earnings_t[P_{t-1}]^{-1} + \Gamma_2 B_{t-1}[P_{t-1}]^{-1} + \varepsilon_t \tag{4}$$

[7] We present a simple derivation of the residual income model in the Appendix. For further insight, see Ohlson (1995) and Feltham and Ohlson (1995).

The objective of our paper is to determine which tax rate investors use when forecasting earnings. Therefore, we decompose $Earnings_t$ from equation (4) into income statement components that investors might use to forecast earnings. If investors forecast earnings on a pretax basis and calculate tax expense by multiplying the forecasted pretax income by a tax rate, then $Earnings_t$ = Pretax Income (PI_t) – $TaxExpense_t$, where $TaxExpense_t = (TXT_t/PI_t) \times PI_t$. Hence, equation (4) becomes:

$$Ret_t = \Gamma_0 + \Gamma_1 PI_t[P_{t-1}]^{-1} + \Gamma_2 TaxExpense_t[P_{t-1}]^{-1} + \Gamma_3 B_{t-1}[P_{t-1}]^{-1} + \varepsilon_t \tag{5}$$

However, prior research documents associations between stock returns and *unexpected* earnings. We thus substitute *surprises* in pretax income (*PI_Surprise*) and tax expense (*Tax_Surprise*) for the levels of each variable (*PI* and *TaxExpense*, respectively), which results in equation (6):

$$Ret_t = \Gamma_0 + \Gamma_1\, PI\_Surprise_t[P_{t-1}]^{-1} + \Gamma_2 Tax\_Surprise_t[P_{t-1}]^{-1} + \Gamma_3 B_{t-1}[P_{t-1}]^{-1} + \varepsilon_t \tag{6}$$

Prior studies typically assume that both pretax income and tax expense follow a random walk and measure income/expense surprise using one-year changes in either pretax income or tax expense (e.g., Lev and Thiagarajan 1993; Thomas and Zhang 2014).[8] That is:

$$PI\_Surprise_{it} = (PI_t - PI_{t-1}) \tag{7}$$
$$Tax\_Surprise_{it} = (TXT_t - ((TXT_{t-1}[PI_{t-1}]^{-1}) \times PI_{t-1})) \tag{8}$$

We measure $PI\_Surprise_{it}$ as the one-year change in pretax income, consistent with equation (7). Our innovation is that we do not use equation (8) to measure $Tax\_Surprise_{it}$. Instead, we substitute one of the five tax rates (*TaxRate*) for $(TXT_{t-1}[PI_{t-1}]^{-1})$ into equation (8):

$$Tax\_Surprise_{it} = (TXT_t - (TaxRate \times PI_{t-1})) \tag{9}$$

where *TaxRate* = *BCG_MTR, Tri_MTR, PY_ETR, FirmAvg_ETR* or *IndAvg_ETR*. This allows $Tax\_Surprise_{it}$ to reflect alternative investor expectations of year *t* tax expense depending on which tax rate investors use when forecasting the payoffs of valuation models.

[8] Some studies use analysts' consensus earnings forecasts as a proxy for investors' income expectations. However, IBES' coverage of *pre-tax* income forecasts is limited, especially prior to 2003 (Mauler 2015). Thus, relying on IBES for pre-tax income forecasts to generate pre-tax income surprise would reduce our sample dramatically. Our analysis focuses on the *relative* explanatory power of the models we test and holds the value of pre-tax income surprise constant across models. Thus, we have no reason to believe that our results would change if we used an alternative measure of pre-tax income surprise.

We define Ret_{it} as the cumulative raw return to security i over a 12-month window beginning at the start of the fourth month of year t and ending at the end of the third month of year t+1. We include the natural log of the book-to-market ratio in t–1 (*LogBM*) as our proxy of $B_{t-1}[P_{t-1}]^{-1}$ and two control variables for the change in market premium, the natural log of market value of equity in t–1 (*LogMVE*) and the prior year's 12-month return (Ret_{t-1}) (Thomas and Zhang 2014). Finally, we control for losses (*Loss*) with an indicator variable equal to one for firms reporting negative pre-tax income in year t–1, and zero otherwise (Balachandran and Mohanram 2011). We interact *Loss* with all regression variables because Hayn (1995) indicates that the information content of accounting variables differs for firms that report losses. The preceding discussion suggests the following annual cross-sectional regression:

$$\begin{aligned} Ret_{it} = {} & \Gamma_0 + \Gamma_1 PI\_Surprise_{it} + \Gamma_2 Tax\_Surprise_{it} + \Gamma_3 LogBM_{it-1} + \Gamma_4 Loss_{it-1} + \\ & \Gamma_5 PI\_Surprise_{it} \times Loss_{it-1} + \Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1} + \Gamma_7 LogBM_{it-1} \times Loss_{it-1} + \\ & \textstyle\sum \Gamma_j Controls_{it-1} + \sum \Gamma_k Controls_{it-1} \times Loss_{it-1} + \varepsilon_t \end{aligned} \tag{10}$$

3.1.1. Explanatory Power Tests

We develop the above regression to test our research question: which measure of tax surprise, and therefore which tax rate, investors use in equity valuation. Francis et al. (2003) examine the association between long-window returns and various measures of firm performance and suggest that the model that has the greatest explanatory power for returns includes the performance metric that is a "relatively good … summary indicator of the information actually used by investors" (p. 126). This is equivalent to testing the relative information content of the tax surprise models; the tax surprise model that has the greatest explanatory power for returns (i.e., R^2) includes the tax rate that best summarizes the tax information investors use.

We estimate equation (10) annually for each measure of tax surprise and calculate a Vuong (1989) z-statistic to test whether the explanatory power of any tax surprise model is significantly higher than the explanatory power of all other models in that year. We consider the model that has the largest adjusted R^2 in the greatest number of years as the one that contains the tax rate investors use in equity valuation. We classify insignificant differences in the explanatory power each year between models as "ties." Similar explanatory power across multiple models is consistent with similar investor preference for the tax rates included in the models, on average.

3.1.2. Portfolio Return Tests

To supplement our explanatory power tests, we follow Francis and Schipper (1999) and Hanlon et al. (2005) and use a hedge portfolio returns test. The portfolio returns test measures the total return that an investor could earn from perfect foreknowledge of different types of accounting information. Consistent with the above specification, we compute 12-month contemporaneous returns, beginning at the start of the fourth month of year *t* and ending at the end of the third month of year *t*+1, to hedge portfolios based on the predicted values from our various tax surprise models. To construct the hedge portfolio, we estimate equation (10) separately for each *Tax_Surprise* measure and use the annual coefficient estimates to rank year *t* observations based on the predicted values of the dependent variable:

$$\begin{aligned} Ret_{it}^{Tax\_Surprise} = {} & \widehat{\Gamma_0} + \widehat{\Gamma_1 PI\_Surprise_{it}} + \widehat{\Gamma_2 Tax\_Surprise_{it}} + \widehat{\Gamma_3 LogBM_{it-1}} + \widehat{\Gamma_4 Loss_{it-1}} + \\ & \widehat{\Gamma_5 PI\_Surprise_{it} \times Loss_{it-1}} + \widehat{\Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1}} + \widehat{\Gamma_7 LogBM_{it-1} \times Loss_{it-1}} + \\ & \widehat{\sum \Gamma_j Controls_{it-1}} + \widehat{\sum \Gamma_k Controls_{it-1} \times Loss_{it-1}} \end{aligned} \quad (11)$$

Thus, we form five separate tax surprise hedge portfolios; each hedge portfolio consists of long positions in the highest 40% of the predicted values of $Ret_{it}^{Tax\_Surprise}$ and short positions in the lowest 40% of the predicted values of $Ret_{it}^{Tax\_Surprise}$. We consider the model with the largest average hedge return to contain the tax rate that investors view as most value relevant.

To help assess the economic magnitude of the $Ret_{it}^{Tax\_Surprise}$ hedge portfolio returns, we also compute the returns to a perfect foresight *returns-based* hedge portfolio (Francis and Schipper 1999; Hanlon et al. 2005). For this portfolio, we take long (short) positions in the stocks from each $Ret_{it}^{Tax\_Surprise}$ hedge portfolio with positive (negative) 12-month raw returns, which we refer to as Ret_{it}^{Sign}. We then scale each $Ret_{it}^{Tax\_Surprise}$ hedge portfolio return by Ret_{it}^{Sign}, the perfect foresight returns-based hedge portfolio. The resulting ratio, *%MKT,* captures the proportion of information in security returns reflected in each

$Ret_{it}^{Tax\_Surprise}$ hedge portfolio. Specifically, *%MKT* = $Ret_{it}^{Tax\_Surprise}$ [Ret_{it}^{Sign}]$^{-1}$. Similar to the interpretation of $Ret_{it}^{Tax\_Surprise}$, we consider the tax surprise model that explains the largest portion of perfect foresight returns to contain the tax rate that investors view as most value relevant.

3.2. Sample

We present our sample selection process in Table 1. We begin with all firm-year observations in the intersection of Compustat and CRSP with data necessary to calculate all regression variables. We want all of the observations in our sample subject to the same accounting for income taxes (ASC 740); therefore, the first year of the sample is 1993. *FirmAvg_ETR* requires three years of data, so our regression period begins in 1996. WRDS reports the Blouin et al. (2010) simulated MTR through 2012, which allows us to calculate *BCG_MTR_Surprise* through 2013. We require all observations to have sufficient data to calculate each of the tax rates and tax surprises we examine so that differing results across model specifications are not due to changes in sample composition. Therefore, we end the sample in 2013 even though data are available beyond 2013 for the other tax rates we examine.[9]

[Insert Table 1 here.]

Consistent with prior work (e.g., Thomas and Zhang 2014), we do not eliminate observations with extreme values of *ETR* in year *t* or *t*–1 but instead winsorize all regression variables (including all values of *Tax_Surprise*) at the top and bottom one percent by year. To calculate meaningful industry-average ETRs, we require each industry to have at least 10 observations per year. Our full sample consists of 65,714 firm-year observations from 8,860 unique firms. Firms are in our sample for 7.4 years, on average (five years at the median). We also create three subsamples for additional tests: (1) firms with significant foreign earnings, defined as the highest quintile of foreign income to total assets (PIFO/AT); (2) firms that are likely eligible for the U.S. credit for increasing research activities (i.e., the U.S. R&D credit), identified

[9] Inferences remain unchanged if we test the remaining models on a sample through 2015.

following Gupta et al. (2011); and (3) firms with an enhanced information environment, identified using the sample selection procedures outlined in Liu and Thomas (2000).

4. MAIN RESULTS

4.1. Descriptive Statistics and Correlations

Table 2 reports descriptive statistics for the five tax rates we test. Average values for the rates are 24.87% for *BCG_MTR,* 22.98% for *Tri_MTR,* 20.80% for *PY_ETR*, 20.97% for *FirmAvg_ETR*, and 20.75% for *IndAvg_ETR*.

[Insert Table 2 here.]

Ret is positive on average and at the median. Except for *PY_ETR_Surprise,* all average measures of *Tax_Surprise* are positive indicating that total reported tax expense exceeds the expected tax expense we construct using the different tax rates, on average. All values of *Tax_Surprise* are positive at the median. *PY_ETR_Surprise* has the smallest average value (-0.0033), while *IndAvg_Surprise* has the largest (0.0229). *NI_Surprise* and *PI_Surprise* are negative on average (positive at the median) and 32% of observations report pre-tax income less than zero. Firms are large, with average market value of equity in excess of $3B (untabulated).

Table 3 provides Pearson and Spearman correlations among regression variables in the full sample. Pearson correlations are listed above the diagonal with Spearman correlations below. Most *Tax_Surprise* variables are significantly correlated with two-tailed *p*-values ≤ 10 percent.

[Insert Table 3 here.]

4.2. Results

4.2.1. Explanatory Power Tests

Table 4 presents adjusted R^2s from annual regressions of equation (10). For parsimony, we refer to each model by referencing the underlying tax rate used to calculate *Tax_Surprise.* Results indicate that the adjusted R^2 of the *Tri_MTR* model is significantly higher than that of every other model in 15 of the

18 years; only the *BCG_MTR* model generates an adjusted R^2 that is statistically equivalent in any year.[10] The explanatory power of the *Tri_MTR* model averages 16.56% and ranges from a low of 9.30% in 2010 to a high of 29.71% in 2009.[11]

[Insert Table 4 here.]

We also graph explanatory power in Figure 1 to better illustrate time-series trends. The tax surprise models have the greatest explanatory power immediately following periods of economic crisis, such as in 2003 after the burst of the dot com bubble, the terrorist attacks of September 11, 2001 and following the financial crisis of 2007-2008. The graph also highlights variation in the extent to which the explanatory power of the models differs over time.

[Insert Figure 1 here.]

Overall, the results in Table 4 and Figure 1 suggest that *Tri_MTR* is the most value-relevant tax rate we test. Because *Tri_MTR* modifies the top U.S. statutory tax rate to incorporate the effect of NOLs, we expect results for a subsample of firms with NOL carryforwards (i.e., where TLCF > 0) to be at least as strong as those in the full sample. Consistent with this expectation, we find that the *Tri_MTR* model outperforms all other models in 16 of the 18 years in the NOL subsample (results untabulated). These results are consistent with investors recognizing the valuation implications of tax loss carryforwards and incorporating their beneficial effects into price.

We also test whether the explanatory power results are sensitive to our research design choices. Recall that we do not eliminate observations or winsorize extreme values of ETR_{t-1} but instead winsorize all regression variables (including all values of *Tax_Surprise*) at the top and bottom one percent by year. In untabulated tests, we confirm that the results in Table 4 are not sensitive to this design choice.

[10] In untabulated tests, we estimate a version of equation (10) that includes only a random-walk net income surprise. We find that the adjusted R^2 of this model is significantly lower than any of the models that decompose net income surprise into pre-tax income and tax expense components. These results suggest that tax expense has incremental value relevance.

[11] We also note that similar to the variation observed in the *Tax_Surprise* models, the average adjusted R^2 of the net income model varies greatly, from a low of 3.93% in 2010 to a high of 27.59% in 2009, averaging 11.40% over the period.

Specifically, we re-estimate the *PY_ETR* model after eliminating 9,176 observations where ETR_{t-1} lies outside of [0, 1]. The average adjusted R^2 of the *PY_ETR* model increases slightly from 12.15% to 13.00%, but the *Tri_MTR* model continues to exhibit the highest explanatory power. Therefore, we conclude that including extreme values of prior year ETRs does not drive the low explanatory power of the *PY_ETR* model. We also eliminate observations where the firm reports a loss in the current year but profit in the prior year; Liu and Thomas (2000) find that these firms contribute to lower earnings response coefficients and R^2. Inferences in Table 4 remain unchanged after eliminating these firms with this "unusual" pattern of losses (Liu and Thomas 2000).

4.2.2. Portfolio Return Tests

Table 5 presents the hedge portfolio results. We report the average return to each tax surprise hedge portfolio in Panel A and the proportion of the returns to the perfect foresight returns-based hedge portfolio explained by each tax surprise measure in Panel B. The average return over the entire sample period is 24.79% for the *Tri_MTR* portfolio, 23.54% for the *IndAvg_ETR* portfolio, 23.49% for the *BCG_MTR* portfolio, 22.30% for the *FirmAvg_ETR* portfolio, and 22.09% for the *PY_ETR* portfolio. Thus, Panel A shows that the average hedge return to each tax surprise portfolio is significantly different from zero, and the average return to the *Tri_MTR* portfolio is significantly larger than the average returns to the other four tax surprise hedge portfolios. Consistent with the results in Panel A, results presented in Panel B show the *Tri_MTR* portfolio explains a significantly higher percentage of perfect foreknowledge returns (*%MKT* = 45.24%) than the other tax surprise portfolios (e.g., the *IndAvg_ETR* portfolio explains 42.53% of perfect foreknowledge returns).[12] The results in Tables 4 and 5 allow us to conclude that, on average,

[12] In untabulated tests, we repeat the portfolio returns tests using market- and size-adjusted returns and 16-month return windows. Whereas the main tests use 12-month raw returns beginning at the start of the fourth month of year *t* and ending at the end of the third month of year *t*+1, we measure the 16-month return window beginning on the first day of the first month of year *t* and ending on the last day of the fourth month of year *t*+1. Inferences from these tests do not change using these alternative returns and return windows.

Tri_MTR is more value-relevant than the other tax rates we study and investors use heuristics to incorporate taxes into forecasts of future payoffs.

5. SUBSAMPLE TESTS

5.1. Motivation and Research Design

Finding that the *Tri_MTR* model is the most value-relevant model we test is perhaps surprising because prior literature (e.g., Ball and Watts 1972; Beaver 1970; Watts and Leftwich 1988) documents that earnings components follow a random walk or a random walk with a drift.[13] As such, tax researchers (e.g., Ayers et al. 2009; Hanlon et al. 2005; Thomas and Zhang 2014) generally calculate tax surprise as the year-over-year change in tax expense, which reflects the random walk assumption. Including *PY_ETR* as a heuristic rate allows us to directly test the random walk assumption; if investors believe that tax expense followed a random walk, we would estimate that the *PY_ETR* model has the highest explanatory power.[14] Our results are inconsistent with this assumption. Our next set of tests, therefore, examines the extent to which investors use tax rates other than the *Tri_MTR* when it is likely a poor representation of the simulated MTR. These analyses allow us to explore whether investors' use of rates when impounding taxes into future payoffs varies across firms and to potentially identify firms for which *PY_ETR* model is more value relevant.

The cost-benefit trade-off of using different rates likely varies with firm characteristics. For example, *Tri_MTR* is easier to estimate than *BCG_MTR* but it omits firm-specific information included in the *BCG_MTR*. *Tri_MTR* also does not incorporate information from industry-ETRs, which may allow for a more precise estimate of simulated MTRs for some firms. We separately examine the value relevance of the five tax rates in two subsamples where we expect *Tri_MTR* may be a relatively weaker proxy for the marginal tax rate such that the low cost of using this heuristic rate does not outweigh the forgone

[13] As noted above, Blouin et al. (2012) document that a non-parametric approach to estimating future *taxable* income is superior to assuming a random walk.

[14] We measure tax surprise as ($TXT_t - (TaxRate \times PI_{t-1})$), therefore when *TaxRate* = *PY_ETR*, the benchmark becomes prior year tax expense (i.e., $PY\_ETR \times PI_{t-1}$).

benefit of incorporation more firm-specific tax information: firm-years with significant foreign earnings and firm-years that are likely eligible for the U.S. R&D tax credit. We also consider a subsample of firms operating in an enhanced information environment where the cost of obtaining and processing more firm-specific tax information is likely lower and therefore facilitates use of rates other than *Tri_MTR*. As in our main analysis, we make no predictions about which rate(s) investors use in these subsamples; our only expectation is that *Tri_MTR* will become less value relevant in these subsamples.

5.1.1. Firms with Significant Foreign Operations

Governments tax the income of multinational firms at different statutory tax rates depending on the country to which the income is sourced. This complexity increases the cost of simulating the MTR because investors must know the source country of each incremental dollar of income as well as the statutory tax rate and NOL carryforward/carry back rules in that country. Substituting a country-weighted average statutory tax rate for the MTR can pose problems if the firm's income is growing at different rates in different countries. Finally, because *Tri_MTR* is based exclusively on U.S. statutory rates, it implicitly assumes that the U.S. will eventually tax all income of U.S. multinationals at 35%. This assumption is problematic because it ignores the significant time value of money implications of deferral. This deferral, which many U.S. multinationals exploit (e.g., Krull 2004, Graham, Hanlon, and Shevlin 2011) can lead to situations where the simulated MTR is much lower than *Tri_MTR* and using *Tri_MTR* to calculate future payoffs can result in biased valuations. Thus, we examine whether the *Tri_MTR* model is less value relevant for firms with significant foreign operations relative to the full sample. We consider firms in the top quintile of pre-tax foreign income scaled by total assets (PIFO/AT) each year to have significant foreign operations. We reset missing values of PIFO to zero before ranking.

5.1.2. Firms that are likely eligible for the U.S. R&D Tax Credit

Income tax credits reduce tax liabilities dollar-for-dollar. The U.S. tax code also allows firms to carry back and carry forward many unused tax credits, which complicates simulating MTRs by requiring projections of future taxable income through the carryforward period (Graham 1996). Further, the extent to which a tax credit shields a marginal dollar of income depends on the availability of the credit and whether a company qualifies for the credit. For example, foreign tax credits shield only foreign source income. Thus, as for firms with multinational operations, estimating the MTR for firms claiming tax credits can be relatively more costly. However, because tax credits generate permanent tax savings, ignoring their impact (e.g., by using *Tri_MTR* to estimate future payoffs) can result in understated future after-tax payoffs and lead to biased valuations.

We examine whether the *Tri_MTR* model is less value relevant for sample firms that are likely eligible for the R&D tax credit than it is for the full sample. We consider firms in the top quintile of incremental R&D spending each year as firms that are likely eligible for the R&D tax credit. Incremental R&D is current R&D expenses less a base amount. We measure incremental R&D using elements of both a fixed and moving average base amount, consistent with the spirit of the traditional R&D credit calculation (IRC §41(c)(3)(A)) and the alternative simplified credit calculation (IRC §41(c)(5)). Specifically, we calculate a base percentage as the minimum of 16 percent or the ratio of a firm's qualified research expenses (*QRE* = *Compustat* R&D expense [XRD]) to its gross receipts (*Sales* = *Compustat* Sales [SALE]) for the previous five years. Then, base period R&D is the greater of: 1) the base percentage multiplied by the average gross receipts in the previous four years, or 2) 50 percent of current year qualified research expenses, as follows:

$$BASERD = max\left[\left\{\left(\frac{1}{4}\sum_{k=1}^{4} Sales_{t-k}\right) \times min\left(0.16, \frac{\sum_{j=1}^{5} QRE_{t-j}}{\sum_{j=1}^{5} Sales_{t-j}}\right)\right\}, 0.50 \times QRE_t\right].$$

5.1.3. Firms that have an enhanced information environment

Financial analysts play an important role in resolving information asymmetry between investors and firms and the related mispricing in capital markets (Healy and Palepu, 2001). This is in part because "investors with limited abilities or time to analyze individual securities often rely on the work of sell-side analysts" (Bradshaw 2011, 2). For example, analysts often provide earnings forecasts for multiple years and/or long-term growth forecasts, which gives investors access to a richer set of firm-specific information without significant additional time or effort. Further, Hutton, Lee, and Shu (2012) suggest that analysts have information advantages from (1) access to macroeconomic expertise, which enables them to better assess how economy-wide changes affect the competitive environment of the firm, and (2) industry specialization, which enables them to better interpret and convey firm-specific industry and market sector trends. Liu and Thomas (2000) show that the returns-earnings association improves when investors have access to information about future earnings from analysts. These enhanced information sets allow lower cost access to aggregated firm- and industry-specific information that could facilitate more complex tax modelling.[15] Therefore, we examine whether the *Tri_MTR* model is less value relevant for sample firms that operate in an enhanced information environment relative to the full sample. To construct the enhanced information sample, we follow the sample selection procedures outlined in Liu and Thomas (2000, 78). Specifically, we require that sample observations have December year-ends, non-missing book values, earnings, and dividends (all per share) in year *t* from *Compustat*, analyst long-term growth rate forecasts and analyst EPS forecasts for years *t*+1 and *t*+2 from *IBES*, and return information for the years *t*–4 to *t*+1 from *CRSP*.

5.2. Results

We summarize the results of the subsample tests in Table 6 and Figure 2. Panels A and B provide average values of all regression variables for the full sample and each subsample. For parsimony, we present only the results of the explanatory power tests but confirm in untabulated analysis that the portfolio returns tests generate identical inferences. Panel C presents the average adjusted R^2 and other summary information from estimating equation (10) on the full sample of firms (from Table 4), for comparison, as well as on each subsample.

[15] Specifically, Liu and Thomas (2000) use current year book values, earnings, and dividends (all per share), analyst EPS forecasts for the next two years, analyst long-term growth rate forecasts, and discount rate information to create additional regressors that represent components of abnormal earnings growth valuations.

[Insert Table 6 here.]

We find that the *Tri_MTR* model exhibits the highest average adjusted R^2 in both the foreign and R&D subsamples, while the average adjusted R^2 of the *Tri_MTR* model is statistically indistinguishable from the other tax rate models in the enhanced information subsample. The relative importance of the *Tri_MTR* model declines in each subsample relative to the full sample as evidenced by the fact that the *Tri_MTR* model wins in fewer years in each subsample relative to the full sample. In the subsample of observations with high foreign income, the *Tri_MTR* model outperforms the other models in only six of the 18 years compared to outperforming the other models in 15 years in the full sample. Further, some of the other tax surprise models are as value relevant (tie) as the *Tri_MTR* model in several years. Specifically, the *IndAvg_ETR* model is as value relevant in ten years, the *BCG_MTR* model is as value relevant in eight years, and the *PY_ETR* and *FirmAvg_ETR* models are both as value relevant in three years. These results suggest that firm- and industry-specific tax information is more value relevant for firms with significant foreign earnings than for the full sample.

Similarly, we find that the other tax surprise models are increasingly relevant for firms we classify as likely eligible for the U.S. R&D Tax Credit. The *Tri_MTR* model outperforms the other models in only two of the 18 years. Further, the *IndAvg_ETR* model ties in 13 years, the *BCG_MTR* model ties in eight years, the *FirmAvg_ETR* model ties in four years, and the *PY_ETR* model ties in three years. Thus, firm- and industry-specific tax information is more value relevant for firms likely eligible for R&D tax credits than for the full sample.

Finally, in the subsample of observations with an enhanced information environment, we find that the *Tri_MTR* model does not outperform the other models in any year. In fact, the *IndAvg_ETR* model is the only model in this subsample that outperforms other models, doing so in five of the 18 years. The *IndAvg_ETR* model ties with at least one other model in the remaining 13 years. The *BCG_MTR* model ties in 12 years, the *PY_ETR* model ties in nine years, the *FirmAvg_ETR* model and *Tri_MTR* model each tie with other models in eight years. Thus, firm- and industry-specific tax information is more value relevant for firms with an enhanced information environment relative to the full sample. Additionally, because we can compute the abnormal earnings components from Liu and Thomas (2000) for this subsample of firms (but we cannot for the full sample), we examine how their inclusion in equation (10) affects inferences. When we estimate equation (10) after including these abnormal earnings components that represent future earnings information, inferences in Table 6 remain unchanged. Therefore, controlling for changes in expected future profitability, which is potentially important when exploring the returns-tax relation, does not alter our conclusion about which tax rate investors use to forecast the future payoffs of valuation models. Overall, the subsample results in Table 6 provide evidence that investors incorporate other firm- and industry-specific tax information when the *Tri_MTR* is likely to deviate from the true MTR or investors have access to lower-cost information that facilitates more complex tax modelling.

[Insert Figure 2 here.]

6. ANALYST FORECASTS OF TAX EXPENSE

To preserve sample size and increase the generalizability of our results, our main tests do not examine analysts' ETR forecasts as a possible heuristic tax rate. However, because we recognize that analysts play an important role in setting investors' expectations, we evaluate analysts' implied ETR forecasts from IBES as an alternative heuristic tax rate in this section. We calculate *Analyst_Surprise* as:

$$Analyst\_Surprise_{it} = (\mathrm{TXT}_t - (IBES\_ETR \times \mathrm{PI}_{t-1}))\ /\ MVE_t \qquad (11)$$

We calculate *IBES_ETR*, which is available after 2003, as the median of all analysts' pre-tax income forecasts less their net income forecasts, scaled by their pre-tax income forecasts. We present descriptive statistics in Panels A and B of Table 7. For comparison, column (1) shows descriptive statistics for the subset of observations from the full sample from years that overlap with IBES ETR forecast data. Column (2) provides statistics for the subsample of observations for which *IBES_ETR* is not missing.

Using IBES analysts' forecasts as a heuristic tax rate has several limitations. First, *IBES_ETR* is not an explicit number available to investors and therefore is likely a more costly alternative to the MTR than some of the other rates we examine.[16] Further, the pre-tax income forecasts from which we derive implicit ETR forecasts are not widely available until after 2002 and the frequency of pre-tax income forecasts varies dramatically by industry (Mauler 2015). Comparing columns (1) and (2) in Panel A reveals that firms with reported IBES pre-tax income forecasts are larger than the average sample firm. Thus, generalizability is also a potential issue for inferences generated using the IBES subsample. Finally, when we test for significant differences across the various tax surprises within the IBES subsample we find *Analyst_Surprise* is not statistically different from *BCG_MTR_Surprise* or *FirmAvg_Surprise.* Therefore, we expect the adjusted R^2 of the *BCG_MTR* and *FirmAvg_ETR* models to be the same as the *IBES* model and remove these models from further analysis.

[Insert Table 7 here.]

Panel C presents the average adjusted R^2s from estimating equation (10). The *Tri_MTR* model produces the highest adjusted R^2 on average in eight of the 11 years. The *IBES_ETR* and *FirmAvg_ETR* models both tie the *Tri_MTR* model in one year but no other model, including the *IBES_ETR* model, has the greatest explanatory power in any year. These results suggest either (i) investors do not use the IBES implied ETR forecast to impound taxes into firm value or (ii) the IBES implied ETR forecast is a poor representation of individual analysts' explicit ETR forecasts.

7. CONCLUSION

Little empirical evidence exists about the tax rates investors use to forecast the future payoffs of valuation models. Our study addresses this research question. Although the marginal tax rate is the theoretically correct rate to use in valuation, it is costly to estimate. We therefore propose that investors rely on heuristic tax rates, which are simpler to obtain and process, to tax-effect expected future payoffs.

[16] In contrast, Value Line does provide explicit ETR forecasts. Prior studies examine IBES and Value Line as alternative sources of EPS forecasts and find they are comparable in terms of their EPS forecast data (Philbrick and Ricks 1991). We have access to Value Line data from 1996 through 2009 and considered using *VL_ETR* as an alternative heuristic tax rate. However, *VL_ETR_Surprise* is not significantly different from the other measures of *Tax_Surprise* in our sample, and thus would not allow us to conclude whether investors use the explicit *VL_ETR* per se or whether *VL_ETR* simply mirrors another rate we test.

However, we make no prediction as to which rate(s) investors use. We examine the value relevance of simulated MTRs along with four heuristic tax rates. Using tests based on explanatory power (Francis et al. 2003) and portfolio returns (Francis and Schipper 1999), we find evidence that investors use a trichotomous MTR that adjusts the top U.S. statutory tax rate of 35% for losses and loss carryforwards to incorporate taxes into payoffs of equity valuation models. This result is consistent with investors trading off the benefits of understanding firm specific tax drivers with the costs of implementing a more complex method such as simulating MTRs. As further evidence of this cost-benefit tradeoff, we find that the trichotomous MTR is less value relevant – and other rates are more value relevant – when the potential benefits (costs) of incorporating more firm- and industry-specific tax information is higher (lower).

This paper extends the literature that examines investor valuation of tax expense (Ayers et al. 2009; Hanlon et al. 2005; Thomas and Zhang 2014) and the literature on how individuals incorporate taxes into decisions (Amberger et al. 2016; Graham et al. 2017). Our finding that investors use a simple heuristic based on the statutory rate is of interest to managers and standard setters because it suggests that investors often ignore or fail to understand industry- and firm-specific tax information. Standard setters, in particular, may want to consider how to simplify the tax footnote to lower investors' information acquisition costs. Our findings also highlight the importance of communicating with shareholders about income taxes, as investors' inability to understand firms' tax planning likely has mispricing implications.

Appendix

The residual income model is a transformation of the dividend discount model (DDM):

$$P_t = \sum_{\tau=1}^{\infty} \frac{d_{t+\tau}}{(1+r)^{\tau}} \tag{DDM}$$

where P_t (price) denotes the total value of all outstanding shares at time t, $d_{t+\tau}$ denotes expected dividends for period $t + \tau$ and r denotes the cost of equity capital. According to the clean surplus relation (CSR), comprehensive earnings ($Earnings_t$) increase and dividends decrease the book value of equity (B_t) as follows:

$$B_t = B_{t-1} + Earnings_t - d_t \text{ or } \Delta B_t = Earnings_t - d_t \tag{CSR}$$

Thus, CSR defines dividends, d_t, as equal to $Earnings_t - (B_t - B_{t-1})$. We substitute $Earnings_t - (B_t - B_{t-1})$ for d_t in the (DDM) to arrive at the residual income model (RIM).

$$P_t = B_t + \sum_{\tau=1}^{\infty} \frac{Earnings_{t+\tau} - rB_{t+\tau-1}}{(1+r)^{\tau}} \tag{RIM}$$

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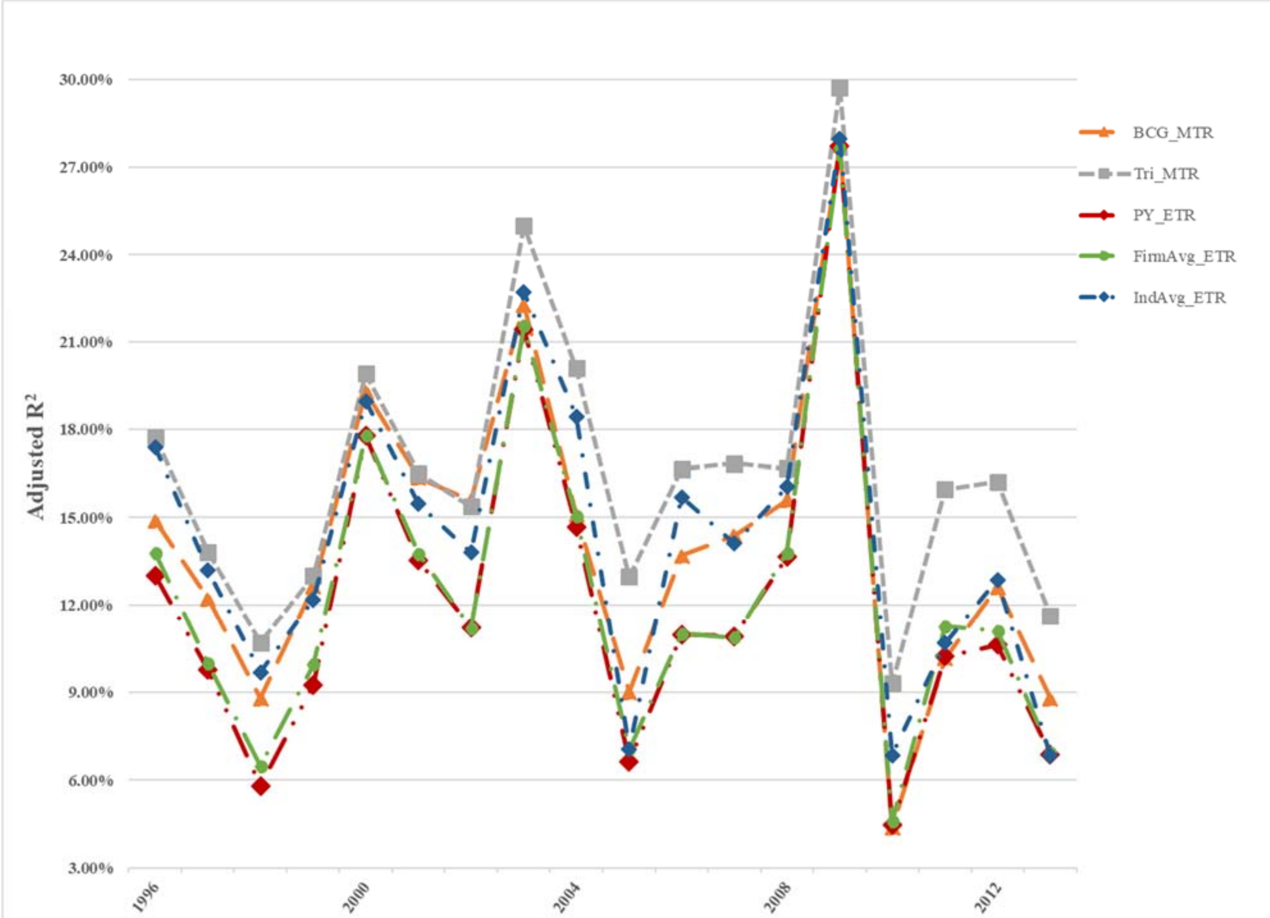
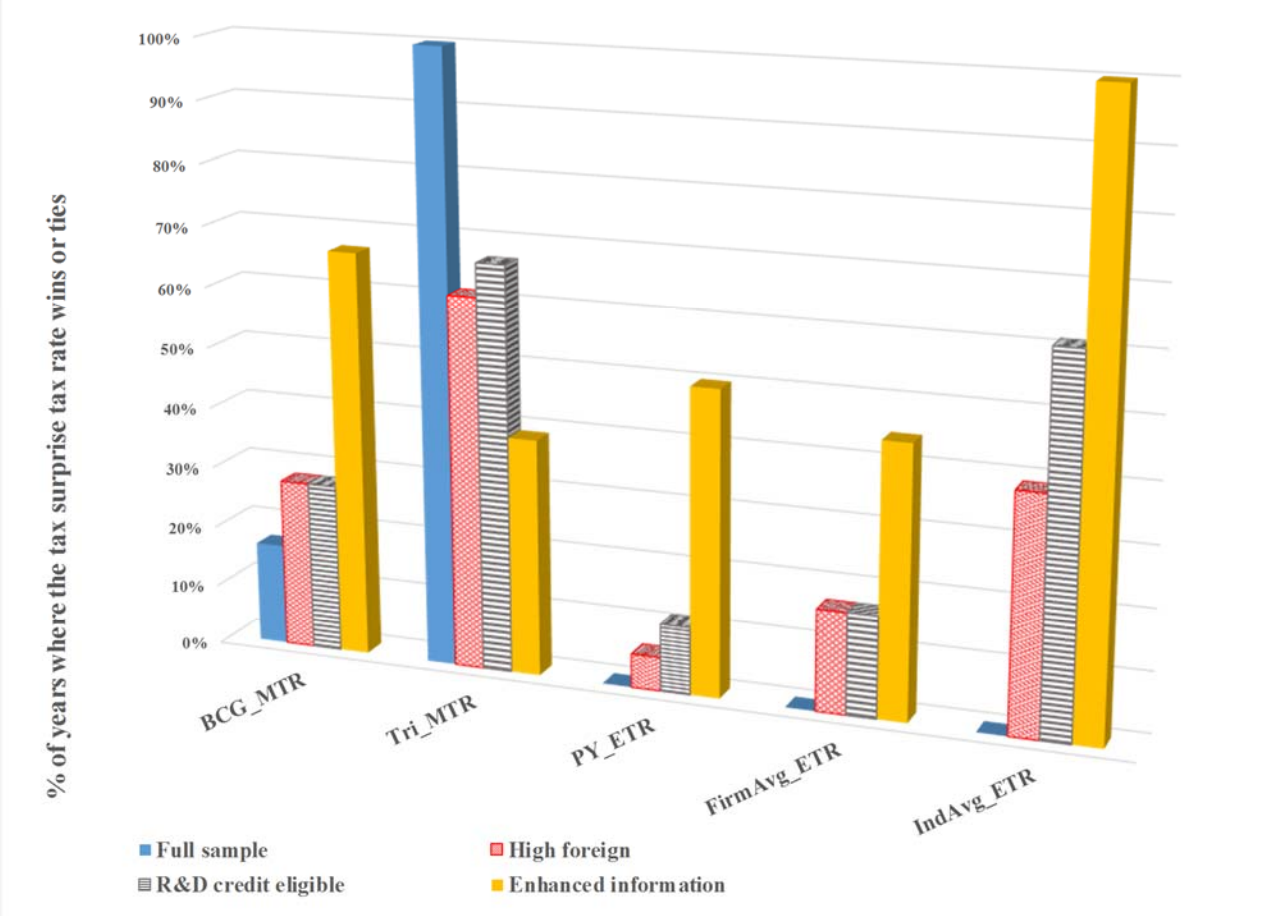
Figure 1
Explanatory power of tax surprise models[1]



[1] Figure 1 presents graphs of adjusted R^2 from estimating the following cross-sectional regression annually from 1996-2013: $Ret_{it} = \Gamma_0 + \Gamma_1 PI\_Surprise_{it} + \Gamma_2 Tax\_Surprise_{it} + \Gamma_3 LogBM_{it-1} + \Gamma_4 Loss_{it-1} + \Gamma_5 PI\_Surprise_{it} \times Loss_{it-1} + \Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1} + \Gamma_7 LogBM_{it-1} \times Loss_{it-1} + \sum \Gamma_j Controls_{it-1} + \sum \Gamma_k Controls_{it-1} \times Loss_{it-1} + \varepsilon_t$. We define the variables as follows: *Ret* is the 12-month buy and hold return from the start of the fourth month of year *t* to the end of the third month of year *t*+1. *PI_Surprise* is the change in pre-tax income (PI) from year *t*–1 to *t*. *Tax_Surprise* is the difference between actual tax expense in year *t* (TXT) and expected tax expense, where expected tax expense equals PI_{t-1} multiplied by one of the following tax rates: *BCG_MTR* is the simulated MTR from Blouin et al. (2010); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in year *t*–1, where *ETR* is TXT/PI; *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; and *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1, where we define industry using the Fama-French 30 industry classifications. We scale *Surprise* variables by MVE, which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT, from CRSP). $LogBM_{t-1}$ is the lagged natural log of the book-to-market ratio (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)). $Loss_{t-1}$ is an indicator variable equal to one if lagged pre-tax (PI_{t-1}) income is less than zero, and zero otherwise. We include two control variables: $LogMVE_{t-1}$ is the lagged natural log of *MVE* and Ret_{t-1} is the lagged value of *Ret.* We winsorize all continuous variables at the 1st and 99th percentile by year.

Figure 2
Explanatory power of models with different measures of tax surprise: Sub-sample tests[1]



[1] Figure 2 presents a graph of the percent of years where the annual adjusted R^2 of a particular tax surprise model outperforms/ties the annual adjusted R^2 of other tax surprise models. We estimate the following cross-sectional regression annually from 1996-2013 for four distinct samples of firms: $Ret_{it} = \Gamma_0 + \Gamma_1 PI\_Surprise_{it} + \Gamma_2 Tax\_Surprise_{it} + \Gamma_3 LogBM_{it-1} + \Gamma_4 Loss_{it-1} + \Gamma_5 PI\_Surprise_{it} \times Loss_{it-1} + \Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1} + \Gamma_7 LogBM_{it-1} \times Loss_{it-1} + \Sigma\, \Gamma_j Controls_{it-1} + \Sigma\, \Gamma_k Controls_{it-1} \times Loss_{it-1} + \varepsilon_t$. We define the subsamples as follows: **Full Sample** = The sample outlined in Table 1 used in our main tests. **High Foreign Sample** = Observations in the top quintile of pre-tax foreign income scaled by total assets (PIFO/AT) each year (we reset missing PIFO to zero before ranking). **R&D Credit Eligible Sample** = Observations considered eligible for the federal R&D credit based on the methodology from Gupta et al. (2011). Eligible firms have estimated qualified research expenditures in the current year that exceed those reported in the base period, typically the prior five years. **Enhanced Information Sample** = Observations that meet the sample requirements outlined in Liu and Thomas (2000); these observations have December year-ends, non-missing book values, earnings, and dividends (all per share) in year *t* from *Compustat*, analyst long-term growth rate forecasts and analyst EPS forecasts for years *t*+1 and *t*+2 from *IBES*, and return information for the years *t*–4 to *t*+1 from *CRSP*. *Tax_Surprise* is the difference between actual tax expense in year *t* (TXT) and expected tax expense, where expected tax expense equals PI_{t-1} multiplied by one of the following five tax rates: *BCG_MTR* is the simulated MTR from Blouin et al. (2010); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in year *t*–1, where *ETR* is TXT/PI; *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; and *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1, where we define industries using the Fama-French 30 industry classifications. We scale *Surprise* variables by MVE, which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT, from CRSP). $LogBM_{t-1}$ is the lagged natural log of the book-to-market ratio (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)). $Loss_{t-1}$ is an indicator variable equal to one if lagged pre-tax (PI_{t-1}) income is less than zero, and zero otherwise. We include two control variables: $LogMVE_{t-1}$ is the lagged natural log of *MVE* and Ret_{t-1} is the lagged value of *Ret.* We winsorize all continuous variables at the 1st and 99th percentile by year. Years win or tie is the number of years the Adj. R^2 is statistically equivalent to the model with the highest Adj. R^2 according to a Vuong (1989) test.

Table 1
Sample selection[1]

Compustat US Firm-Year Observations from 1993-2013	226,284
Less: Observations with missing $\boldsymbol{Ret_t}$ or $\boldsymbol{PI_t}$	(106,681)
Less: Observations with missing $\boldsymbol{MVE_t}$ or $\boldsymbol{BM_{t-1}}$	(16,277)
Less: Observations with missing $\boldsymbol{ETR_t}$, $\boldsymbol{ETR_{t-1}}$, $\boldsymbol{FirmAvg\_ETR_{t-1}}$ or $\boldsymbol{IndAvg\_ETR_{t-1}}$	(12,703)
Less: Observations with missing $\boldsymbol{BCG\_MTR_{t-1}}$	(24,909)
Sample	**65,714**

[1] Table 1 presents the sample selection process for our main tests. Ret_t is the 12-month raw return from the start of the fourth month of year t to the end of the third month of year t+1. PI_t is pre-tax income (PI) in year t. MVE_t is the market value of equity measured three months after the end of year t (PRC*SHROUT, from CRSP). BM_{t-1} is the book value of equity at year t–1 divided by the market value of equity at year t–1 (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)). ETR_t is the GAAP effective tax rate (TXT/PI) for year t. $FirmAvg\_ETR_{t-1}$ is the firm's average ETR from year t–3 through year t–1. $IndAvg\_ETR_{t-1}$ is the firm's industry-average ETR in t–1 where we define industries using the Fama-French 30 industry classification system.

Table 2
Descriptive statistics (n=65,714)[1]

	Mean	**Std Dev**	**P25**	**P50**	**P75**
Panel A: Heuristic Tax Rates					
BCG_MTR	0.2487	0.1099	0.1559	0.3023	0.3400
Tri_MTR	0.2298	0.1278	0.1750	0.1750	0.3500
PY_ETR	0.2080	0.3700	0.0000	0.3134	0.3800
FirmAvg_ETR	0.2097	0.3444	0.0075	0.2987	0.3759
IndAvg_ETR	0.2075	0.5822	0.1168	0.1819	0.2598
Panel B: Regression Variables					
Ret_t	0.1730	0.8148	-0.2719	0.0421	0.3827
BCG_MTR_Surprise	0.0113	0.1301	-0.0061	0.0049	0.0186
Tri_MTR_Surprise	0.0036	0.1165	-0.0072	0.0032	0.0165
PY_ETR_Surprise	-0.0033	0.1166	-0.0069	0.0002	0.0097
FirmAvg_Surprise	0.0042	0.1437	-0.0063	0.0011	0.0133
IndAvg_Surprise	0.0229	0.1705	-0.0023	0.0115	0.0300
NI_Surprise	-0.0512	0.6428	-0.0393	0.0042	0.0293
PI_Surprise	-0.0440	0.6608	-0.0427	0.0073	0.0401
$LogBM_{t-1}$	0.6130	0.6146	0.2614	0.4778	0.7894
Ret_{t-1}	0.1908	0.8591	-0.2602	0.0457	0.3902
$LogMVE_{t-1}$	5.6295	2.0961	4.0646	5.5539	7.0672
$Loss_{t-1}$	0.3221	0.4673	0.0000	0.0000	1.0000

[1] Table 2 provides descriptive statistics for the sample. We define the variables in Panel A as follows: *BCG_MTR* is the simulated MTR from Blouin et al. (2010); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in *t*-1, where *ETR* is TXT/PI; *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; and *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1, where we define industries using the Fama-French 30 industry classification system. We define the variables in Panel B as follows: *Ret* is the 12-month raw return from the start of the fourth month of year *t* to the end of the third month of year *t*+1. We calculate all *Tax_Surprise* variables as the difference between actual tax expense in year *t* (TXT) and expected tax expense, where expected tax expense equals PI_{t-1} multiplied by one of the tax rates from Panel A. *NI_Surprise* is the change in net income (NI) from year *t*–1 to *t*. *PI_Surprise* is the change in pre-tax income (PI) from year *t*–1 to *t*. We scale all *Surprise* variables by *MVE,* which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT, from CRSP). $LogBM_{t-1}$ is the lagged natural log of the book-to-market ratio (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)); Ret_{t-1} is the lagged value of *Ret*; $LogMVE_{t-1}$ is the lagged natural log of *MVE;* and $Loss_{t-1}$ is an indicator variable equal to one if pre-tax (PI) income is less than zero, and zero otherwise. We winsorize all continuous variables at the 1st and 99th percentile by year.

Table 3
Correlations (n=65,714)[1]

Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
[1] *Ret_t*		**0.1472**	**0.1415**	-0.0051	**0.0280**	**0.0672**	**0.0405**	**-0.0359**
[2] *NI_Surprise*	**0.2803**		**0.9249**	**0.2261**	**0.2887**	**0.2382**	**0.1975**	**0.1431**
[3] *PI_Surprise*	**0.2692**	**0.9009**		**0.3731**	**0.4260**	**0.4362**	**0.3701**	**0.2651**
[4] *BCG_MTR_Surprise*	**0.0359**	**0.4673**	**0.5878**		**0.8281**	**0.6903**	**0.7068**	**0.7862**
[5] *Tri_MTR_Surprise*	**0.0932**	**0.4290**	**0.5416**	**0.8189**		**0.7122**	**0.6841**	**0.6852**
[6] *PY_ETR_Surprise*	**0.1620**	**0.3931**	**0.5689**	**0.6876**	**0.6725**		**0.7539**	**0.5305**
[7] *FirmAvg_Surprise*	**0.1290**	**0.3935**	**0.5387**	**0.6926**	**0.6578**	**0.8028**		**0.5522**
[8] *IndAvg_Surprise*	**-0.0278**	**0.3685**	**0.4712**	**0.7742**	**0.7006**	**0.5329**	**0.5443**	

[1] Table 3 presents correlatioins for the full sample. We list Spearman (Pearson) correlations below (above) the diagonal. We include the following variables in the table: *Ret* is the 12-month raw return from the start of the fourth month of year *t* to the end of the third month of year *t*+1. *NI_Surprise* is the change in net income (NI) from year *t*–1 to *t*. *PI_Surprise* is the change in pre-tax income (PI) from year *t*–1 to *t*. We calculate all *Tax_Surprise* variables as the difference between actual tax expense in year *t* (TXT) and expected tax expense, where expected tax equals PI_{t-1} multiplied by one of the following tax rates: *BCG_MTR* is the simulated MTR from Blouin et al. (2010); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in *t*–1, where *ETR* is TXT/PI; *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; and *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1, where we define industries using the Fama-French 30 industry classification system. We scale all *Surprise* variables by *MVE,* which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT, from CRSP). We winsorize all continuous variables at the 1st and 99th percentile by year. Correlation coefficients in **BOLD** are significant at the 10% level or better (two-tailed).

Table 4
Explanatory power of models with different measures of tax surprise (n=65,714)[1]

Year	BCG_MTR [1]	Tri_MTR [2]	PY_ETR [3]	FirmAvg_ETR [4]	IndAvg_ETR [5]
1996	14.89%	**17.74%**	13.02%	13.79%	17.40%
1997	12.22%	**13.81%**	9.77%	9.99%	13.18%
1998	8.79%	**10.71%**	5.81%	6.49%	9.69%
1999	12.63%	**13.01%**	9.27%	9.96%	12.18%
2000	19.29%	**19.91%**	17.78%	17.80%	18.97%
2001	16.36%	**16.50%**	13.53%	13.75%	15.46%
2002	**15.60%**	15.38%	11.23%	11.20%	13.81%
2003	22.27%	**25.00%**	21.44%	21.54%	22.71%
2004	15.11%	**20.09%**	14.69%	15.05%	18.44%
2005	9.02%	**12.97%**	6.64%	7.06%	7.07%
2006	13.70%	**16.66%**	10.98%	11.01%	15.70%
2007	14.39%	**16.85%**	10.92%	10.87%	14.11%
2008	15.60%	**16.67%**	13.65%	13.79%	16.05%
2009	27.75%	**29.71%**	27.73%	27.65%	27.97%
2010	4.38%	**9.30%**	4.49%	4.60%	6.85%
2011	10.17%	**15.96%**	10.24%	11.27%	10.70%
2012	12.61%	**16.22%**	10.64%	11.11%	12.87%
2013	8.80%	**11.62%**	6.88%	6.95%	6.84%
Average Adj R^2	14.09%	16.56%	12.15%	12.44%	14.44%
Years win (of 18)	0	15	0	0	0
Years win/tie (of 18)	3	18	0	0	0

[1] Table 4 presents average adjusted R^2 from estimating the following cross-sectional regression annually from 1996-2013: $Ret_{it} = \Gamma_0 + \Gamma_1 PI\_Surprise_{it} + \Gamma_2 Tax\_Surprise_{it} + \Gamma_3 LogBM_{it-1} + \Gamma_4 Loss_{it-1} + \Gamma_5 PI\_Surprise_{it} \times Loss_{it-1} + \Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1} + \Gamma_7 LogBM_{it-1} \times Loss_{it-1} + \sum \Gamma_j Controls_{it-1} + \sum \Gamma_k Controls_{it-1} \times Loss_{it-1} + \varepsilon_t$. *Ret* is the 12-month raw return from the start of the fourth month of year *t* to the end of the third month of year *t*+1. *PI_Surprise* is the change in pre-tax income (PI) from year *t*–1 to *t*. *Tax_Surprise* is the difference between actual tax expense year *t* (TXT) and expected tax expense, where expected tax expense equals PI_{t-1} multiplied by one of the following five tax rates: *BCG_MTR* is the simulated MTR from Blouin et al. (2010); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in *t*–1, where *ETR* is TXT/PI; *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; and *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1, where we define industries using the Fama-French 30 industry classification system. We scale *Surprise* variables by MVE, which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT, from CRSP). $LogBM_{t-1}$ is the lagged natural log of the book-to-market ratio (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)). $Loss_{t-1}$ is an indicator variable equal to one if lagged pre-tax (PI_{t-1}) income is less than zero, and zero otherwise. We include two control variables: $LogMVE_{t-1}$ is the lagged natural log of *MVE* and Ret_{t-1} is the lagged value of *Ret*. We winsorize all continuous variables at the 1st and 99th percentile by year. Years win (Years win/tie) is the number of years the Adj. R^2 is statistically higher than all other models (statistically equivalent to the model with the highest Adj. R^2) according to a Vuong (1989) test.

Table 5
Portfolio return tests: Hedge portfolios based on tax surprises[1]

	BCG_MTR [1]	Tri_MTR [2]	PY_ETR [3]	FirmAvg_ETR [4]	IndAvg_ETR [5]
Panel A: Average Return to Hedge Portfolios Based on Tax Surprises					
Hedge Return	0.2349	0.2479	0.2209	0.2230	0.2354
t-stat ≠ 0	6.42	6.94	6.01	6.08	6.57
t-stat < Tri	4.10	NA	8.27	8.88	6.86
Panel B: Percent of Perfect Foreknowledge Hedge Returns Captured by Tax Surprises					
Hedge Return	0.4226	0.4524	0.3936	0.3976	0.4253
t-stat ≠ 0	17.12	21.77	14.96	15.51	18.56
t-stat < Tri	3.88	NA	6.98	7.21	5.76

[1] Table 5 presents results from estimating perfect foreknowledge hedge portfolios based on tax surprise for our sample of firm-year observations from 1996-2013. Specifically, we estimate the following cross-sectional regression annually from 1996-2013: $Ret_{it} = \Gamma_0 + \Gamma_1 PI\_Surprise_{it} + \Gamma_2 Tax\_Surprise_{it} + \Gamma_3 LogBM_{it-1} + \Gamma_4 Loss_{it-1} + \Gamma_5 PI\_Surprise_{it} \times Loss_{it-1} + \Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1} + \Gamma_7 LogBM_{it-1} \times Loss_{it-1} + \sum \Gamma_j Controls_{it-1} + \sum \Gamma_k Controls_{it-1} \times Loss_{it-1} + \varepsilon_t$. *Ret* is the 12-month raw return from the start of the fourth month of year *t* to the end of the third month of year *t*+1. *PI_Surprise* is the change in pre-tax income (PI) from year *t*–1 to *t*. *Tax_Surprise* is the difference between actual tax expense year *t* (TXT) and expected tax expense, where expected tax expense equals PI_{t-1} multiplied by one of the following tax rates: *BCG_MTR* is the simulated MTR from Blouin et al. (2012); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in *t*–1, where *ETR* is TXT/PI; *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; and *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1, where we define industries using the Fama-French 30 industry classification system. We scale *Surprise* variables by MVE, which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT, from CRSP). $LogBM_{t-1}$ is the lagged natural log of the book-to-market ratio (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)). $Loss_{t-1}$ is an indicator variable equal to one if lagged pre-tax (PI_{t-1}) income is less than zero, and zero otherwise. We include two control variables: $LogMVE_{t-1}$ is the lagged natural log of *MVE* and Ret_{t-1} is the lagged value of *Ret*. We winsorize all continuous variables at the 1st and 99th percentile by year. We use the annual coefficient estimates to rank the year *t* observations based on the predicted values of the dependent variable, Ret_{it} using the full sample of 65,714 observations to estimate Ret_{it}. The hedge portfolio consists of long positions in the highest 40 % of the Ret_{it} predicted values and a short position in the lowest 40 % of the Ret_{it} predicted values. We scale these hedge returns by the returns to a prefect foresight returns-based hedge portfolio to generate a ratio that represents the percentage of all information in returns that is captured by various measures of tax expense.

Table 6
Subsample Tests: Explanatory power of models with different measures of tax surprise[1]

	Full Sample [1]	**High Foreign [2]**	**R&D Credit Eligible [3]**	**Enhanced Information [4]**
Panel A: Heuristic Tax Rates – Mean values				
BCG_MTR	0.2487	0.2885	0.2507	0.3136
Tri_MTR	0.2298	0.2343	0.2208	0.2784
PY_ETR	0.2080	0.2331	0.2142	0.2984
FirmAvg_ETR	0.2097	0.2408	0.2077	0.2959
IndAvg_ETR	0.2075	0.1732	0.1796	0.2213
Panel B: Regression Variables – Mean values				
Ret_t	0.1730	0.1676	0.1912	0.1475
BCG_MTR_Surprise	0.0113	-0.0316	0.0385	-0.0003
Tri_MTR_Surprise	0.0036	-0.0267	-0.0016	0.0000
PY_Surprise	-0.0033	0.0054	0.0249	-0.0022
FirmAvg_Surprise	0.0042	0.0285	-0.0290	-0.0008
IndAvg_Surprise	0.0229	-0.0032	-0.0211	0.0048
NI_Surprise	-0.0512	0.0046	0.0115	-0.0116
PI_Surprise	-0.0440	0.0218	0.0069	-0.0104
$LogBM_{t-1}$	0.6130	0.5070	0.4786	0.5091
Ret_{t-1}	0.1908	0.1858	0.2630	0.1855
$LogMVE_{t-1}$	5.6295	6.7167	5.8204	7.0351
$Loss_{t-1}$	0.3221	0.2137	0.3513	0.0957
Firm-Year Observations	**65,714**	**13,139**	**6,801**	**23,371**

(*continued on next page*)

Table 6 (Continued)

	BCG_MTR [1]	Tri_MTR [2]	PY_ETR [3]	FirmAvg_ETR [4]	IndAvg_ETR [5]
PANEL C: Explanatory Power Tests					
Full Sample Results					
Average Adj R^2	14.09%	**16.56%**	12.15%	12.44%	14.44%
Years win (of 18)	0	**15**	0	0	0
Years win/tie (of 18)	3	**18**	0	0	0
High Foreign Sample					
Average Adj R^2	15.34%	**17.38%**	13.35%	13.85%	15.73%
Years win (of 18)	0	**6**	0	0	0
Years win/tie (of 18)	8	**18**	3	3	10
R&D Credit Eligible Sample					
Average Adj R^2	14.73%	**17.39%**	12.26%	12.39%	15.68%
Years win (of 18)	0	**2**	0	0	0
Years win/tie (of 18)	8	**18**	3	4	13
Enhanced Information Sample					
Average Adj R^2	15.83%	15.54%	15.42%	15.37%	**16.29%**
Years win (of 18)	0	0	0	0	**5**
Years win/tie (of 18)	12	8	9	8	**18**

[1] Table 6 presents mean values of regression variables and results of explanatory power tests estimated on various subsamples of firms. Panels A and B present mean values of regression variables. We define the subsamples as follows: **Full Sample** = The sample outined in Table 1 used in our main tests. **High Foreign Sample** = Observations in the top quintile of pre-tax foreign income scaled by total assets (PIFO/AT) each year (we reset missing PIFO to zero before ranking). **R&D Credit Eligible Sample** = Observations considered eligible for the federal R&D credit based on the methodology from Gupta et al. (2011). Eligible firms have estimated qualified research expenditures in the current year that exceed those reported in the base period, typically the prior five years. **Enhanced Information Sample** = Observations that meet the sample requirements outlined in Liu and Thomas (2000); these observations have December year-ends, non-missing book values, earnings, and dividends (all per share) in year *t* from *Compustat*, analyst long-term growth rate forecasts and analyst EPS forecasts for years *t*+1 and *t*+2 from *IBES*, and return information for the years *t*–4 to *t*+1 from *CRSP*. We define the variables in Panel A as follows: *BCG_MTR* is the simulated MTR from Blouin et al. (2010); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in *t*-1, where *ETR* is TXT/PI; *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; and *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1*,* where we define industries using the Fama-French 30 industry classification system. We define the variables in Panel B as follows: *Ret* is the 12-month raw return from the start of the fourth month of year *t* to the end of the third month of year *t*+1. We calculate all *Tax_Surprise* variables as the difference between actual tax expense in year *t* (TXT) and expected tax expense, where expected tax expense equals PI_{t-1} multiplied by one of the tax rates from Panel A. *NI_Surprise* is the change in net income (NI) from year *t*–1 to *t.* *PI_Surprise* is the change in pre-tax income (PI) from year *t*–1 to *t*. We scale all *Surprise* variables by *MVE,* which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT*,* from CRSP). $LogBM_{t-1}$ is the lagged natural log of the book-to-market ratio (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)); Ret_{t-1} is the lagged value of *Ret*; $LogMVE_{t-1}$ is the lagged natural log of *MVE;* and $Loss_{t-1}$ is an indicator variable equal to one if lagged pre-tax (PI_{t-1}) income is less than zero, and zero otherwise. Panel C presents the average Adj R^2 from estimating the following cross-sectional regression annually from 1996-2013 for subsamples of firms. $Ret_{it} = \Gamma_0 + \Gamma_1 PI\_Surprise_{it} + \Gamma_2 Tax\_Surprise_{it} + \Gamma_3 LogBM_{it-1} + \Gamma_4 Loss_{it-1} + \Gamma_5 PI\_Surprise_{it} \times Loss_{it-1} + \Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1} + \Gamma_7 LogBM_{it-1} \times Loss_{it-1} + \sum \Gamma_j Controls_{it-1} + \sum \Gamma_k Controls_{it-1} \times Loss_{it-1} + \varepsilon_{t.}$ We winsorize all continuous variables at the 1st and 99th percentile by year. Years win (Years win/tie) is the number of years the Adj R^2 is statistically higher than all other models (statistically equivalent to the model with the highest Adj R^2) according to a Vuong (1989) test.

Table 7
Analyst ETR Forecast Tests[1]

	Full Sample (2003-2013) [1]	IBES Subsample (2003-2013) [2]
Panel A: Tax Rates – Mean values		
BCG_MTR	0.2380	0.2632
Tri_MTR	0.2165	0.2222
PY_ETR	0.1847	0.2048
FirmAvg_ETR	0.1882	0.2073
IndAvg_ETR	0.1572	0.1558
IBES_ETR	0.2705	0.2705
Panel B: Regression Variables – Mean values		
Ret_t	0.2252	0.1817
BCG_MTR_Surprise	0.0054	0.0016
Tri_MTR_Surprise	0.0008	-0.0019
PY_Surprise	-0.0033	-0.0055
FirmAvg_Surprise	0.0021	-0.0006
IndAvg_Surprise	0.0171	0.0114
NI_Surprise	0.0015	0.0015
PI_Surprise	-0.0390	-0.0443
$LogBM_{t-1}$	-0.0395	-0.0467
Ret_{t-1}	0.5988	0.5315
$LogMVE_{t-1}$	0.1872	0.1675
$Loss_{t-1}$	6.0904	6.8918
Firm-Year Observations	**34,322**	**20,843**

Panel C: Explanatory Power Tests

	BCG_MTR [1]	Tri_MTR [2]	PY_ETR [3]	FirmAvg_ETR [4]	IndAvg_ETR [5]	IBES_ETR [6]
Average Adj R^2	15.60%	**18.31%**	13.98%	14.33%	16.01%	14.29%
Years win (of 11)	0	**8**	0	0	0	0
Years win/tie (of 11)	1	**11**	0	1	3	1

(*continued on next page*)

Table 7 (Continued)

[1] Table 7 presents mean values of regression variables and results of explanatory power tests that include IBES implied analyst ETR forecasts as a heuristic tax rate. Panels A and B present mean values of regression variables. Column (1) shows all observations from our main sample from 2003-2013, the years for which IBES ETR data are available. Column (2) shows all observations with non-missing values of IBES implied ETR forecasts. We define the variables in Panel A as follows: *BCG_MTR* is the simulated MTR from Blouin et al. (2010); *Tri_MTR* is a trichotomous MTR in the spirit of Graham (1996); *PY_ETR* is the firm's *ETR* in *t*-1 where *ETR* is (TXT/PI); *FirmAvg_ETR* is the firm's average *ETR* from year *t*–3 through year *t*–1; *IndAvg_ETR* is the firm's industry-average *ETR* in year *t*–1, where we define industries using the Fama-French 30 industry classification system; and *IBES_ETR* is the implicit IBES analyst ETR forecast. To calculate the implied IBES ETR forecast, we calculate the median pre-tax income and net income forecasts from IBES, subtract the median net income forecast from the median pre-income forecast to arrive at median implied tax expense, and divide median implied tax expense by median pre-tax income to arrive at the median implied ETR forecast. We define the variables in Panel B as follows: *Ret* is the 12-month raw return from the start of the fourth month of year *t* to the end of the third month of year *t*+1. We calculate all *Tax_Surprise* variables as the difference between actual tax expense in year *t* (TXT) and expected tax expense, where expected tax equals PI_{t-1} multiplied by one of the tax rates from Panel A. *NI_Surprise* is the change in net income (NI) from year *t*–1 to *t*. *PI_Surprise* is the change in pre-tax income (PI) from year *t*–1 to *t*. We scale all *Surprise* variables by *MVE,* which is the market value of equity at the end of the third month of year *t* (PRC*SHROUT, from CRSP). $LogBM_{t-1}$ is the lagged natural log of the book-to-market ratio (CEQ_{t-1} / ($PRCC\_F_{t-1}$*$CSHO_{t-1}$)); Ret_{t-1} is the lagged value of *Ret*; $LogMVE_{t-1}$ is the lagged natural log of *MVE;* and $Loss_{t-1}$ is an indicator variable equal to one if lagged pre-tax (PI_{t-1}) income is less than zero, and zero otherwise. We winsorize all continuous variables at the 1st and 99th percentile by year. Panel C presents the average Adj R^2 from estimating the following cross-sectional regression annually for subsamples of firms with an implied IBES analyst ETR forecast: $Ret_{it} = \Gamma_0 + \Gamma_1 PI\_Surprise_{it} + \Gamma_2 Tax\_Surprise_{it} + \Gamma_3 LogBM_{it-1} + \Gamma_4 Loss_{it-1} + \Gamma_5 PI\_Surprise_{it} \times Loss_{it-1} + \Gamma_6 Tax\_Surprise_{it} \times Loss_{it-1} + \Gamma_7 LogBM_{it-1} \times Loss_{it-1} + \sum \Gamma_j Controls_{it-1} + \sum \Gamma_k Controls_{it-1} \times Loss_{it-1} + \varepsilon_t$. Years win (Years win/tie) is the number of years the Adj R^2 is statistically higher than all other models (statistically equivalent to the model with the highest Adj R^2) according to a Vuong (1989) test.