Accounting Method Heterogeneity and Analysts' Forecasts*

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May 25, 2009

Abstract: We examine whether accounting methods atypical within an industry affect analysts' forecasts of future performance for a firm. Following a rich literature on accounting methods, our objective is to contribute evidence on the extent to which accounting method variability impacts information processing activities of financial statement users. We construct an index that measures how different a firm's portfolio of accounting methods is from its industry peers. We predict and find that the use of atypical accounting methods is associated with larger analyst forecast errors and increased forecast dispersion, consistent with variation in accounting procedures imposing processing costs on external users.

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* We thank participants at the Columbia University Burton Workshop, Duke University, Michigan State University, University of British Columbia, University of Connecticut and University of Utah for extremely helpful comments. Ted Christensen, Trevor Harris, and John Phillips provided particularly valuable insights and comments on the first draft. All errors and omissions are our responsibility.

1. Introduction

Accounting methods provide the basis for management's communication of financial performance to the firm's stakeholders, and prior research has documented the importance of such financial reporting procedures in market analysis. For example, Bae, Tan, and Welker (2008) find strong evidence that analyst following is negatively related to differences between the home country GAAP a firm follows and the GAAP of the home country of the analyst. Further, international investors also exhibit preference for accounting methods that are more familiar (e.g., Bradshaw, Bushee, and Miller 2004, Covrig, Lau, and Ng 2006, Covrig, DeFond and Hung 2007). Additionally, analysts provide more accurate forecasts when accounting method disclosures are more extensive (Hope 2003) or if the analyst is more familiar with the country-level GAAP of the covered firm (Bae, Tan, and Welker 2008). Together, such studies indicate that accounting methods can impact capital market participants' processing of firms' financial information. This paper contributes to this literature by examining the effects of employing accounting methods different from those predominant within an industry. We predict that atypical accounting methods (defined below) result in less accurate forecasts of future earnings and greater disagreement among analysts. To test this prediction, we incorporate a measure of each firm's portfolio of accounting methods relative to its industry peers.

Our tests are based on an index that combines eleven accounting methods to measure the similarity of a firm's accounting method portfolio to that of its peers. Because accounting methods tend to cluster within industry (e.g., Gilman 1939, Foster 1986, Bowen, DuCharme, and Shores 1999), we analyze firms within Fama and French (1997) defined industries. We identify the modal accounting method for each of the eleven methods in each industry and accumulate instances where a firm uses an atypical accounting method (e.g., accelerated depreciation when most firms in the industry use straight-line). This score is then scaled so that our primary variable is an index ("*METHOD_DIFF*") ranging from 0 to 1 with higher values reflecting more atypical accounting methods. Using analysts as a proxy for external financial statement users, we examine both earnings forecast accuracy and forecast dispersion to determine whether atypical accounting method portfolios are associated with the ability to more accurately forecast future earnings.

Consistent with our prediction, we find that *METHOD_DIFF* is associated with higher absolute forecast errors and larger forecast dispersion. These findings are consistent with atypical accounting methods impeding analysts' abilities to forecast future performance. We also examine whether the detrimental impact of *METHOD_DIFF* on analysts' forecasts is mitigated for firms with richer information environments, but find mixed results and that the overall negative association between atypical accounting methods and forecast accuracy is most evident for large firms.

While the primary results are consistent with our prediction, they are also consistent with the alternative explanation that firms deviate from industry accounting methods when underlying economics are inherently more complex than their competitors, which might be expected for larger firms. We attempt to address this alternative explanation in various ways. First, the primary tests include several control variables (e.g., number of operating segments) as an attempt to capture underlying economic-driven complexity that might be expected to reduce forecast accuracy. Second, we incorporate a control for the variance of a firm's earnings series to capture inherent variability in earnings due to underlying economic complexity. Third, we perform two matched sample analyses where firms are matched on measures such as industry, year, size, and number of operating segments. Finally, we examine a number of secondary tests to provide additional insights into the primary results. *METHOD_DIFF* remains significantly associated with forecast errors and dispersion in all of these analyses, suggesting that the accounting method index is unlikely simply proxying for underlying economic complexity.

These findings contribute to the literatures on accounting method choices and external user processing of accounting information. The findings that intra-industry variation in accounting methods has economic consequences extends the literature on accounting method choices and external users by indicating that attributes beyond disclosure impact outsiders' use of the information. Additionally, these results contribute to the literature on financial analysis and complexity. Our findings are consistent with analysts either ignoring or not efficiently processing information in accounting methods. In either case, it suggests that variability in accounting methods creates frictions in external analysis. Finally, from a practical standpoint, the results demonstrating negative effects of atypical accounting methods are relevant to managers and investor relations personnel interested in how their stakeholders process information (Bushee and Miller 2007).

Our study is currently subject to several observations and caveats. First, we document that our primary variable of interest – *METHOD_DIFF* – is strongly positively correlated with firm size, and firm size is well-known to be negatively correlated with forecast errors and analyst dispersion.[1] However, these correlations are opposite those one might extrapolate to our setting. We find that atypical accounting methods are more prevalent for larger firms, but that forecast errors and dispersion are *higher* for larger firms with higher values of *METHOD_DIFF*. Second, the index of atypical accounting methods treats all deviations from industry accounting practice

[1] The size mystery was noted by Christie (1990), who concludes, "While the size variable is often included as a proxy for political exposure, this is not exclusively the case, and it may be proxying for other unspecified factors." As noted by Leftwich (1990) and echoed by Fields et al. (2001), "little doubt remains about whether accounting choice and size are related. However, there is no such thing as a 'size hypothesis'; the interesting question is not whether size matters, but why."

equally, and the accounting methods we measure are based on data availability rather than a deliberately constructed data set of optimally identified accounting methods. Refinements that attempt to capture the relative economic impact of a firm's portfolio accounting methods might provide better visibility into the nature of the accounting method effect we document. While we find our results robust to different sets of accounting methods (both super and subsets of those presented), documented t-statistics are not large, leaving the possibility that further refinements of sample selection procedures could alter the tenor of the results. Finally, while we are attempting to isolate the information impact of atypical accounting methods, the reasonable alternative hypothesis of more complex firms being both harder to analyze and forecast is still possible, despite current efforts to rule out this explanation.

The rest of the paper proceeds as follows. The next section provides a brief discussion of related studies and our empirical predictions. Section 3 describes the data and our variables. The fourth section provides the primary results, the fifth section provides test of the alternative hypothesis of complexity, and the final section concludes.

2. Prior work and prediction=

2.1 Determinants of accounting methods and economic consequences

Accounting standards and regulation allow varying levels of discretion to managers. While a limited number of transactions involve little managerial discretion and are uniformly reported, most transactions involve financial reporting discretion on the selection of alternative accounting methods as well as the application of estimates for a particular accounting method.[2]

[2] For example, the recording of accrued interest revenue for interest-bearing bank accounts or base salary expense for administrative staff are what we would consider straightforward accounting accruals subject to limited, if any, preparer judgment.

A large number of academic studies show that accounting methods matter, in the sense that they affect contracts, reported performance, and stock prices.

There are two views on this wide accounting discretion available to preparers. On one hand, managers are presumed to be driven by incentive effects of compensation contracts, debt contracts, a desire to affect stock prices, and other factors (e.g., Holthausen and Leftwich 1983, Watts and Zimmerman 1986).[3] Alternatively, managers may use discretion to tailor accounting methods to their particular setting, so that financial results better capture the underlying economics of its net assets, performance, and investment opportunities (e.g., Gordon 1964, Skinner 1993). Based on these opposing views, many studies have examined why managers select from various accounting methods or apply biased assumptions, and results are varied. In contrast to explaining accounting methods themselves, we are interested in the effects of accounting methods on external users who are focused on assessing future performance. However, given the endogeneity of the methods we observe and the underlying reason for their selection by managers, later in the paper we attempt to isolate 'unexpected' variability in accounting methods.

We are primarily motivated by a desire to better understand how accounting methods are associated with expectations of financial statements users. Much has been written on the effects of specific accounting methods, which encompasses the selection from among alternative accounting methods (e.g., straight-line vs. accelerated depreciation) and the exercise of judgment for selected accounting methods (e.g., depreciable life, estimated salvage value, etc.). Fields, Lys, and Vincent (2001) estimate that over ten percent of research published in the top three accounting journals during the 1990s directly related to accounting method investigations. These

[3] Under this view, discretion is viewed unfavorably by external users. Consistent with this interpretation, noted accounting critic Abraham Briloff called for the denial of accounting method choice selection by managers, instead letting such choices be under the purview of a consortium of representative stakeholders (*Wall Street Journal* 1970).

types of studies take one of two approaches. They either focus on a particular set of managerial motivations (e.g., compensation contracts, debt covenants, etc.) and examine accounting methods, or they focus on a specific accounting method (e.g., purchase vs. pooling, stock option expense, etc.) and examine whether there are economic effects on financial performance or stock prices. Fields, Lys, and Vincent (2001) conclude that these studies provided little progress beyond what we know about accounting methods from earlier research in the 1970s and 1980s. This disheartening conclusion is attributed to the focus within individual studies on a single accounting method and the difficulty in isolating the impact of related incentives for a singular accounting decision (e.g. meeting debt covenants vs. maximizing compensation).

2.2 Motivation and empirical predictions

We seek to contribute to our understanding of accounting methods by examining the impact that such methods have on external users such as financial analysts. Foster (1986, p. 138) highlights several examples of intra-industry uniformity as a reason for accounting methods. For example, Alexander and Baldwin (a sugar production/real estate company), stated "The change was made principally to conform with the predominant depreciation method used by other companies in the industries." Similarly, Hesston Corporation stated, "In order to achieve greater comparability with the accounting practices of other companies in the industry, the Company changed its method of accounting for finance costs it incurs on dealer receivables transferred with recourse to finance companies." However, Foster (1986) observes that it is not obvious why managers would want to conform, other than managers possibly believing investors mechanically convert earnings into stock prices.[4] Thus, on the flip side of this view, one

[4] We are not directly testing the managerial motivation for comparability. Rather, we are testing a potential outcome and its impact on external users, which may or may not be associated with managerial preferences.

possible explanation for why managers might not be concerned with using atypical accounting methods is a belief that the market is efficient at processing such information.

Evidence in the literature is consistent with comparability reducing costs borne by external stakeholders who are analyzing a firm's financial statements. Indeed, regulators like the FASB and IASB continually emphasize the benefits of comparability. Our paper is motivated by the premise that intra-industry variation in accounting methods creates information processing demands on analysts, who are well-known to specialize by industry (Dunn and Nathan 2005). As discussed in Plumlee (2003), higher information complexity generates two effects on analysts. Analysts may adopt simpler strategies for dealing with more complex information (e.g., Payne 1976). This is similar to findings in Bradshaw (2002), where large standard deviations in consensus earnings forecasts are associated with lower frequency of target price forecast disclosures and increased use of heuristic valuations as the basis of target prices that are disclosed. Or, analysts' abilities to process more complex information can be impaired by information complexity (e.g., Hirst and Hopkins 1998). This is consistent with the findings in Plumlee (2003), where six tax-law changes under the Tax Reform Act of 1986 are associated with increased forecast errors.[5]

Similar to Hope (2003), we focus on absolute earnings forecast error and forecast dispersion. Our primary empirical prediction is as follows:

> P1: Analysts' forecasts are less accurate and dispersion is greater for firms that adopt atypical accounting methods.

Note that this prediction is independent of the reason for the atypical method choices (e.g., to obfuscate proprietary operations, non-strategic choice, etc.). Prediction 1 is tested using

[5] Given a rich literature that finds sell-side financial analysts serve as proxies for investors (see Bradshaw 2008 for a discussion), we use analysts as the source of expectations to test for predicted impacts of atypical accounting methods. While some of our motivations refer to analysts-specific attributes, we believe these impacts carry over to other market participants, due to similar direct issues and market reliance on information disseminated by analysts.

consensus analyst data. Prior research documents a strong negative association between size and forecast errors and dispersion (see Garcia-Meca and Sanchez-Ballesta 2006 for a meta-analysis). The effect of size is generally interpreted as proxying for a richer information environment, which results in more precise and less disperse expectations. In addition to being a first-order determinant of earnings forecast accuracy and dispersion, it is likely that size (i.e., market capitalization, analyst following) interacts with atypical accounting methods to mitigate the impact predicted under P1. Thus, our second prediction is:

> P2: The detrimental effect of atypical accounting methods on forecast errors and dispersion is mitigated for firms with richer information environments.

3. Sample selection and descriptive statistics

Our sample represents U.S. firms, but the data on accounting methods are from Worldscope, which is typically used by accounting researchers examining non-U.S. firms. These data include information for approximately thirty accounting methods. Several of these data do not actually reflect accounting methods (e.g., audit opinion, extraordinary items), are not subject to alternatives in the U.S. (e.g., accounting for deferred taxes), or exhibit minimal variation within the U.S. (e.g., accounting for long-term investments). Thus, we restrict our accounting method data to eleven that seem *ex ante* subject to variability. The Appendix presents the accounting methods used, alternatives available, and the percentage of observations classified as ‘common’ or ‘atypical’ across the pooled sample. The benchmark is the modal accounting method reported by other firms in the same industry, and our measure of atypical accounting methods is relative to the industry mode for that method.

We use the 48 Fama and French (1997) industry classifications. *METHOD_DIFF* is an index based on the ratio formed from a firm’s accounting methods that differ from the mode of their industry peers scaled by the number of accounting methods for which we have disclosures. The index is computed by assigning a value of 1 for each reported accounting method that differs from the industry mode, and zero otherwise. The aggregate value is then scaled by the number of accounting methods available for the industry.[6] Non-disclosure of an accounting method is also coded according to industry practices. If the majority of the industry firms disclose the method, a non-disclosing firm is classified as using an atypical choice. However, if most firms do not disclose a specific method, that method is excluded from the portfolio of methods for that industry. Therefore, *METHOD_DIFF* takes values from 0 to 1, with firms adopting atypical accounting methods having higher values. For example, a value of 0.10 means that a firm has one atypical accounting method for every ten accounting methods relevant within the industry. *METHOD_DIFF* is similar to a measure used by DeFond and Hung (2003) that explains the decision by analysts to provide cash flow forecasts.

Additional data were obtained from I/B/E/S and Compustat. The initial sample included 9,310 U.S. firms with data on accounting methods. We combined these data with consensus analyst forecasts from I/B/E/S, resulting in a merged dataset of 6,383 firms across 1985-1999. Requiring data on stock prices at the end of the previous fiscal year, common shareholders' equity and number of shares outstanding further reduces our sample to 4,029 firms. The final sample includes 19,986 firm-years, but some tests that require additional data use subsets of these data.

Absolute forecast error is computed as the absolute difference between the consensus earnings per share forecast and actual earnings per share (as reported by I/B/E/S), scaled by share

[6] In addition, we note that accounting method changed for the funds definition on the statement of change in financial position, where the Appendix shows 14.7% atypical choices. This reflects uncertainties that continued to exist after the issuance of Statement of Financial Accounting Standards No. 95 regarding what definition of cash was to be reconciled on the statement of cash flows. In unreported analysis, we find that the variation in this method is concentrated around the adoption of Statement No. 95.

price as of the beginning of the fiscal year. *Forecast dispersion* is the standard deviation of individual analyst forecasts comprising the consensus, also scaled by stock price at the beginning of the fiscal year. The number of analysts *(#ANALYSTS*) is obtained from I/B/E/S. *SIZE* is market value of equity as of the beginning of the fiscal year, obtained from Compustat (data item #25*data item #199). Book-to-market ratios (*B/M*) are computed as of the beginning of the fiscal year, based on book value (data item #60) and market value of equity. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items or extraordinary items in the year being forecasted, and is a control for the effect of special items on *ex post* forecast errors, particularly during most of our sample period (Bradshaw and Sloan 2002). The number of business segments (*#SEGMENTS*) proxies for operational complexity, and is based on the list of all applicable four-digit SIC codes for each firm as reported by Worldscope. All control variables with the exception of dummy variables and *B/M* are log transformed to reduce skewness. Unless otherwise noted, all forecast data reflect consensus forecasts for an eight-month forecast horizon (e.g., approximately April for a December fiscal year end).

The number of firms with available data per year grows from approximately 1,000 in 1985 to around 3,500 by 1999.[7] The analyst data reflects approximately 200 brokers per year, and the number of different analysts included across the consensus forecast data is between approximately 1,300 and 3,500 per year. Overall, the distribution of firms, brokers, and analysts is consistent with our sample representing a broad-cross-section of publicly traded U.S. firms, minimizing concerns about external validity.

[7] Our Worldscope data cut off in April 2000, so there we have a partial sample of firms for that year.

4. Impact of accounting methods on analysts' forecasts

4.1 Descriptive statistics

Descriptive statistics for *METHOD_DIFF*, primary control variables and other variables are presented in table 1. *METHOD_DIFF* has a mean and standard deviation of 0.11. Approximately 30% of the observations have a *METHOD_DIFF* value of 0, indicating no accounting methods that differ from the prevalent practice within the industry. We suspect that accounting methods are sticky, in the sense that they rarely change. To confirm this intuition, we estimated a first order autoregression for all firms within each year, and report the mean of these coefficients at the bottom of table 1. The mean autocorrelation coefficient is 0.75 and the median 0.81, consistent with intuition.

Panel B of table 1 provides a distribution of the sample across Fama and French (1997) industries, benchmarked against the distribution of all firms available on Compustat. The sample reflects a similar distribution to the Compustat population, with concentrations of firms similar across the second and third columns. Additionally, panel B shows the distribution of *METHOD_DIFF* across industries. Most industries have means close to the overall mean, with several exceptions. The beverages (Soda) industry has the highest mean for *METHOD_DIFF*, followed by weapons (Guns), tobacco (Smoke), alcoholic beverages (Beer), and automobile (Auto) industries, indicating wide variation in accounting methods for these firms.

Panel A of table 1 also provides descriptive statistics for all other variables. *Absolute forecast error* has a mean (median) of 0.03 (0.01).[8] *Forecast dispersion* has a mean of 0.008 (0.004). Both are similar to levels in prior studies (e.g., Hope 2003). The mean (median) of

[8] Recall that unless otherwise noted, forecast data are as of the fourth month of the fiscal year (i.e., 8-month forecast horizon). Thus, forecast errors are significantly different from zero given the long forecast horizon, consistent with prior research. In table 6, which provides results for various forecast horizons, intercepts in the forecast error regressions uniformly approach zero as the forecast horizon shrinks.

#ANALYSTS is 7.9 (5.0), and mean (median) *SIZE* is 2.3 billion (337 million). Mean (median) *B/M* is 0.63 (0.53). *SPECIAL ITEMS*, an indicator variable, has a mean of 0.40, consistent with a relatively high frequency of firms reporting various nonrecurring charges. Finally mean (median) *#SEGMENTS* is 2.7 (2.0). The lower section of panel A provides descriptive statistics on several other variables utilized in some tests.

Univariate correlations are shown in table 2.[9] The correlations between *METHOD_DIFF* and both *Forecast dispersion* and *Absolute forecast error* are close to zero. As we confirm later, however, the first order determinant of *Absolute forecast error* (and to a lesser extent, *Forecast dispersion*) is size; after controlling for size, the partial correlations are both significantly positive. This is particularly important, as the univariate correlation between *METHOD_DIFF* and *log(SIZE)* is significantly positive (0.19) and also between *METHOD_DIFF* and *log(#ANALYSTS)* (0.14). *Absolute forecast error* and *Forecast dispersion* are highly correlated (0.51), which is consistent with uncertainty being associated with inaccuracy. *Absolute forecast error* exhibits a strong negative correlation with both *log(SIZE)* (-0.34) and *log(#ANALYSTS)* (-0.20), consistent with prior research. The correlations between *Forecast dispersion* and *log(SIZE)*and *log(#ANALYSTS)* are similarly negative, but smaller. *B/M* is positively correlated with both *Absolute forecast error* (0.37) and *Forecast dispersion* (0.27), consistent with value firms being associated with greater market uncertainty. Finally, *log(SIZE)* and *log(#ANALYSTS)* are very highly correlated (0.73), consistent with both serving as complementary proxies for information environment.

As noted above, both dependent variables – *Absolute forecast error* and *Forecast dispersion* – have been shown to be strongly negatively associated with measures of firm size,

[9] To minimize the influence of outliers, *SIZE*, *#ANALYSTS*, and *#SEGMENTS* are transformed to logarithms in all statistical analyses beginning with the correlation table. Means of the log transformations of each variable are 6.0, 1.6, and 0.8, respectively.

consistent with such firms having more stable earnings, higher disclosure, and stronger ties between management and analysts (Atiase 1985). To confirm these findings for our sample and provide some insight into the correlation between size proxies and our primary independent variable – *METHOD_DIFF* – table 3 provides results of portfolios based on firm size. Firms are allocated to four portfolios based on either *#ANALYSTS* or *SIZE*, and means and medians of *Absolute forecast error*, *Forecast dispersion*, and *METHOD_DIFF* are tabulated.

Table 3 indicates a strong monotonic association between both measures of size (i.e., information environment) and *Absolute forecast error* and *Forecast dispersion*. The stronger associations appear to be in panel B (i.e., *SIZE*). For example, mean *Absolute forecast error* for small firms is 0.067 and falls to 0.013 for large firms. Similarly, *Forecast dispersion* for small firms is 0.014 and falls to 0.005 for large firms. This emphasizes the importance of controlling for measures of size in our regressions that attempt to explain both *Absolute forecast error* and *Forecast dispersion*. The last two columns present the means and medians of *METHOD_DIFF* across size portfolios. There is a clear positive monotonic association between size and *METHOD_DIFF*. For small firms, mean *METHOD_DIFF* is 0.074 but climbs to 0.127 for large firms. Thus, it is large firms that appear more likely to deviate from standard industry accounting practices. Either such firms are more willing to deviate or do so out of necessity, perhaps due to more complex operations (e.g., supply chains, geographic diversity, etc.).[10] In subsequent analyses, we address this latter possibility through control variables and methodological procedures (e.g., matched sample analyses, two-stage regression analyses).

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[10] Our inclusion of *#SEGMENTS* and *EARNVOL*, as well as alternative empirical specifications, in the results discussed below is meant to address this latter possibility by serving as a proxy for complexity.

4.2 Primary results

Table 4 provides a first-stage regression of a prediction model for *METHOD_DIFF*. The objective of this model is to filter complexity from our primary variable of interest, *METHOD_DIFF*, using econometric modeling.][11] In the first stage prediction model, we include variables that might explain the use of atypical accounting methods. For example, we include measures likely associated with complexity such as *log(SIZE)*, *log(#SEGMENTS)*, *LEVERAGE*, external financing (*XFIN*), and a *HERFINDAHL* index of segment sales. Additionally, we include various measures that might capture investor scrutiny, which may affect firms' accounting methods (i.e., *B/M*, dividend yield (*DIVYLD*), sales growth (*SALESGROWTH*), *ROE*, and *BIG5*. The results indicate that several variables have significant explanatory power. Both *SIZE* and *#SEGMENTS* are positively associated with *METHOD_DIFF*, consistent with both measures proxying for complexity of operations. On the other hand, BIG5, XFIN, and the *HERFINDAHL* index of segment sales are negatively associated with *METHOD_DIFF*. The negative associations are consistent with BIG 5 auditors, firms needing external financing, and focused firms (i.e., higher *HERFINDAHL* values) having less atypical accounting methods (i.e., lower *METHOD_DIFF*). The explanatory power of the model is moderate, with an adjusted R^2 of 11.5%.

The main results appear in table 5. Prediction 1 is that atypical accounting methods result in analysts providing more inaccurate forecasts and exhibiting greater disagreement. This is tested by estimating a multivariate regression with either *Absolute forecast error* (panel A) or *Forecast dispersion* (panel B) as the dependent variable, and the primary explanatory variable is *METHOD_DIFF*. Each panel reports the results of three alternative specifications, with the base model including controls for two measures of size (*#ANALYSTS* and *SIZE*), *B/M*, *SPECIAL*

[11] The residuals from this prediction model are utilized in our primary results (table 5).

ITEMS, and *#SEGMENTS*. In addition, because there is variation in forecast horizons due to variation in earnings announcement dates relative to the monthly consensus calculations performed by I/B/E/S, we also control for the number of days between the consensus forecast and the earnings announcement date. The regressions are estimated with year fixed effects and t-statistics are based on standard errors robust to heteroscedacsticity and clustered at the firm level. The second specification includes a control for earnings volatility (*EARNVOL*), which significantly reduces the sample size due to the requirement of prior five-years of earnings.

For the base model, the coefficient on *METHOD_DIFF* in the *Absolute forecast error* regression is 0.0178, with a t-statistic of 3.7. Thus, deviation from standard accounting practice is associated with larger forecast errors, consistent with a detrimental impact of employing atypical accounting methods. The effect appears economically meaningful. For example, based on the interquartile range of *METHOD_DIFF* (i.e., 0.0000 to 0.167), a move from the first to third quartile is estimated to increase *Absolute forecast error* by approximately 0.3% of price (0.0178*0.167), which is approximately 10% of the mean *Absolute forecast error*. In the second model where *EARNVOL* is included as a control, the coefficient on *EARNVOL* is positive and significant, as expected (t=11.9). The coefficient on *METHOD_DIFF* remains significant, although both the coefficient and t-statistic decline.

Most of the control variables yield coefficients with expected signs. For example, in the base model *Absolute forecast error* regression, the coefficient on *log(SIZE)* is negative and significant (t=-15.4), whereas the coefficient on *log(#ANALYSTS)* is positive and significant (t=17.2), possibly due to high correlation between both variables (0.73). Variance inflation factors on both variables are the highest of the independent variables (3.0 for *log(SIZE)* and 2.4 for *log(#ANALYSTS)*, but neither approaches levels of concern (i.e., 10 per Neter, Wasserman, and Kutnuer 1985). In untabulated tests, when *log(SIZE)* or *log(#ANALYSTS)* are omitted, which alleviates collinearity between these variables, the results yield significant negative coefficients on *log(#ANALYSTS),* and vice versa. Thus, both variables appear to be reliable proxies for firm information environment.

The coefficients on the remaining control variables are consistent with our expectations. Coefficients on *B/M* are positive (and significant when *EARNVOL* is included), consistent with value firms having larger forecast errors and dispersion. Not surprisingly, the control for *SPECIAL ITEMS* is positively associated with both dependent variables. The control for firm-level complexity – *log(#SEGMENTS)* – is not significant.

In the third specification, we provide the results of a second stage regression using residuals from the *METHOD_DIFF* prediction model in table 4. In this specification, we substitute *Residual METHOD_DIFF* for *METHOD_DIFF* in the primary regression. Residual *METHOD_DIFF* is the intra-industry variation in accounting methods that is unexplained by the factors included in the first-stage estimation, which controls for characteristics related to inherent complexity. Thus, the remaining unexplained variation in *METHOD_DIFF* can be interpreted as that unrelated to complexity captured by the first-stage controls. The coefficients on *Residual METHOD_DIFF* remain positive and significant at similar levels, reinforcing the primary results.

The results in panel B for *Forecast Dispersion* are similar to those in panel A for *Absolute forecast error*, but with somewhat weaker significance. Across the three models, the t-statistics for the *METHOD_DIFF* (or *Residual METHOD_DIFF*) coefficient estimates are 2.4, 1.7, and 2.1. These results are consistent with forecast dispersion not being as sensitive to atypical accounting methods as is forecast error. Another difference in panel B is the significantly negative coefficients on *log(#SEGMENTS)*, which is specification is consistent with required segment disclosures reducing dispersion in analysts' forecasts (Baldwin 1984).

4.3 Matched sample analysis

To more directly control for the possibility that *METHOD_DIFF* is proxying for economic complexity, we perform a matched sample analysis. Table 6 reports differences in characteristics between two samples of firms matched on variables that proxy for underlying complexity. To construct the matched pairs, we partition firms into two subsamples with one including firms with nonzero *METHOD_DIFF* (i.e., atypical accounting methods) and the other with *METHOD_DIFF*=0 (i.e., accounting methods mirror those of industry peers). In panel A, the matching process was based on industry, year, *SIZE*, and *B/M*; in panel B, the matching process was based on year, *#ANALYSTS*, and *#SEGMENTS*.[12] The panels report the mean and median differences between the two subsamples (e.g., positive values indicate the subsample with *METHOD_DIFF*>0 exhibits a larger value of the corresponding variable).

In panel A, the mean (median) difference in *METHOD_DIFF* is 0.1514 (0.1250), both significant at the <0.0001 level (by design). Moreover, both *Absolute forecast error* and *Forecast dispersion* are higher for the *METHOD_DIFF*>0 subsample. The matching process was not entirely successful at controlling for firm size, in the sense that the *METHOD_DIFF*>0 subsample has a slightly larger mean and median value for *SIZE*.[13] Similarly, for the fourth matching criterion, the subsamples exhibit a statistically significant difference in *B/M*, with the *METHOD_DIFF*>0 subsample having slightly higher *B/M*. Nevertheless, even with the

[12] While we believe it is important to match on industry as in the first comparison, we found it often resulted in poor matches on the remaining factors. Thus, the second set of matches loosens this constraint.
[13] Although statistically significant, the difference in mean *SIZE* between the subsamples is only $5.3 million, which is economically immaterial given the overall sample mean (median) of $2.3 billion ($337 million)

difference in size working against finding higher forecast errors and dispersion for the *METHOD_DIFF*>0 subsample, results are consistent with the primary results. The positive associations between *METHOD_DIFF* and both *Absolute forecast error* and *Forecast dispersion* are statistically significant.

Panel B, where the matching process is based on *#ANALYSTS* and *#SEGMENTS*, is more successful as evidenced by no differences in mean (or median) *#ANALYSTS* and *#SEGMENTS*. Moreover, the matching process actually yielded a better control for *SIZE* than in panel A, as the differences in mean and median *SIZE* are both insignificant.[14] The *METHOD_DIFF*>0 subsample has significantly higher *Absolute forecast error* and *Forecast dispersion*. To the extent that *#SEGMENTS* and the two proxies for size (*#ANALYSTS* and *SIZE*) capture firm complexity, this panel provides some comfort that complexity is not driving the association between *METHOD_DIFF* and our information processing measures – *Absolute forecast error* and *Forecast dispersion*.

Given the importance of control variables in our primary results, table 7 provides a regression approach for each of the matched samples. In these regressions, the unit of analysis is the matched-pair difference. All variables are calculated by subtracting the value for *METHOD_DIFF*=0 firms from that of the matched firm with *METHOD_DIFF* >0. For both samples, there is a significant positive intercept, again supporting the inference that *METHOD_DIFF* has a significant influence on both forecast errors and dispersion.

[14] The first matching process performed within industry matching, whereas the second matching process performed both cross and within industry matching. Loosening the constraint on finding a match within the industry, the cross-industry matches turned out to be more similar in size.

4.4 Effect of information environment on primary results

Our second primary result pertains to Prediction 2, which is that the negative impact of accounting methods on forecast errors and dispersion is mitigated for firms with richer information environments. We continue to use *#ANALYSTS* and *SIZE* as proxies for information environment. Results appear in table 8. To examine whether information environment mitigates the negative impacts of *METHOD_DIFF*, we wish to test for differences in the associations between *METHOD_DIFF* and our forecast variables across firms with disparate information environments, proxied by *log(#ANALYSTS)* or *log(SIZE)*.

The results in table 8 indicate that the significant positive coefficients on *METHOD_DIFF* persist for both large and small firms; similarly, the weaker results for forecast dispersion are evident, but concentrated among small firms. The second prediction is that the association between *METHOD_DIFF* and the forecast measures would be less positive for larger firms due to the enhanced information flows likely present. The last row of table 8 thus provides p-values for tests of differences in the coefficient estimates on *METHOD_DIFF* across large and small firms. For *Absolute forecast error*, there is no difference in the associations across large and small firms, inconsistent with information environment attenuating the detrimental effect of *METHOD_DIFF* on forecast accuracy and dispersion. For *Forecast dispersion*, we obtain conflicting results, with insignificance when large firms are those with high analyst following. We do find that the association between *METHOD_DIFF* and Forecast dispersion is attenuated for large firms when measured by large market capitalization. However, given the disparity of results across these four specifications, we are hesitant to infer that the results overall are consistent with our second prediction.

5. Alternative analysis and robustness tests

The primary findings are consistent with accounting method heterogeneity resulting in information processing costs for analysts, as evidenced by higher absolute forecast errors and greater forecast dispersion. However, as we have noted, they could be interpreted as consistent with an alternative interpretation of complexity, despite attempts to mitigate this concern through alternative specifications of the primary results. The use of an accounting method atypical within an industry may be a proxy for complexities inherent in a firm's operations. For example, if all firms within an industry use FIFO, but one firm uses LIFO, it might be due to a different supply chain arrangement, unique contracts or tax strategies, or idiosyncratic regulatory issues. These underlying economic complexities (as opposed to *information* complexities) may negatively affect analysts' abilities to forecast future performance.

In addition to the alternative tests reported above, we have also subjected the primary results to numerous robustness tests. Our first set of tests examines the sensitivity to our definition of *METHOD_DIFF*. We computed ten different versions of *METHOD_DIFF*, alternately dropping one of the accounting methods from the computation. For all computations, the results mirror the primary results. In addition, we compute *METHOD_DIFF* using a superset of accounting methods from the Worldscope database (including such methods as long-term investments, contingent liabilities, etc.), and the significant positive associations between our index and *Forecast error* and *Forecast dispersion* persist. Finally, we also limited the index to various subsets, with similar results. Thus, our definition of *METHOD_DIFF* in the primary results does not appear to be sensitive to alternative configurations.

All results are based upon analyst data at a horizon of eight months prior to the next fiscal year end, which approximates the release of the previous year's earnings. Given the simultaneous release of prior year results, information processing of those results may detract from analysts' efforts to incorporate this information into forecasts for the following fiscal year. Indeed, there is a well-documented walkdown of earnings forecasts from this point through to the release of the end of year results (e.g., Richardson, Teoh, and Wysocki 2004). Although this phenomenon has been attributed to factors such as management guidance, it is also plausible that analysts only gradually incorporate information from the prior year's earnings announcement (e.g., Bradshaw, Richardson, and Sloan 2001). As a result, our selection of forecast measurement date may lead to spurious results due simply to analyst inattention at this horizon. We thus examine alternative forecast horizons in table 9.

These horizons are labeled according to the months before fiscal year end, ranging from horizon 8 (e.g., April for a December fiscal year end) to horizon 0 (December of year t for a December year t fiscal year end). Horizon 8 corresponds to results shown in table 5.[15] The results in table 9 are consistent with the declining pattern of analyst forecast errors and dispersion documented in previous research. For example, in panel A the intercept for the *Absolute forecast error* regression monotonically falls from 0.048 at horizon 8 to 0.017 at horizon 0. However, in contrast, the coefficients on *METHOD_DIFF* are fairly stable across forecast horizons earlier than the last fiscal month, and are always positive and significant. The tenor of these results is also reflected in the *Forecast dispersion* results in panel B. These results give comfort that the primary results for the associations between *METHOD_DIFF* and either *Absolute forecast error* or *Forecast dispersion* are not spurious or horizon-specific.

The final supplemental test appears in table 10, and addresses the question of why analysts would appear to persistently exhibit higher errors and dispersion for firms reporting

[15] The tabulated figures differ slightly across tables, however, because we omit *Forecast horizon* from the horizon-specific forecasts in table 5.

under atypical accounting methods, as the pooled regressions suggest. We estimate a seemingly unrelated regression specification where firms partitioned into 'stable' and 'non-stable' based on the number of years they reported under a stable set of accounting methods (either 5 years, 4 years, or 3 years). Panel A provides regressions for *Absolute forecast error*; panel B provides regressions for *Forecast dispersion*. The coefficients on *METHOD_DIFF* for firms with non-stable accounting methods are always greater than for firms with stable accounting methods, consistent with analysts actually learning. However, tests for differences in coefficients across stable and non-stable firms fail to reject the null of equivalence. Thus, although the direction of differences is consistent with learning, significance tests are not.

6. Conclusion

In this paper, we predict that firms using atypical accounting methods for their industry suffer from higher forecast errors and forecast dispersion. Our primary results are consistent with this prediction. This association is consistent at all forecast horizons, indicating the phenomenon is systematic. There appear to be costs to firms using accounting methods that differ from their industry peers. Given this unconditional finding, it would be interesting to investigate whether firms that report using atypical accounting methods can overcome the average effect we document through enhanced investor communication or whether the market reaction to earnings releases by firms with atypical accounting methods differs in any meaningful way.

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Appendix
Accounting methods

	Accounting Method Choice	Options	% Common	% Atypical	% Not disclosed
1	Depreciation Method	Straight line	73.0%	11.8%	15.2%
		Straight line with excess depreciation			
		Accelerated depreciation			
		Sinking fund method			
		Mixed depreciation methods			
		Unit of production			
		Other			
2	Acquisition method	Pooling of interest	27.3%	5.9%	66.8%
		Purchase			
		Mixed			
3	Foreign currency translation gain/loss	Taken to income statement	26.3%	20.3%	53.4%
		Taken to shareholder's equity			
		Deferred			
4	Funds definition on statement of changes in financial position	Working capital	85. 2%	14.5%	0.3%
		Cash			
		Modified cash			
		Unique definition			
		Net liquid assets			
5	Accounting for inventory	FIFO	43.0%	40.8%	16.2%
		LIFO			
		Weighted average			
		Specific identification			
		Mixed			
		Current cost			
		Moving average			
		No inventory method			

6	Marketable securities valuation	Lower of cost or market	91.9%	1. 1%	7.1%
		Current market value			
		Historical cost			
		Moving average			
		Weighted average			
		Periodic average			
		Cost with periodic revaluation			
7	Accounting for research & development	Expensed currently	39.9%	3.4%	56.7%
		Capitalized and amortized later			
		Expensed and capitalized later			
		Mixed			
8	Accounting for long-term financial leases	Capitalized and amortized	92.0%	0.9%	7.1%
		Expensed			
		Mixed			
9	Accounting for other intangibles/deferred charges	Amortized	99.3%	0.7%	0.0%
		Capitalized not amortized			
		Expensed when incurred			
		Capitalized, written off at management discretion			
10	Accounting for minority interest effect	Before bottom line in income, excluded from shareholder's equity	99.5%	0.5%	0.0%
		In statement of retained earnings after bottom line on income statement and included in equity			
		Not disclosed in income statement, excluded from shareholder's equity. Reported elsewhere in balance sheet			
		Before bottom line in income, included in shareholder's equity			
		In statement of retained earnings after bottom line on income statement and excluded from equity			
11	Loan loss reserves	Specific reserve against loan losses	9.2%	0.3%	90.5%
		Specific loan loss reserve exists but is not separately disclosed			

Table 1
Descriptive statistics

Panel A: Descriptive statistics for all variables

DESCRIPTIVE STATISTICS						
Variable	**Mean**	**Median**	**σ**	**Q1**	**Q3**	**# of observations**
METHOD_DIFF	0.093	0.091	0.102	0.000	0.167	19,986
Absolute forecast error	0.031	0.011	0.056	0.004	0.032	19,986
Forecast dispersion	0.008	0.004	0.012	0.002	0.009	17,508
#ANALYSTS	7.910	5.000	7.660	2.000	11.000	19,986
SIZE ($mm)	2329	337	10787	110	1174	19,986
B/M	0.625	0.531	0.445	0.325	0.795	19,986
SPECIAL ITEMS	0.398	0.000	0.489	0.000	1.000	19,986
# SEGMENTS	2.708	2.000	1.541	2.000	4.000	19,986
EARNVOL	0.897	0.547	1.074	0.305	1.039	16,783
DIVYLD	1.424	0.548	1.915	0.000	2.359	19,904
SALESGROWTH	18.533	10.639	30.849	1.916	24.257	19,665
LEVERAGE	0.624	0.303	0.981	0.037	0.792	19,909
ROE	11.918	13.314	18.077	5.244	20.108	19,552
BIG 5	0.946	1.000	0.225	1.000	1.000	19,986
XFIN	0.115	0.010	0.432	-0.046	0.163	18,749
HERFINDAL	0.834	1.000	0.227	0.657	1.000	15,007
AR(1) for *METHOD_DIFF*	0.747	0.808	0.184	0.580	0.919	15

Table 1 (cont.)
Descriptive statistics

Panel B: Distribution of sample firms and *METHOD_DIFF* across industries

			METHOD_DIFF				
Industry	**Compustat**	**Sample**	**Mean**	**Median**	**σ**	**Q1**	**Q3**
Aero	0.3%	0.58%	0.13	0.10	0.09	0.08	0.18
Agric	0.3%	0.29%	0.07	0.09	0.07	0.00	0.11
Autos	1.2%	1.90%	0.19	0.17	0.11	0.10	0.25
Banks	10.4%	10.23%	0.04	0.00	0.08	0.00	0.11
Beer	0.3%	0.27%	0.20	0.17	0.15	0.09	0.33
BldMt	1.6%	2.47%	0.14	0.11	0.11	0.08	0.18
Books	0.7%	1.35%	0.12	0.10	0.09	0.09	0.20
Boxes	0.3%	0.43%	0.16	0.17	0.10	0.08	0.25
BusSv	13.4%	9.96%	0.06	0.00	0.08	0.00	0.10
Chems	1.5%	2.04%	0.18	0.17	0.11	0.08	0.25
Chips	5.2%	6.43%	0.07	0.08	0.09	0.00	0.10
Clths	1.2%	1.05%	0.10	0.10	0.08	0.00	0.18
Cnstr	1.1%	1.09%	0.10	0.10	0.10	0.00	0.13
Coal	0.1%	0.02%	0.19	0.17	0.17	0.08	0.29
Comps	4.4%	4.26%	0.11	0.09	0.10	0.00	0.17
Drugs	4.8%	2.86%	0.07	0.00	0.10	0.00	0.10
ElcEq	0.8%	1.85%	0.15	0.17	0.11	0.08	0.25
Enrgy	3.4%	2.66%	0.11	0.10	0.10	0.00	0.18
FabPr	0.4%	0.41%	0.14	0.17	0.10	0.08	0.25
Fin	4.7%	1.90%	0.07	0.00	0.13	0.00	0.13
Food	1.3%	1.96%	0.11	0.10	0.09	0.08	0.18
Fun	1.7%	0.98%	0.04	0.00	0.07	0.00	0.10
Gold	0.8%	0.16%	0.13	0.11	0.10	0.00	0.22
Guns	0.1%	0.12%	0.23	0.24	0.08	0.19	0.30
Hlth	1.3%	1.30%	0.05	0.00	0.07	0.00	0.11

Hshld	1.3%	2.26%	0.15	0.17	0.12	0.08	0.25
Insur	3.5%	4.68%	0.04	0.00	0.08	0.00	0.00
LabEq	1.8%	2.23%	0.13	0.10	0.09	0.08	0.17
Mach	3.0%	3.71%	0.18	0.17	0.10	0.08	0.25
Meals	1.6%	1.97%	0.06	0.00	0.07	0.00	0.11
MedEq	3.2%	3.24%	0.07	0.08	0.09	0.00	0.09
Mines	0.3%	0.22%	0.10	0.10	0.10	0.00	0.11
Misc	0.4%	0.04%	0.05	0.05	0.05	0.00	0.10
Paper	1.2%	1.89%	0.18	0.17	0.10	0.10	0.25
PerSv	1.0%	0.86%	0.05	0.00	0.07	0.00	0.10
RlEst	0.3%	0.26%	0.03	0.00	0.07	0.00	0.00
Rtail	5.4%	5.94%	0.10	0.11	0.09	0.00	0.11
Rubbr	0.6%	0.76%	0.16	0.17	0.11	0.08	0.21
Ships	0.2%	0.26%	0.13	0.11	0.09	0.08	0.18
Smoke	0.1%	0.07%	0.21	0.25	0.11	0.17	0.25
Soda	0.2%	0.16%	0.24	0.25	0.17	0.09	0.36
Steel	1.5%	1.92%	0.12	0.10	0.09	0.09	0.17
Telcm	3.8%	1.72%	0.11	0.09	0.15	0.00	0.18
Toys	0.5%	0.74%	0.11	0.08	0.10	0.08	0.17
Trans	2.5%	2.38%	0.07	0.09	0.08	0.00	0.11
Txtls	0.4%	0.80%	0.08	0.10	0.07	0.00	0.11
Util	3.0%	3.83%	0.06	0.00	0.08	0.00	0.11
Whlsl	3.0%	3.57%	0.09	0.10	0.09	0.00	0.11
	100.0%	100.0%					

Notes: Industries are as defined in Fama and French (1997). *METHOD_DIFF* is the mean value of 11 dummies that take the value of 1 if the firm uses an accounting method that differs from the mode of its industry peers, scaled by the number of choices applicable for the industry. *Absolute forecast error* is the absolute difference between consensus forecast and actual earnings deflated by the stock price at the end of the previous fiscal year. *Forecast dispersion* is the standard deviation of individual analyst forecasts deflated by the stock price at the end of the previous fiscal year. *#ANALYSTS* is the number of analysts included in the consensus earnings forecast. *SIZE* is market value as of the end of the previous fiscal year. *B/M* is the book-to-market ratio, measured as of the end of the previous fiscal year. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items in the year being forecasted, and 0 otherwise. *#SEGMENTS* is the number of different SIC codes the company operates in. The autoregressive parameters are derived from an AR(1) process on *METHOD_DIFF*. Fama-McBeth regressions were estimated and the coefficient is the average of all the coefficients over the years.

Table 2
Pearson correlations

	Absolute forecast error	*Forecast dispersion*	*METHOD _DIFF*	*B/M*	*log(SIZE)*	*log(#ANALYSTS)*	*SPECIAL ITEMS*	*log(#SEGMENTS)*
Absolute forecast error	1.000							
Forecast dispersion	0.505	1.000						
METHOD_DIFF	-0.017	0.000	1.000					
B/M	0.368	0.266	-0.045	1.000				
log(SIZE)	-0.340	-0.237	0.185	-0.428	1.000			
log(#ANALYSTS)	-0.200	-0.099	0.141	-0.192	0.731	1.000		
SPECIAL ITEMS	0.111	0.055	-0.031	0.046	0.072	0.061	1.000	
log(#SEGMENTS)	-0.070	-0.066	0.230	-0.077	0.290	0.218	0.042	1.000
EARNVOL	0.121	0.207	0.057	0.121	0.209	0.167	0.095	0.108

Notes: The table shows univariate correlations for all variables used in the paper. *Absolute forecast error* is the absolute difference between consensus forecast and actual earnings deflated by the stock price at the end of the previous fiscal year. *Forecast dispersion* is the standard deviation of individual analyst forecasts deflated by the stock price at the end of the previous fiscal year. *METHOD_DIFF* is the mean value of 11 dummies that take the value of 1 if the firm uses an accounting method that differs from the mode of its industry peers, scaled by the number of choices applicable for the industry. *#ANALYSTS* is the number of analysts included in the consensus earnings forecast. *SIZE* is market value as of the end of the previous fiscal year. *B/M* is the book-to-market ratio, measured as of the end of the previous fiscal year. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items in the year being forecasted, and 0 otherwise. *#SEGMENTS* is the number of different SIC codes the company operates in.

Table 3
Distribution of *METHOD*_DIFF across Size Portfolios

Panel A: *#ANALYSTS* portfolios

#ANALYSTS* *portfolio	**N**	***Absolute forecast error*** **Mean**	**Median**	***Forecast dispersion*** **Mean**	**Median**	***METHOD_DIFF*** **Mean**	**Median**
1 (Few)	5,183	0.049	0.020	0.010	0.004	0.081	0.000
2	3,831	0.035	0.014	0.009	0.004	0.087	0.083
3	3,453	0.027	0.011	0.007	0.004	0.092	0.091
4	3,817	0.023	0.008	0.007	0.003	0.097	0.091
5 (Many)	3,702	0.017	0.006	0.006	0.003	0.116	0.100

Panel B: *SIZE* portfolios

SIZE* *portfolio	**N**	***Absolute forecast error*** **Mean**	**Median**	***Forecast dispersion*** **Mean**	**Median**	***METHOD_DIFF*** **Mean**	**Median**
1 (Small)	4,006	0.067	0.035	0.014	0.007	0.074	0.000
2	3,997	0.036	0.016	0.009	0.005	0.081	0.083
3	3,995	0.024	0.010	0.007	0.004	0.084	0.083
4	3,997	0.018	0.007	0.006	0.003	0.101	0.091
5 (Large)	3,991	0.013	0.005	0.005	0.003	0.127	0.100

Notes: Firms are allocated to quintiles according to analyst following (panel A) or size (panel B). *METHOD_DIFF* is the mean value of 11 dummies that take the value of 1 if the firm uses an accounting method that differs from the mode of its industry peers, scaled by the number of choices applicable for the industry. *Absolute forecast error* is the absolute difference between the consensus forecast and actual earnings, deflated by the stock price at the end of the previous fiscal year. *Forecast dispersion* is the standard deviation of individual analyst forecasts, deflated by the stock price at the end of the previous fiscal year. Mean and medians are shown for *Absolute forecast error, Forecast dispersion*, and *METHOD_DIFF* for each portfolio.

Table 4
Determinants of *METHOD_DIFF*

Variable	Coefficient	t-statistic
Intercept	0.0963	7.6
log(SIZE)	0.0067	5.4
B/M	0.0024	0.7
log(#SEGMENTS)	0.0290	9.8
DIVYLD	0.0015	1.7
SALESGROWTH	-0.0001	-1.4
LEVERAGE	-0.0020	-1.3
ROE	0.0001	0.8
BIG5	-0.0203	-2.3
XFIN	-0.0083	-3.5
HERFINDAHL	-0.0702	-9.5
EARNVOL	-0.0009	-0.6
Year fixed effects	No	
Adj R^2	11.5%	
N	11,156	

Notes: This table presents the results of a first-stage regression in which *METHOD_DIFF* is modeled as a function of various expected determinants of firms adopting atypical accounting methods; in the second stage, the residual from the first stage is included as a regressor along with control variables. *#ANALYSTS* is the number of analysts included in the consensus earnings forecast. *SIZE* is market value as of the end of the previous fiscal year. *B/M* is the book-to-market ratio, measured as of the end of the previous fiscal year. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items or extraordinary items in the year being forecasted, and 0 otherwise. *#SEGMENTS* is the number of different SIC codes the company operates in. *Forecast horizon* is the number of days between the consensus forecast and the fiscal year end date. *Sales growth* is 1-year percentage change in sales. Leverage is long-term debt over book value of common equity. *Dividend yield* is dividend per share divided by end of year closing stock price. *ROE* is net income before extraordinary items divided by book value of equity. *BIG5* is a dummy taking the value of 1 when a firm is audited by a Big 5 accounting firm. *External financing* is change in capital over the year divided by book value of common equity. *HERFINDAHL* is an index of a firm's sales concentration among operating segments, defined as the sum of the squares of each segment's sales over the total sales. Standard errors are robust to heteroscedasticity and clustered at the firm level to eliminate serial autocorrelation.

Table 5
Regressions of Forecast Error (panel A) and Forecast Dispersion (panel B) on *METHOD_DIFF* and Control Variables

Panel A: Dependent variable = *Absolute forecast error*

Variable	Base Model		Earnings Volatility control		Second-stage Model	
	Coef. est.	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**
Intercept	0.0068	0.1	-0.0125	-0.2	-0.0208	-0.3
METHOD_DIFF	0.0178	3.7	0.0120	2.4		
Residual METHOD_DIFF	-	-	-	-	0.0155	2.5
log (#ANALYSTS)	0.0314	17.2	0.0018	2.2	0.0006	0.7
log(SIZE)	-0.0085	-15.4	-0.0104	-16.1	-0.0097	-13.3
B/M	0.0012	1.6	0.0273	13.7	0.0246	10.1
SPECIAL ITEMS	0.0143	16.2	0.0128	13.5	0.0117	11.1
log (#SEGMENTS)	0.0003	0.3	-0.0004	-0.4	0.0020	1.9
Forecast horizon	0.0002	0.9	0.0003	1.4	0.0003	1.3
EARNVOL	-	-	0.0077	11.9	0.0071	9.7
Year fixed effects	Yes		Yes		Yes	
Adj. R-squared	19.9%		22.3%		22.2%	
N	19,986		13,501		11,156	

Table 5 (cont.)
Regressions of Forecast Error (panel A) and Forecast Dispersion (panel B) on *METHOD_DIFF* and Control Variables

Panel B: Dependent variable = *Forecast dispersion*

Variable	**Base Model**		**Earnings Volatility control**		**Second-stage Model**	
	Coef. est.	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**
Intercept	0.0171	1.3	0.0083	0.6	0.0109	0.7
METHOD_DIFF	0.0036	2.4	0.0026	1.7	-	-
Residual METHOD_DIFF	-	-	-	-	0.0043	2.1
log (#ANALYSTS)	0.0011	4.2	0.0013	4.6	0.0010	3.1
log(SIZE)	-0.0016	-10.6	-0.0022	-13.0	-0.0021	-11.0
B/M	0.0049	10.1	0.0035	7.3	0.0028	4.7
SPECIAL ITEMS	0.0018	8.1	0.0014	6.5	0.0015	5.9
log (#SEGMENTS)	-0.0005	-1.8	-0.0007	-2.7	-0.0002	-0.9
Forecast horizon	0.0000	-0.5	0.0000	0.4	0.0000	0.2
EARNVOL			0.0025	12.4	0.0024	10.9
Year fixed effects	Yes		Yes		Yes	
Adj R-squared	11.3%		17.1%		16.2%	
N	17,508		12,797		9,791	

Notes: This table presents OLS regressions with dependent variables of forecast error and standard deviation of forecasts, respectively (first two models); the third model reflects the results of a two-stage regression. In the first stage (table 4), *METHOD_DIFF* is modeled as a function of various expected determinants of firms adopting atypical accounting methods; in the second stage, the residual from the first stage is included as a regressor along with control variables. *Absolute forecast error* is the absolute difference between the consensus earnings forecast and actual earnings, deflated by the stock price at the end of the previous fiscal year. *Forecast dispersion* is the standard deviation of individual analyst forecasts, deflated by the stock price at the end of the previous fiscal year. *METHOD_DIFF* is the mean value of 12 dummies that take the value of 1 if the firm uses an accounting method that differs from the mode of its industry peers, scaled by the number of choices applicable for the industry. *#ANALYSTS* is the number of analysts included in the consensus earnings forecast. *SIZE* is market value as of the end of the previous fiscal year. *B/M* is the book-to-market ratio, measured as of the end of the previous fiscal year. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items or extraordinary items in the year being forecasted, and 0 otherwise. *#SEGMENTS* is the number of different SIC codes the company operates in. *Forecast horizon* is the number of days between the consensus forecast and the fiscal year end date. Standard errors are robust to heteroscedasticity and clustered at the firm level to eliminate serial autocorrelation.

Table 6
Matched Sample Univariate Statistics (N=1,037 pairs)

Panel A: Matching based on industry, year, *SIZE*, and *B/M*

Difference between firm with *METHOD_DIFF*>0 and match firm with *METHOD_DIFF*=0

	METHOD_DIFF	*Absolute forecast error*	*Forecast dispersion*	*#ANALYSTS*	*SIZE*	*B/M*	*SPECIAL ITEMS*	*#SEGMENTS*	*Forecast horizon*
Mean	0.1514	0.0038	0.0012	-0.1908	5.2767	0.0266	0.03252	0.1101	0.2627
Median	0.1250	0.0018	0.0001	0.0000	5.5170	0.0188	0.00000	0.0000	0.0000
t-test	<.0001	0.0031	0.0002	0.0002	0.0012	<.0001	0.0024	<.0001	<.0001
Signed rank	<.0001	<.0001	0.0133	0.0002	0.0011	0.0002	0.0026	0.0014	<.0001

Panel B: Matching based on industry (where successful), year, *#ANALYSTS*, and *#SEGMENTS*

Difference between firm with *METHOD_DIFF*>0 and match firm with *METHOD_DIFF*=0

	METHOD_DIFF	*Absolute forecast error*	*Forecast dispersion*	*#ANALYSTS*	*SIZE*	*B/M*	*SPECIAL ITEMS*	*#SEGMENTS*	*Forecast horizon*
Mean	0.1505	0.0059	0.0009	0.0000	-0.1000	-0.0331	0.01362	0.0000	0.3729
Median	0.1250	0.0020	0.0000	0.0000	-1.2940	-0.0409	0.00000	0.0000	0.0000
t-test	<.0001	<.0000	0.0041	-	0.9458	<.0001	0.1778	-	<.0001
Signed rank	<.0001	<.0001	0.0330	-	0.6500	<.0001	0.1778	-	<.0001

Notes: This table presents differences in key variables across two samples of firms, those with *METHOD_DIFF*>0 and those with *METHOD_DIFF*=0. For every sample firm with a nonzero value of *METHOD_DIFF*, we obtained a match in two different ways. For panel A, a matched firm was chosen from the same industry and year, and then matched on *SIZE* and *B/M*; if not firm was available for the same industry and year, the firm is excluded from the matched sample analysis. Similarly, in panel B, a matched firm was selected from the same year, and then on *#ANALYSTS* and *#SEGMENTS*. Sample size for panel A (B) is 3,905 (4,259) for all variables, except *Forecast dispersion*, where the sample size is 2,653 (3,302).

Table 7
Matched Sample Regression of Matched Pair Differences in *METHOD_DIFF* on Differences in Matched Pair Control Variables (N=1,037 pairs)

	Matching based on industry, year, *SIZE*, and *B/M*				**Matching based on year, *#ANALYSTS*, and *#SEGMENTS***			
	Absolute forecast error		***Forecast dispersion***		***Absolute forecast error***		***Forecast dispersion***	
Parameter	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Intercept	**0.0031**	**2.5**	**0.0012**	**3.5**	**0.0058**	**4.6**	**0.0009**	**3.0**
Diff #ANALYSTS	0.0002	0.5	-0.0001	-0.7				
Diff log(SIZE)	-0.0001	-12.4	-0.0000	-4.6	-0.0001	-10.7	-0.0000	-7.0
Diff B/M	0.0287	7.8	0.0037	3.7	0.0121	3.5	0.0018	2.2
Diff SPECIAL ITEMS	0.0194	9.7	0.0023	4.3	0.0168	8.4	0.0025	5.1
Diff log(#SEGMENTS)	0.0013	1.71	-0.0005	-2.4				
Diff Forecast horizon	-0.0000	-0.0	0.0001	1.0	0.0005	1.4	-0.0000	-0.5
Adj R^2	8.89%		2.76%		4.70%		2.56%	

Notes: This table presents differences in key variables across two samples of firms, those with *METHOD_DIFF*>0 and those with *METHOD_DIFF*=0. For every sample firm with a nonzero value of *METHOD_DIFF*, we obtained a match in two different ways, as described in table 6. We calculate differences for each matched pair of firms and estimate the average difference (intercept) in forecast errors and dispersion after controlling for all other determinants. Differences are computed by subtracting the firm characteristic for a firm with *METHOD_DIFF* =0 from the firm characteristic for a firm with *METHOD_DIFF* >0. Standard errors are robust to heteroscedasticity and clustered at the firm level to eliminate serial autocorrelation.

Table 8

Tests of Attenuation of *METHOD_DIFF* Impact for Firms with Richer Information Environments, based on Seemingly Unrelated Regression of *Absolute Forecast Error* (panel A) and *Forecast Dispersion* (panel B) on *METHOD_DIFF* and Control Variables with Partitions of Firms based on Size

	Large=1 if *#ANALYSTS*>3rd Quartile				**Large=1 if *SIZE*>3rd Quartile**			
	Absolute forecast error		**Forecast dispersion**		**Absolute forecast error**		**Forecast dispersion**	
	Coef. est.	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**
Large Firms	-0.0995	-1.7	0.0109	0.6	-0.0689	-1.3	-0.0017	-0.1
METHOD_DIFF	0.0141	2.1	0.0080	2.8	0.0132	2.5	0.0079	3.8
log(#ANALYSTS)	0.0063	2.7	0.0005	0.6	-0.0029	-2.3	-0.0008	-2.3
log (SIZE)	-0.0035	-4.3	-0.0009	-3.2	0.0001	0.2	0.0001	0.3
B/M	0.0351	7.7	0.0091	8.9	0.0317	8.6	0.0095	11.1
SPECIAL ITEMS	0.0076	6.2	0.0018	5.1	0.0053	5.4	0.0011	4.1
log(#SEGMENTS)	-0.0027	-1.8	-0.0006	-1.1	-0.0026	-2.1	-0.0006	-1.7
Forecast horizon	0.0004	1.7	0.0000	-0.3	0.0003	1.3	0.0000	0.1
Small Firms	0.0300	0.6	0.0163	1.2	0.0570	1.1	0.0241	1.7
METHOD_DIFF	0.0202	3.6	0.0027	1.6	0.0123	2.1	0.0006	0.3
log(#ANALYSTS)	-0.0005	-0.6	0.0006	2.0	0.0027	3.3	0.0017	5.4
log (SIZE)	-0.0110	-16.5	-0.0019	-11.0	-0.0146	-18.8	-0.0025	-12.0
B/M	0.0289	14.9	0.0039	7.7	0.0275	13.9	0.0038	7.0
SPECIAL ITEMS	0.0156	15.4	0.0018	7.1	0.0163	15.6	0.0020	7.4
log(#SEGMENTS)	0.0007	0.6	-0.0004	-1.6	0.0004	0.4	-0.0005	-1.5
Forecast horizon	0.0001	0.6	0.0000	-0.2	0.0001	0.4	0.0000	-0.6
Year fixed effects	Yes		Yes		Yes		Yes	
N	19,986		17,508		19,986		17,508	
Adj R^2	39.82%		37.90%		40.51%		38.18%	
p-value for test of difference in *METHOD_DIFF* coefficients	0.4805		0.0946		0.9005		0.0039	

Notes: This table presents the results of a seemingly unrelated regression with partitions of firms based on firm size. *Absolute forecast error* is the absolute difference between the consensus earnings forecast and actual earnings, deflated by the stock price at the end of the previous fiscal year. *Forecast dispersion* is the standard deviation of individual analyst forecasts, deflated by the stock price at the end of the previous fiscal year. *METHOD_DIFF* is the mean value of 12 dummies that take the value of 1 if the firm uses an accounting method that differs from the mode of its industry peers, scaled by the number of choices applicable for the industry. *#ANALYSTS* is the number of analysts included in the consensus earnings forecast. *SIZE* is market value as of the end of the previous fiscal year. *B/M* is the book-to-market ratio, measured as of the end of the previous fiscal year. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items or extraordinary items in the year being forecasted, and 0 otherwise. *#SEGMENTS* is the number of different SIC codes the company operates in. *Forecast horizon* is the number of days between the consensus forecast and the fiscal year end date. Standard errors are robust to heteroscedasticity and clustered at the firm level to eliminate serial autocorrelation.

Table 9
Regressions Across Alternative Horizons

Panel A: Absolute forecast error

	Horizon 8		Horizon 6		Horizon 4		Horizon 2		Horizon 0	
Variable	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	
Intercept	0.0481	11.9	0.0491	12.2	0.0354	10.6	0.0251	8.5	0.0167	6.4
METHOD_DIFF	0.0133	2.5	0.0181	3.4	0.0160	3.3	0.0122	2.7	0.0082	2.0
log(#ANALYSTS)	0.0314	17.1	0.0262	15.0	0.0225	14.3	0.0206	13.6	0.0161	11.6
log(SIZE)	-0.0084	-15.2	-0.0077	-13.8	-0.0054	-11.7	-0.0038	-9.0	-0.0022	-5.9
B/M	0.0012	1.6	-0.0007	-0.9	-0.0031	-4.6	-0.0040	-6.3	-0.0050	-8.8
SPECIAL ITEMS	0.0143	16.2	0.0147	16.8	0.0123	15.8	0.0103	14.3	0.0086	13.5
log(#SEGMENTS)	0.0005	0.5	0.0006	0.7	0.0008	1.0	0.0009	1.3	0.0007	1.2
Year fixed effects	Yes		Yes		Yes		Yes		Yes	
Adj R^2	19.88%		18.14%		16.52%		15.05%		12.55%	
N	19986		21329		21491		21500		21494	

Table 9 (cont.)
Regressions Across Alternative Horizons

Panel B: Forecast dispersion

	Horizon 8		**Horizon 6**		**Horizon 4**		**Horizon 2**		**Horizon 0**	
Variable	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**	**Coef. est.**	**t-stat.**
Intercept	0.0103	9.9	0.0098	10.4	0.0083	9.3	0.0066	8.2	0.0048	6.4
METHOD_DIFF	0.0032	2.0	0.0034	2.3	0.0046	3.2	0.0042	3.0	0.0039	2.6
log(#ANALYSTS)	0.0049	10.1	0.0050	11.1	0.0052	12.3	0.0051	11.9	0.0053	12.9
log(SIZE)	-0.0016	-10.5	-0.0014	-10.2	-0.0012	-9.2	-0.0010	-8.0	-0.0007	-6.2
B/M	0.0011	4.2	0.0005	2.0	-0.0001	-0.4	-0.0002	-1.0	-0.0004	-2.0
SPECIAL ITEMS	0.0018	8.1	0.0020	9.1	0.0022	10.7	0.0022	11.1	0.0021	10.8
log(#SEGMENTS)	-0.0005	-1.7	-0.0003	-1.0	-0.0003	-1.4	-0.0004	-1.7	-0.0004	-1.7
Year fixed effects	Yes		Yes		Yes		Yes		Yes	
Adj R^2	11.31%		11.36%		12.03%		11.51%		11.49%	
N	17508		18383		18594		18630		18662	

Notes: OLS regressions with dependent variable forecast error and standard deviation of forecasts. Forecast error is the absolute difference between consensus forecast and actual earnings deflated by the stock price at the end of the previous fiscal year. Forecast dispersion is the standard deviation of individual analyst forecasts deflated by the stock price at the end of the previous fiscal year. *METHOD_DIFF* is the mean value of 11 dummies that take the value of 1 if the firm uses an accounting method that differs from the mode of its industry peers, scaled by the number of choices applicable for the industry. *#ANALYSTS* is the number of analysts included in the consensus earnings forecast. *SIZE* is market value as of the end of the previous fiscal year. *B/M* is the book-to-market ratio, measured as of the end of the previous fiscal year. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items or extraordinary in the year being forecasted, and 0 otherwise. *#SEGMENTS* is the number of different SIC codes the company operates in. Forecasts are tracked across horizons from two months subsequent to the previous fiscal year end through the fiscal year end. Horizon 10 is for forecasts made approximately 10 months prior to the fiscal year end, horizon 8 reflects forecasts made approximately 8 months prior to the fiscal year end, and so on. Standard errors are robust to heteroscedasticity and clustered at the firm level to eliminate serial autocorrelation.

Table 10

Seemingly Unrelated Regression of Absolute Forecast Error (panel A) and Forecast Dispersion (panel B) on METHOD_DIFF and Control Variables with Partitions of Firms based on Stability of Accounting Methods over Varying Intervals

Panel A: Dependent variable = *Absolute forecast error*

	5-year stability interval		**4-year stability interval**		**3-year stability interval**	
	Coef. estimate	**t-stat.**	**Coef. estimate**	**t-stat.**	**Coef. estimate**	**t-stat.**
Non-stable method firms	0.0484	11.8	0.0489	11.9	0.0489	11.8
METHOD_DIFF	0.0230	4.8	0.0236	4.9	0.0242	4.9
log(#ANALYSTS)	0.0317	16.8	0.0313	16.4	0.0318	16.1
log (SIZE)	-0.0087	-15.4	-0.0087	-15.5	-0.0087	-15.3
B/M	0.0014	1.8	0.0014	1.7	0.0013	1.7
SPECIAL ITEMS	0.0002	0.2	-0.0002	-0.2	-0.0006	-0.6
log(#SEGMENTS)	0.0146	15.7	0.0148	15.4	0.0151	14.7
Stable method firms	0.0443	4.3	0.0404	4.7	0.0442	6.1
METHOD_DIFF	0.0171	1.1	0.0171	1.4	0.0152	1.6
log(#ANALYSTS)	0.0261	4.7	0.0323	6.4	0.0294	7.4
log (SIZE)	-0.0071	-4.3	-0.0074	-5.1	-0.0079	-6.8
B/M	-0.0002	-0.1	0.0004	0.2	0.0010	0.6
SPECIAL ITEMS	0.0015	0.7	0.0036	1.7	0.0035	2.2
log(#SEGMENTS)	0.0110	4.8	0.0113	5.7	0.0116	7.6
t-test for difference in coefficients on *METHOD_DIFF*	-0.4		-0.6		-0.9	

Table 10 (cont.)
Seemingly Unrelated Regression of Absolute Forecast Error (panel A) and Forecast Dispersion (panel B) on METHOD_DIFF and Control Variables with Partitions of Firms based on Stability of Accounting Methods over Varying Intervals

Panel B: Dependent variable = *Forecast dispersion*

	5-year stability interval		4-year stability interval		3-year stability interval	
	Coef. estimate	**t-stat.**	**Coef. estimate**	**t-stat.**	**Coef. estimate**	**t-stat.**
Non-stable method firms	0.0103	9.7	0.0100	9.3	0.0099	9.1
METHOD_DIFF	0.0063	4.2	0.0065	4.2	0.0067	4.2
log(#ANALYSTS)	0.0050	10.0	0.0051	9.9	0.0051	9.8
log (SIZE)	-0.0016	-10.6	-0.0016	-10.4	-0.0016	-10.0
B/M	0.0011	4.2	0.0011	4.1	0.0011	4.0
SPECIAL ITEMS	-0.0005	-1.9	-0.0006	-2.1	-0.0006	-2.4
log(#SEGMENTS)	0.0018	7.8	0.0018	7.5	0.0018	7.3
Stable method firms	0.0100	4.0	0.0127	6.0	0.0120	7.0
METHOD_DIFF	0.0052	1.3	0.0046	1.5	0.0046	1.8
log(#ANALYSTS)	0.0031	2.6	0.0032	3.2	0.0038	4.8
log (SIZE)	-0.0014	-3.4	-0.0019	-5.4	-0.0019	-6.7
B/M	0.0011	1.6	0.0014	2.4	0.0014	3.0
SPECIAL ITEMS	-0.0006	-1.2	-0.0003	-0.6	-0.0001	-0.2
log(#SEGMENTS)	0.0017	2.9	0.0017	3.4	0.0018	4.5
t-test for difference in coefficients on *METHOD_DIFF*	-0.3		-0.5		-0.8	

Notes: This table presents the results of a seemingly unrelated regression with partitions of firms based on the measured stability of their accounting methods over preceding years (horizons of 3 to 5 years). *Absolute forecast error* is the absolute difference between the consensus earnings forecast and actual earnings, deflated by the stock price at the end of the previous fiscal year. *Forecast dispersion* is the standard deviation of individual analyst forecasts, deflated by the stock price at the end of the previous fiscal year. *METHOD_DIFF* is the mean value of 12 dummies that take the value of 1 if the firm uses an accounting method that differs from the mode of its industry peers, scaled by the number of choices applicable for the industry. *#ANALYSTS* is the number of analysts included in the consensus earnings forecast. *SIZE* is market value as of the end of the previous fiscal year. *B/M* is the book-to-market ratio, measured as of the end of the previous fiscal year. *SPECIAL ITEMS* is an indicator variable equal to 1 if the firm reports special items or extraordinary items in the year being forecasted, and 0 otherwise. *#SEGMENTS* is the number of different SIC codes the company operates in. *Forecast horizon* is the number of days between the consensus forecast and the fiscal year end date. Standard errors are robust to heteroscedasticity and clustered at the firm level to eliminate serial autocorrelation.