9-2017

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## Citation

EVANS, Mark E.; NJOROGE, Kenneth; and OW YONG, Keng Kevin. An examination of the statistical significance and economic relevance of profitability and earnings forecasts from models and analysts. (2017). *Contemporary Accounting Research*. 34, (3), 1453-1488.

**Available at:** https://ink.library.smu.edu.sg/soa_research_all/4

Accepted in Contemporary Accounting Research, 9 April 2017, http://doi.org/10.1111/1911-3846.12307

Article Type: Original Article

**An Examination of the Statistical Significance and Economic Relevance of Profitability and Earnings Forecasts from Models and Analysts**

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Draft: May 2016

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Accepted by Jeffrey Callen. An earlier draft of this paper was entitled "Bias and Accuracy in Long-Horizon Earnings Forecasts: Does a Cross-Sectional Model Improve Analysts' Forecasts?". We have received many helpful comments from the following sources: Jeffrey Callen, two anonymous reviewers, Christine Botosan, Asher Curtis, Ro Gutierrez, Linda Krull, Steve Matsunaga, Sarah McVay, Dale Morse, Stephen Penman, Marlene Plumlee, Katherine Schipper, Cathy Schrand, Teri Lombardi Yohn, and workshop participants at the College of William and Mary, University of Miami, University of Oregon, University of Utah, the 2010 Midwest Accounting Research Conference, the 2010 Northwest Accounting Research Conference, the 2013 American Accounting Association Annual Meeting, the 2013 Accounting Conference at Temple University, and the 2013 European Accounting Association Annual Congress. We also gratefully acknowledge financial support from the School of Business at Wake Forest University, the Frank Wood Accounting Research Fund at the Raymond A. Mason School of Business at the College of William and Mary, and the School of Accountancy Research Center (SOAR) at Singapore Management University.

**An Examination of the Statistical Significance and Economic Relevance of Profitability and Earnings Forecasts from Models and Analysts**

ABSTRACT: In this paper, we propose and empirically test a cross-sectional profitability forecasting model which incorporates two major improvements relative to extant models. First, in terms of model construction, we incorporate mean reversion through the use of a two-stage partial adjustment model and inclusion of a number of additional relevant determinants of profitability. Second, in terms of model estimation, we employ least absolute deviation (LAD) analysis instead of ordinary least squares (OLS) because the former approach is able to better accommodate outliers. Results reveal that forecasts from our model are more accurate than three extant models at every forecast horizon considered and more accurate than consensus analyst forecasts at forecast horizons of two through five years. Further analysis reveals that LAD estimation provides the greatest incremental accuracy improvement followed by the inclusion of income subcomponents as predictor variables, and implementation of the two-stage partial adjustment model. In terms of economic relevance, we find that forecasts from our model are informative about future returns, incremental to forecasts from other models, analysts' forecasts, and standard risk factors. Overall, our results are important because they document the increased accuracy and economic relevance of a cross-sectional profitability forecasting model which incorporates improvements to extant models in terms of model construction and estimation.

Keywords: Profitability Forecasts; Earnings Forecasts; Financial Statement Analysis; Security Analysts

JEL Codes: M40; G11; G17

Data Availability: All data are publicly available from the sources identified in the paper.

**1. Introduction**

Forecasts of future performance are important in the investment and academic communities because of the key role they play in valuation (Richardson, Tuna, and Wysocki 2010; Chee, Sloan, and Uysal 2013). While researchers often use analysts' forecasts to capture expectations about future performance, concerns about accuracy, bias, and lack of coverage make the use of analysts' forecasts less desirable.[1] In recent years, the use of cross-sectional model forecasts as a substitute for analyst forecasts has increased in accounting research. For example, Hou et al. (2012) find that using forecasts from an unscaled net income prediction model (including drivers such as dividends, income, accruals, and size) provides more reliable estimates of cost of equity capital vis-à-vis consensus analysts' forecasts.

On the other hand, research has also shown that more complex cross-sectional models are no better—or worse—than very simple models. For example, Gerakos and Gramacy (2013) show that random walk and autoregressive models perform better than other, more complex models at short forecast horizons, and that expanding the number of predictors is only helpful over long forecast horizons. Additionally, Li and Mohanram (2014) find that cross-sectional earnings forecasts based on either the earnings-to-price model or the residual-income model outperform other model-based forecasts, such as that used by Hou et al., in terms of forecast bias, accuracy and earnings response coefficients. Finally, Bradshaw et al. (2012) find that a naïve random walk model provides more accurate long horizon forecasts of future earnings than consensus analysts' forecasts.

The aim of this paper is improve upon these models and extend the literature regarding reliable, accurate, and value-relevant forecasts which are suitable for a broad set of firms. We propose a forecasting model that differs from extant cross-sectional prediction models in two ways: first, by way of model construction and, second, by way of model estimation. With regard to model construction, we explicitly model

[1] With regard to limited analyst coverage, the aggregate market value (sales) of COMPUSTAT firms that are not covered by I/B/E/S analysts in 2012 is approximately \$1.66 (\$1.64) trillion for U.S. firms, and about \$985 (\$826) billion for Canadian firms.

the mean reversion in firm profitability by incorporating a classic partial adjustment model often used in finance (e.g., Flannery and Rangan 2006; Fama and French 2000). The idea that profitability is mean reverting has strong theoretical and empirical support from a long stream of accounting research (e.g., Beaver, 1970; Brooks and Buckmaster 1976; Freeman, Ohlson, and Penman 1982; Lev 1983; Fairfield, Sweeney, and Yohn 1996; Nissim and Penman 2001; Fairfield, Ramnath, and Yohn 2009). Most cross-sectional forecasting models typically incorporate mean reversion of profitability in their model specification and interpret (one minus) the coefficient on current period profitability as the mean reversion rate. In contrast, we model the rate of mean reversion in profitability more explicitly by using a two-stage partial adjustment model (e.g., Flannery and Rangan 2006; Fama and French 2000).

In our first stage, we develop a model that captures cross-sectional variation in future profitability, using relevant explanatory variables identified in prior literature. Specifically, we incorporate decompositions of profitability into operating and nonoperating components to account for differential persistence among these components. We also include relevant financing variables such as distributions to shareholders, debt repayments and stock splits in our model specification. The out-of-sample fitted value from this first-stage model serves as an input to our second-stage model in the form of a proxy for firm-specific expected profitability. The second-stage model uses the partial adjustment method to explicitly estimate the rate at which actual profitability reverts to the fitted expected profitability from the first-stage model. We also allow the rate of mean reversion to vary nonlinearly with firm characteristics such as firms' competitiveness, equity valuation multiples, and levels of accruals.

Our second innovation addresses empirical concerns about samples of firms without analyst coverage. Presently, common approaches to incorporate earnings expectations for firms without analyst coverage include the use of a random walk forecast model (e.g., Bradshaw et al. 2012), an autoregressive model (e.g., Gerakos and Gramacy 2013), or a cross-sectional forecasting model (e.g., Fama and French 2000; Hou et al. 2012).[2] However, the cross-sectional model in Fama and French (2000) excludes firms with less than $10 million in assets or $5 million in book equity to alleviate concerns about influential observations on OLS coefficient estimates. Likewise, Hou et al. (2012) express concerns about whether the OLS estimation of their model potentially overweighs firms with extreme dollar earnings.

[2] We do not include time-series forecasting models fitted to individual firms because time-series models induce survivor bias that may be more problematic than the selection bias induced by analyst coverage. Hence, the ability to predict earnings for long-term survivors may not be representative to a broad sample of firms. In contrast, cross-sectional models have been shown to be able to explain a large percentage of the variation in expected profitability across firms (Fama and French 2000; Hou et al. 2012).

We provide an alternative approach to address the concern of influential observations by using least absolute deviation estimation (LAD) to estimate our model instead of ordinary least squares (OLS). One advantage of the LAD approach, compared with OLS, is that extreme values are less influential; specifically, LAD minimizes the sum of *absolute* errors, rather than *squared* errors, as in OLS.[3] Accordingly, our estimation method can incorporate small firms and firms with frequent or large losses. Thus, we develop a feasible method of generating reliable ex ante earnings forecasts for these firms that differs from currently adopted approaches in this stream of research.

We evaluate our model in terms of both its statistical significance and economic relevance, relative to extant model-based forecasts and to consensus analyst forecasts. We determine our model's statistical significance by testing whether its out-of-sample forecast errors are lower than errors from other models and analysts. We establish our model's economic relevance by testing whether it provides incremental information about future returns, compared with other models, analysts, and standard risk factors. With regard to statistical significance, we find that our proposed model is more accurate than three other cross-sectional models in forecasting profitability, or future return on equity (ROE), at every forecast horizon that we consider in our tests (i.e., one to five years; also, subject to the caveat that the sample size for longer forecast horizons is much smaller than the sample size for shorter horizons). For example, at the one year horizon, our full model's ROE forecasts are more accurate than a scaled version of Hou et al.'s OLS (LAD) model by 81 (22) basis points. Also, at the four and five year horizons, our full model is more accurate than a random walk model by 77 and 86 basis points, respectively. This latter result is important because it documents the significant accuracy improvement of our model relative to simple, yet reasonably accurate, long-horizon random walk forecasts.[4]

In additional tests, we convert our ROE (profitability) forecasts to EPS (earnings) forecasts and find that out-of-sample forecasts from our proposed model are more accurate, on average, than consensus analyst forecasts for two, three, four, and five year forecast horizons. Specifically, our model is more accurate than consensus analysts' EPS forecasts by 0.02 percent, 0.17 percent, 0.32 percent, and 0.56 percent of stock price at the two year, three year, four year, and five year horizon, respectively.[5] In all our accuracy tests, we find that

[3] See Gu and Wu (2003) and Basu and Markov (2004) for examples of LAD estimation in the accounting literature. More recently, Dyckman and Zeff (2014) call for researchers to incorporate alternative estimation techniques to deal with influential observations, rather than exclusively rely on outlier deletion or winsorization.

[4] Further evidence for the economic relevance of our model's forecasts, relative to other, simpler alternatives, is probed in future returns tests.

[5] For a hypothetical firm with EPS of $1 and share price of $15, this accuracy improvement translates to an EPS forecast improvement of 0.3 cents, 2.6 cents, 4.8 cents and 8.4 cents at the two year, three year, four year, and five year horizons, respectively.

LAD estimation provides the greatest incremental impact, followed by profitability decomposition into subcomponents and second stage estimation.

With regard to the economic relevance of our model's forecasts, we assume that investors incorporate expectations about future earnings in making investment decisions and, therefore, we expect our model's earnings forecasts will have predictive ability for future returns, incremental to other forecasts and standard risk factors. We also expect the strength of this association to increase with forecast accuracy. Accordingly, we infer the economic relevance of differential forecast accuracy across models and analysts by the predictive ability of earnings forecasts for future equity returns (Poon and Granger 2003; Lev, Li, and Sougiannis 2010). In empirical analyses, we follow Lyle, Callen, and Elliott (2013), who use asset pricing theory to develop an equilibrium returns model which is particularly suitable in answering our research question because it includes earnings forecasts as one of the determinants for future expected returns. We use this model to directly compare expected returns implied by model forecasts relative to analyst forecasts, holding constant the other known determinants of future expected returns.

To the extent that errors in variables diminish the precision of the Lyle et al. model's cost of capital estimates, we expect that differential *accuracy* in earnings forecasts should translate to *economically* meaningful differences in cost of capital estimates. Thus, we evaluate the economic relevance of earnings forecast accuracy through the following analyses. First, we establish the in-sample association between earnings forecasts and future raw returns, controlling for other known determinants of cross-sectional variation in stock returns. Second, we assess the validity of expected returns as a proxy for cost of capital by examining the association between out-of-sample expected returns (estimated based, in part, on proxies for expected earnings) and future realized raw returns, at the firm level. Third, we examine the association between these out-of-sample expected return estimates and future raw (and risk-adjusted) returns at the portfolio level.

We find evidence that earnings expectations generated from our model are positively associated with future raw returns in firm-level tests, and positively associated with future raw returns and future excess returns in portfolio-based tests. More importantly, in portfolio-based tests, our model's forecasts provide incremental information about future returns, relative to analyst-based (19 to 27 basis points per month), other model-based forecasts (19 to 42 basis points per month), and beyond standard risk factors. Taken together, our results validate the efficacy of forecasts from a theoretically motivated cross-sectional earnings forecasting model that incorporates explicit modeling of mean-reversion and LAD estimation. In addition, evidence that our model provides incremental information for future returns, relative to analysts and other simpler models, emphasizes the benefit of using our model's forecasts compared to other, easier to implement, alternatives such as an autoregressive model.

We contribute to the forecasting literature by developing and evaluating an improved profitability forecasting model which can be reliably estimated for a wide range of firms, including those with little or no analyst coverage. Specifically, we empirically assess the extent to which innovations with regard to model construction and model estimation improve the accuracy and economic relevance of profitability forecasts. We find that expanding the set of explanatory variables and partial adjustment modeling of mean reversion (model construction) and LAD estimation (model estimation) contribute to forecast accuracy improvements. Of these refinements, LAD estimation (relative to OLS estimation) provides the largest improvement for accuracy, followed by profitability decomposition and explicit modeling of mean reversion through a partial adjustment model. These results should be useful to researchers and investors interested in forecasting profitability, especially for samples of firms with "extreme" levels of earnings, small firms, and firms without analyst coverage. More broadly, our findings also address concerns raised by Richardson, Tuna, and Wysocki (2010) who call upon researchers to apply more structure to the earnings forecasting framework.

The rest of the paper is organized as follows. In section 2, we describe our forecasting model as well as competing forecasting models. We present the results of our statistical tests in section 3 and the results of our market tests in section 4. Results of robustness tests are included in section 5 and we conclude in section 6.

## 2. Model development and description of competing forecasts

In this section, we discuss our proposed cross-sectional profitability forecasting model and then summarize the differences between our forecasting model vis-à-vis various extant competing models and consensus analyst forecasts.

***Our proposed cross-sectional forecasting model***

Our model is predicated on what Stigler (1963) describes as the most important proposition in economic theory: that under competition, the rate of return on investment tends toward equality in all industries. Over time, competitors mimic innovations that generate above-normal profits, and the threat of failure or takeover incentivizes firms to reallocate resources to more productive projects. The idea that profitability is mean reverting has strong theoretical and empirical support from a long stream of accounting research (e.g., Beaver 1970; Brooks and Buckmaster 1976; Freeman, Ohlson, and Penman 1982; Lev 1983; Fairfield, Sweeney, and Yohn 1996; Nissim and Penman 2001; Fairfield, Ramnath, and Yohn 2009). We follow this research and measure profitability as the rate of return on investment (e.g., ROE) instead of earnings (e.g., EPS).[6] However, in later comparisons to analysts and in expected returns tests, we convert ROE (profitability) forecasts to EPS (earnings) forecasts because: (1) analysts overwhelming tend to forecast EPS rather than ROE, and (2) the accounting-based valuation model used in returns tests includes EPS forecasts as an input. This conversion follows prior research (e.g., Frankel and Lee 1998; Banker and Chen 2006) and is discussed further in section 3.

We model profitability mean reversion using a two-stage partial adjustment model and we empirically test whether our model specification holds in the cross section. Partial adjustment models have been used in modeling target capital structures (e.g., Flannery and Rangan 2006; Lemmon, Roberts, and Zender 2008) and in modeling future profitability (e.g., Fama and French 2000). The model incorporates two stages. The first stage model predicts expected future profitability as follows:

$$ROE_{t+1} = \gamma_0 + \gamma_1 X_t + \varepsilon_{t+1}, \quad (1)$$

where $ROE_{t+1}$ is return on equity, or net income before extraordinary items deflated by average book value of common equity, and $X_t$ includes a set of variables useful in predicting future profitability. The fitted value $\left(\widehat{ROE}_{t+1}\right)$ is used as a proxy for the expected level of future profitability in the second stage partial adjustment model, which is predicated on the idea that next year's profitability is a weighted average of expected future profitability and actual profitability:

$$ROE_{t+1} = \omega E_t[ROE_{t+1}] + (1-\omega) ROE_t, \quad (2)$$

[6] Profitability (measured by ROE) and earnings (measured by EPS) are distinct but related. Notably, Fama and French (2000, 163) suggest that their "results imply that real-world forecasts of earnings (e.g., by security analysts) should incorporate the mean reversion in profitability."

where the weight is between zero and one ($0 \leq \omega \leq 1$). We obtain a partial adjustment specification by rearranging equation (2) to express next year's change in profitability as a function of the difference between actual and expected profitability, with $\omega$ representing the partial adjustment (or partial reversion) to expected levels:

$$ROE_{t+1} - ROE_t = \omega[E_t[ROE_{t+1}] - ROE_t]. \tag{2a}$$

Specifically, $\omega$ captures the extent of adjustment between expected and actual profitability in period $t + 1$ for the average firm in the sample. At the extremes, $\omega = 0$ suggests no adjustment, or reversion—as in random walk—while $\omega = 1$ suggests complete adjustment—where next year's profitability equals *expected* profitability. However, since the true $E_t[ROE_{t+1}]$ is unobservable, we use $\widehat{ROE}_{t+1}$, the fitted value from the first-stage regression as a proxy, and estimate the following second-stage model, subject to the errors-in-variables problem:

$$ROE_{t+1} - ROE_t = \varphi_0 + \widetilde{\omega}_{exp}\widehat{ROE}_{t+1} + \widetilde{\omega}_{act}ROE_t + \varphi_2 Controls_t + \epsilon_{t+1}. \tag{2b}$$

By construction, equation (2a)—and, by extension, equation (2b)—predicts a positive coefficient on expected profitability (i.e., $\widetilde{\omega}_{exp} \cong \omega$) and a negative coefficient on actual profitability (i.e., $\widetilde{\omega}_{act} \cong -\omega$), such that: $\widetilde{\omega}_{exp} \cong -\widetilde{\omega}_{act} \cong \omega$. However, classical errors-in-variables theory shows that measurement error in $\widehat{ROE}_{t+1}$ will attenuate coefficient estimates away from $\omega$ toward zero, and the extent of this attenuation will be bigger for $\widetilde{\omega}_{exp}$ than for $\widetilde{\omega}_{act}$ (Carroll, Ruppert, Stefanski, and Cariniceanu 2006; Wooldridge 2002).[7] Thus, the difference $\left(|\widetilde{\omega}_{act}| - |\widetilde{\omega}_{exp}|\right)$ reflects the extent of measurement error in $\widehat{ROE}_{t+1}$ and the model's susceptibility to misestimate the rate of mean reversion.

In our first stage estimation of expected future profitability, we include established signals of future performance, and we allow for the differential persistence between losses and profits. In addition, we follow research that emphasizes the importance of disaggregating earnings into specific components (Fairfield et al. 1996).

*Stage one estimation: Expected profitability* (**FULL$_1$**)

$$\begin{aligned} ROE_{t+h} = {} & \alpha_0 + \alpha_1 Dividends_t + \alpha_2 Dividend\ payer_t + \alpha_3 Market\ to\ book_t \\ & + \alpha_4 Debt\ reduction_t + \alpha_5 Stock\ split_t + \alpha_6 Operating\ income_t \\ & + \alpha_7 Non\ operating\ Income_t + \alpha_8 Interest\ expense_t \\ & + \alpha_9\ Special\ items_t + \alpha_{10} Income\ tax\ expense_t \\ & + \alpha_{11-15} Loss \times \{ROE\ components\}_t + \alpha_{16} \log{(Assets)_t} + \varepsilon_{t+h}, \end{aligned} \tag{3}$$

[7] This is reminiscent of measurement error in accruals causing accruals to have lower persistence than cash flows as in the classical errors-in-variables accrual model of Richardson, Sloan, Soliman and Tuna (2005).

where $h \in \{1,2,3,4,5\}$ is the forecast horizon. Our first three variables are based on the first stage model estimated by Fama and French (2000): *Dividends* is the amount of cash dividends paid, *Dividend payer* is a dummy that equals to one for dividend payers and zero otherwise, and *Market to book* is market value of equity divided by book value of equity. Firms target dividends to the permanent component of earnings (Miller and Modigliani 1961)—thus, dividends signal expected future profitability. Furthermore, firms that pay dividends are more profitable than those that do not (Fama and French 2000). We therefore expect the coefficient estimates on *Dividends* and *Dividend payer* to be significantly positive. Finally, the market-to-book ratio captures variation in expected profitability and growth opportunities that may not be captured by the dividend variables—we expect firms with high growth opportunities to have high future profitability and, therefore, a positive coefficient estimate on *Market to book*.

We also include additional signals of future performance in the form of current-period *Debt reduction*, a stock split factor dummy (*Stock split*) and disaggregated *ROE*. As Nissim and Penman (2001) and Dechow, Richardson, and Sloan (2008) argue, distributions to debtholders tend to be persistent since debt is contractual and default is costly. These distributions are also more likely to come from core (persistent) earnings rather than from noncore (transitory) earnings. Thus, like dividends, distributions to debtholders should be positively associated with future profitability—we therefore expect a positive coefficient estimate on *Debt reduction*. We include a stock split factor dummy because McNichols and Dravid (1990) document evidence that firms incorporate their private information about future earnings in choosing their split factor. They also show that the split factor signal is credible to investors. We therefore expect the coefficient estimate on *Stock split* to be positive.

Following Fairfield et al. (1996), we also decompose *ROE* into the following five components and interact *Loss* with each: *Operating income, Nonoperating income, Interest expense, Special items, and Income tax expense*. *Operating income* reflects the financial performance of a firm's recurring core activities while *Nonoperating income* is from noncore activities that are typically less sustainable or predictable. Therefore, we expect *Operating income* to be highly persistent and, thus, more persistent than *Nonoperating income*. Since debt financing is mostly long-term and interest payments are contractually binding, we expect *Interest expense* to have similar persistence as *Operating income*. Since temporary book-tax differences reverse over time, and nonrecurring income is taxable, we expect *Income tax expense* to be less persistent than operating income. Finally, by definition, *Special items* typically comprises nonrecurring items (restricting charges, asset write-offs, litigation, or insurance settlements, etc.), so we expect this component to have the lowest persistence. In summary, we expect persistence to be high for *Operating income* and *Interest expense*, moderate for *Income tax expense* and *Nonoperating income* and low for *Special items*. We also include a dummy for losses and interact it with *ROE* components to allow for the difference in persistence between losses and profits. Based on prior research, we expect lower persistence for losses. Finally, we control for firm size with the natural log of total assets and expect that larger firms will, on average, have higher future profitability than smaller firms. All continuous explanatory variables, except for firm size, are deflated by the average book value of equity. All variable calculation details, including COMPUSTAT variable names, are included in the Appendix.

In our stage two partial adjustment model, we use $\widehat{ROE}_{t+h}$, the fitted value from regression (3), labeled the **FULL$_1$** model, as an input in our second stage partial adjustment model as follows. Recall that this second-stage model is analogous to equation (2b).

*Stage two estimation: Partial adjustment model* (**FULL$_2$)**

$$\begin{aligned} ROE_{t+h} - ROE_{i,t} = \beta_0 + \beta_1\, \widehat{ROE}_{i,t+h} + \beta_2 ROE_{i,t} + \ \beta_3 Below\ Expected_{i,t} \\ + \beta_4 Below\ expected \times \widehat{ROE}_{i,t+h} + \beta_5 Below\ expected \times ROE_{i,t} \\ + \beta_6 Dev\ Squared_{i,t} + \beta_7 Below\ expected \times Dev\ Squared_{i,t} \\ + \beta_8 Market\ share_{i,t} + \beta_9 Tobins\ Q_{i,t} + \beta_{10} Abs(Total\ accruals)_{i,t} \\ + \beta_{11} Dev \times Market\ share_{i,t} + \beta_{12} \times Dev \times Tobins\ Q_{i,t} \\ + \beta_{13} Dev \times Abs(Total\ accruals)_{i,t} + \epsilon_{i,t+h}\,. \end{aligned} \quad (4)$$

The second stage of our proposed model enables us to: (1) explicitly allow for nonlinear mean reversion of profitability to firm-specific expected/target profitability, (2) incorporate the rate of mean reversion to vary with firm and industry characteristics, and (3) gauge the extent to which our first-stage model measures expected profitability with error. In our second-stage regression—as specified by regression (4) above—*Dev* represents the deviation between expected and actual profitability (i.e., $Dev_t = \widehat{ROE}_{t+h} - ROE_t$); *Below expectation* is a dummy that equals one if $ROE_t < \ \widehat{ROE}_{t+h}$, and zero otherwise; *Market share* is quintile-ranked industry-adjusted sales market share (where industry is defined by 3-digit SIC code); *Tobins Q* is industry quintile-rank of Tobin's Q; and *Abs(Total accruals)* is the industry quintile-rank of absolute total accruals.

If $\widehat{ROE}_{t+1}$ accurately captures expected profitability, mean reversion implies that $|\beta_1| = |\beta_2|$. Thus, we expect the results from our stage-two model to provide evidence as to how accurately we measure firm-specific expected profitability in our first-stage model—the greater the difference between these coefficients, the greater the measurement error in expected profitability. In accordance with equation (2b), we expect $\beta_1 > 0$ and $\beta_2 < 0$. Following Fama and French (2000), we also allow the speed of adjustment to vary nonlinearly across firms depending on whether actual profitability is above or below its expected level. When actual profitability is below expected profitability (*Below expectation* = 1), firms are incentivized to quickly reallocate resources to more profitable projects. We expect this adjustment to be more urgent than when actual profitability is greater than expected (*Below expectation* = 0), because poor profitability cannot continue indefinitely—a firm will either discontinue operations or be acquired.[8] Accordingly, we expect the rate of reversion to be faster for firms with below expected profitability than for firms with above expected profitability. Because we expect $\beta_1 > 0$ and $\beta_2 < 0$, faster reversion for firms with below expected profitability implies that $\beta_4 > 0$ and $\beta_5 < 0$ (i.e., faster reversion implies $\beta_1$ and $\beta_4$ should have the same, positive sign, and $\beta_2$ and $\beta_5$ should have the same, negative sign).

We also expect that the speed of mean reversion is faster when profitability is far from its expectation in either direction. The curvature of this nonlinearity should also be asymmetric between above and below expected profitability. As in Fama and French (2000), we include *Dev squared*, the square of the deviation between expected and actual profitability and interact it with the *Below expectation* dummy to accommodate this asymmetric nonlinear nature in mean reversion. If profitability is above expectations, the coefficient estimate on *Dev squared* should be negative, consistent with a concave reversion toward expectation ($\beta_6 < 0$). If profitability is below expected, we expect a positive association, consistent with a convex reversion toward expectation ($\beta_6 + \beta_7 > 0$).[9]

Because competitive forces accelerate the speed of mean reversion (and sales market share and competition are inversely related), we expect the coefficient on *Dev×Market share* to be negative.[10] In addition, we posit that the capacity to sustain profits or losses increases with growth prospects, all else equal. Thus, we expect the speed of adjustment to decline with growth prospects, and expect a negative coefficient on *Dev×Tobins Q*. Finally, since accruals are less persistent than cash flows (e.g., Sloan 1996), and extreme accruals are often nonrecurring, we expect the speed of adjustment to increase with the magnitude of total accruals, which implies a positive coefficient on *Dev×Abs(Total accruals).*

***Comparisons among models and analysts***

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[8] We thank an anonymous referee for pointing out this insight.

[9] To see this, consider a mean reversion graph of *Dev* on the y-axis and time (in years) on the x-axis. *Dev Squared* captures the curvature of mean reversion. A negative sign on the coefficient estimate on *Dev squared* indicates concavity while a positive sign indicates convexity. If profitability is above expected (i.e., *Below expectation* = 0), so that *Dev* is negative and below the x-axis, upward reversion should be concave (negative coefficient estimate, i.e., $\beta_6 < 0$), toward expectation and the x-axis. However, if profitability is below expected (i.e., *Below expectation*= 1), so that *Dev* is positive and above the x-axis, downward reversion should be convex (positive coefficient estimate i.e., $\beta_6 + \beta_7 > 0$) toward expectation and the x-axis.

[10] To the extent that a firm's market share of total sales is a good *inverse* proxy of a firm's exposure to competition, we would expect that the speed of profitability mean reversion is low for a monopolist, whose market share equals one. Conversely, the speed of profitability mean reversion is high for a price-taker, whose market share is near zero. The rate of profitability mean reversion for oligopoly would decrease with market share between these two extremes.

In all of our analyses, we compare forecasts from our aforementioned model to three models that are commonly used in prior literature: a scaled (i.e., where the deflator is the average book value of equity) version of the cross-sectional earnings model developed by Hou et al. (**sHDZ**), which includes accruals and losses—in additional to earnings and firm size—as predictor variables; an autoregressive model (**AR**), which only includes current-period profitability as a predictor variable; and a random walk model (**RW**), which assumes future profitability will be the same as current profitability. Complete details for all three models are discussed in Appendix A.[11] We expect our model to be more accurate than these three models in forecasting profitability for the following reasons. First, random walk and autoregressive forecasts are typically used in the interest of parsimony (e.g., Bradshaw et al. 2012). However, both the random walk and autoregressive models restrict the set of explanatory variables to current-period profitability and ignore many variables known to predict future performance. In contrast, our model's set of explanatory variables includes additional signals and our model allows persistence to vary nonlinearly across earnings components. Second, unlike prior models, our model uses a second-stage partial adjustment model to explicitly incorporate nonlinear variation in the speed of adjustment across firms. Third, we use least absolute deviation (LAD) estimation, which is more efficient than OLS in the presence of outliers. Accordingly, all else equal, we expect LAD estimation to provide more accurate out-of-sample forecasts than OLS estimation.[12]

We also compare our model's forecasts to consensus analysts' forecasts because they are commonly used as proxies for expected earnings. While analysts possess both timing and information advantages over model-based approaches, their forecasts are subject to incentive and behavioral biases. In addition, analysts nonrandomly select *both* the firms they follow *and* the length of forecast horizon. Specifically, about half of our full sample of firms are not covered by I/B/E/S analysts. Nonetheless, we also compare our model-based forecasts to consensus analyst forecasts, in terms of both forecast accuracy and economic relevance.[13] Consistent with prior research (e.g., Richardson et al. 2004), we expect analysts to be least biased (and most accurate) at short forecast horizons.

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[11] Please see supporting information, "Appendix A: Extant cross-sectional forecast models" as an addition to the online article.

[12] Notwithstanding these reasons, it remains an empirical question whether our model can outperform these extant models. For example, Li and Mohanram (2014) find that the Hou et al**.** model does not outperform a simple AR1 model in out-of-sample tests even through this model incorporates a larger information set than the AR1 model. Additionally, Gerakos and Gramcy (2013) find that the Hou et al. model forecasts underperform a naïve random walk model that simply sets future earnings to past earnings.

[13] As discussed later, in accuracy tests relative to analysts, we modify our models to forecast "I/B/E/S actual" EPS rather than ROE or "GAAP actual" EPS. Because analysts do not forecast "GAAP actual" EPS, this allows for appropriate comparisons between models and analysts.

## 3. Results on statistical significance of model-based forecasts

In this section, we discuss results of in-sample model estimation, and out-of-sample comparisons between our model and other models as well as our model and analysts' forecasts.

***In-sample estimation of cross-sectional earnings forecasting model***

Our sample includes firms with required data from COMPUSTAT for the years 1966 to 2012, consisting of 181,912 firm-year observations and 18,371 unique firms. Descriptive statistics reported in panel A of Table 1 reveal that *ROE* is highly skewed (mean = 4.9 percent, median = 10.1 percent), which provides further motivation for using LAD estimation instead of OLS. Panel B of Table 1 presents stage 1 in-sample estimation results for progressively advanced forecasting models: first, an autoregressive model estimated by OLS ($\mathbf{AR_{OLS}}$); second, a scaled version of the Hou et al. model estimated by OLS ($\mathbf{sHDZ_{OLS}}$); third, Hou et al.'s scaled model estimated by LAD ($\mathbf{sHDZ_{LAD}}$); and finally, our proposed model estimated by LAD ($\mathbf{FULL_{LAD1}}$). Results from estimating the $\mathbf{AR_{OLS}}$ model reveal that ROE is highly persistent (coefficient = 0.794; we reject the null that persistence coefficient equals zero at the 1 percent level ($p$-value < 0.001)). Results from both **sHDZ** models reveal nonlinearity between dividends and future profitability; that is, the expected profitability of dividend payers is significantly higher than predicted by the relation between future profitability and dividend yield (coefficient estimate on the *Dividend payer* dummy is 0.012; $p$-value < 0.001). The persistence of accruals is significantly lower than that of cash flows for both $\mathbf{sHDZ_{OLS}}$ and $\mathbf{sHDZ_{LAD}}$, suggesting accruals are incrementally useful in forecasting future profitability (coefficients = −0.075 and −0.021 for OLS and LAD, respectively; both $p$-values < 0.001). Both **sHDZ** models also show that firm size is positively associated with future profitability (coefficients = 0.003 and 0.001 for OLS and LAD, respectively; both $p$-values < 0.001). These results are consistent with prior research.

In panel B, we present our model's stage one regression ($\mathbf{FULL_{LAD1}}$), which incorporates distributions to debt holders, a split factor dummy, and subcomponents of income. Consistent with our expectations, debt reduction, market to book ratio and the stock split factor are incremental signals with significant positive associations with future profitability (coefficient estimates are 0.009, 0.003, and 0.018, respectively; all $p$-values < 0.001). As predicted, we confirm that *Operating income* and *Interest expense* are significantly (at the 1 percent level) more persistent than all other profitability components. *Nonoperating income* and *Income tax expense* are the next most persistent profitability components, while *Special items* has the lowest persistence.[14]

Panel C reports our model's second stage regression (**FULL$_{\mathbf{LAD2}}$**). Sample firms with actual profitability greater than expectations (*Below expectation* = 0) close the gap between actual and expected profitability at a rate of between 62.7 percent and 62.9 percent per year. We fail to reject the null that the absolute values of these coefficients are equal ($p$-value = 0.484). In addition, consistent with our expectations, reversion is faster when actual profitability is below expected profitability (*Below expectation* = 1); coefficients on the interaction terms imply a reversion rate ranging from 71.9 percent ($\beta_1 + \beta_4$ = 62.9 percent + 9.0 percent) to 74.0 percent ($\beta_2 + \beta_5$ = 62.7 percent + 11.3 percent) when profitability is below expectations. Specifically, we reject the null that $\beta_1 + \beta_4 = 0$ and the null that $\beta_2 + \beta_5 = 0$ at the 1 percent level ($p$-value < 0.001 for both tests).

As predicted, if profitability is above expectations, the coefficient estimate on *Dev squared* should be negative, consistent with a concave reversion toward expectation ($\beta_6 < 0$). Our coefficient estimate for *Dev squared* is −3.208, which is significantly negative at the 1 percent level ($p$-value < 0.001). We also expect a positive reversal if profitability is below expected, consistent with a convex reversion toward expectation, such that $\beta_6 + \beta_7 > 0$. Our result confirms that when profitability is far below expectation, the speed of positive reversal increases: $\beta_6 + \beta_7 = 0.248 > 0$. We reject the null that $\beta_6 + \beta_7 \leq 0$ at the 1 percent level ($p$-value < 0.001). In addition, we find that the speed of adjustment declines with growth prospects (coefficient = −0.028, $p$-value < 0.001) but increases with the magnitude of accruals (coefficient = 0.071, $p$-value < 0.001). In unreported tests, we estimate our model for longer horizons (years 2 through 5) and find similar results as those reported, except that we find that the absolute values of $\beta_1$ and $\beta_2$ in our Stage 2 regressions are not equal. This latter result suggests that our expected profitability model is measured with more error for longer forecast horizons, as expected. Taken together, the evidence in these empirical results is consistent with our predictions. Whether these in-sample results translate into an improvement in forecast accuracy, out-of-sample, is an empirical question that we address in the following section.

[14] We also test three other restrictions, in-sample. First, we reject the null that the AR coefficient equals one at the 1 percent level. In a more formal, unreported unit root test, we also reject the null that profitability has a unit root, at the 1 percent level. Based on this evidence, profitability does not appear to follow random walk, within our sample. Second, based on the **sHDZ** regression, we reject the null that the coefficients on size, dividends and dividend dummy are jointly zero at the 1 percent level, suggesting these variables have incremental predictive ability; thus, the data rejects the **AR** model in favor of **sHDZ,** in-sample. Third, based on the **FULL** regression, we reject the null that the coefficients on market value, distributions to debt holders and the split factor dummy are jointly equal to zero at the 1 percent level, suggesting these three additional profitability signals have incremental predictive ability.

*Out-of-sample comparison of cross-sectional earnings forecasting model vs. other models*

We first report results comparing the out-of-sample accuracy of our proposed cross-sectional model with the other models described in Appendix A, online. We estimate all models using a 10-year rolling window with in-sample data beginning in 1966, and out-of-sample forecasts beginning in 1981.[15] Because our model predicts the change in *ROE* rather than the level (see $\mathbf{FULL_2}$), we obtain our *ROE* forecast by converting $\Delta\widehat{ROE}_{t+h}$ to a level as follows: $\widehat{ROE}_{t+h} = \Delta\widehat{ROE}_{t+h} + ROE_t$. We evaluate accuracy by comparing out-of-sample absolute forecast errors. We calculate the $h$-years ahead out-of-sample absolute forecast error for firm *i* by model *k* in year *t* as: $AFE_{i,t}^{k} = |ROE_{i,t+h} - forecast_{i,t+h}|$, where $ROE_{i,t+h}$ is firm *i*'s actual GAAP *ROE* in fiscal year $t + h$, and $forecast_{i,t+h}^{k}$ is the $h$-years ahead out-of-sample forecast of $ROE_{i,t+h}$ by model *k*. Following prior research (e.g., Fairfield et al. 1996, 2009) we do not scale the ROE forecast error since it is already scaled by book-value of equity.

In Table 2, we first present descriptive information in column (0) by presenting the median AFE for each model. We make three observations regarding these findings. First, estimating **FULL** using LAD yields smaller AFEs than any of the other models at any horizon. For example, the median AFE for one-year horizon forecasts ranges from 0.051, or 5.1 percent ($\mathbf{FULL_{LAD2}}$) to 0.073, or 7.3 percent (**AR**); these values are consistent with prior research in ROE forecasting (e.g., Esplin et al. 2014 report a median AFE of 0.079, or 7.9 percent, for their AR model of one-year ahead ROE). Second, **RW** performs well vis-à-vis OLS models at short horizons, which suggests that OLS overweights transitory items. Third, while AFEs increase as forecast horizons increase, LAD models outperform OLS and RW models at every horizon.

In terms of statistical significance, we use the Wilcoxon signed rank test to make accuracy comparisons in columns (1) through (7). Specifically, we subtract the AFE of the "row model" from the AFE of the "column model" and report the cross-sectional median of this difference. Under the null that two models have equal accuracy, this difference should be close to zero. If the "column model" is significantly more (less) accurate than the "row model", this difference is significantly negative (positive), based on the *Z*-statistic. For

[15] For example, in predicting ROE for five years ahead for 1986, we first estimate coefficients for the 1966 – 1975 time period on ROE five years ahead ending in 1971 – 1980. We then apply these coefficients to 1981 variables to predict 1986 ROE, out-of-sample:

$$\begin{bmatrix} Y_{1971} \\ \vdots \\ Y_{1980} \end{bmatrix} = \boldsymbol{\beta} \begin{bmatrix} \boldsymbol{X_{1966}} \\ \vdots \\ \boldsymbol{X_{1975}} \end{bmatrix} + \begin{bmatrix} e_{1966} \\ \vdots \\ e_{1975} \end{bmatrix}$$

$$\hat{Y}_{1986} = \widehat{\boldsymbol{\beta}}[\boldsymbol{X_{1981}}]$$

example, at the one year forecast horizon, median difference between AFEs for the $\mathbf{FULL_{LAD2}}$ and $\mathbf{sHDZ_{OLS}}$ models is -0.809 percent. The negative sign indicates $\mathbf{FULL_{LAD2}}$'s AFE is smaller and, thus, more accurate.

We make several observations regarding the accuracy of the ROE forecasts.[16] First, at all forecast horizons, $\mathbf{FULL_{LAD2}}$ is significantly more accurate than $\mathbf{FULL_{LAD1}}$ (one year horizon difference = −4 basis points), and $\mathbf{FULL_{OLS2}}$ is significantly more accurate than $\mathbf{FULL_{OLS1}}$ (one year horizon difference = −21 basis points). These comparisons hold the explanatory variables and estimation method constant, thereby showing the extent to which incorporating mean reversion via our Stage 2 estimation improves accuracy. Effectively, at the 1-year horizon, incorporating mean reversion improves ROE forecast accuracy 4 basis points under LAD estimation and by 21 basis points under OLS estimation. Second, at all forecast horizons, $\mathbf{FULL_{LAD2}}$ is significantly more accurate than $\mathbf{FULL_{OLS2}}$ (one year horizon difference = −45 basis points), $\mathbf{FULL_{LAD1}}$ is significantly more accurate than $\mathbf{FULL_{OLS1}}$ (one year horizon difference = −63 basis points) and $\mathbf{sHDZ_{LAD1}}$ is significantly more accurate than $\mathbf{sHDZ_{OLS1}}$ (one year horizon difference = −51 basis points). These comparisons hold the explanatory variables and the stage of estimation constant, thereby showing that LAD estimation yields significant accuracy improvements ranging from 45 to 63 basis points relative to OLS estimation. Third, at all forecast horizons, $\mathbf{FULL_{LAD1}}$ is significantly more accurate than $\mathbf{sHDZ_{LAD1}}$ (one year horizon difference = −19 basis points, five year horizon difference = −30 basis points), indicating that under LAD estimation, profitability decomposition and including additional variables in the **sHDZ** model (i.e., *Debt reduction* , *Market to book* and *Stock split*) significantly improves forecast accuracy. In contrast, under OLS estimation, including additional explanatory variables to the **sHDZ** model improves accuracy to a smaller extent and only in the short term (i.e., one year horizon difference = −16 basis points, three year horizon difference = −8 basis points, five year horizon difference = +5 basis points). Finally, consistent with prior research, we confirm that the random walk model outperforms all OLS models at one and two year horizons; however, LAD estimation provides more accurate forecasts than random walk at all horizons.

Overall, these ROE accuracy results suggest each of our model innovations improve forecast accuracy at short and long horizons when compared with other extant models. Our results also suggest that LAD estimation yields the largest accuracy improvement, followed by profitability decomposition and inclusion of mean reversion via our partial adjustment model in Stage 2.

[16] Figure 1 provides a graphical representation of ROE accuracy comparisons, using $\mathbf{FULL_{LAD2}}$ as the benchmark.

***Out-of-sample comparison of cross-sectional earnings forecasting model vs. analysts***

In this section, we compare our model's out-of-sample forecasts to consensus analysts' forecasts. While analysts possess both timing and information advantages over statistical approaches, their forecasts are subject to incentive and behavioral biases. Accordingly, whether analysts outperform our proposed model is an empirical question. In all our analyses, we use consensus analyst forecasts rather than individual analyst forecasts because cost of capital and valuation studies typically use consensus forecasts in their tests.

The accuracy of consensus analyst forecasts improves as the earnings announcement date approaches and information incremental to the preceding 10-K arrives (Richardson et al. 2004). To ensure a fair accuracy comparison between the model and analysts, we obtain analysts' forecasts at a date late enough in the year to ensure the model's inputs are available (e.g., after the year *t* annual SEC filing date ), and early enough in the year to limit their information advantage (e.g., before year $t$+1's quarterly earnings announcements). Accordingly, we use the consensus forecast issued immediately following the prior fiscal year's 10-K filing date. When the 10-K filing date is unavailable, we use the consensus forecast issued immediately before the current fiscal year's first quarter earnings announcement, but after the prior fiscal year's fourth quarter earnings announcement.[17]

As noted previously, in accuracy comparisons of model-based and analysts' forecasts, we convert our ROE forecasting model into an EPS forecasting model for the following reasons. First, analyst ROE forecasts are sparse, relative to analyst EPS forecasts. Second, research suggests that analysts care more about—and are, therefore, more accurate in—forecasting EPS as opposed to ROE. Third, and most importantly, the Lyle et al. (2013) accounting-based valuation model that we deploy in our stock return tests uses EPS forecasts as an input. Accordingly, since our ROE results may not be generalizable to EPS forecasting, we follow prior research (see, e.g., Banker and Chen 2006; Frankel and Lee 1998) and modify our model to predict EPS to provide a direct comparison between our model's forecasts and analysts' EPS forecasts. The complete details of the ROE-to-EPS modification and its algebraic derivation are included in Appendix B. [18]

[17] The overwhelming majority of firms file 10-Ks *after* their annual earnings announcement date but *before* the next year's 1st quarter earnings announcement date. We confirm that our results remain qualitatively similar if we restrict the sample to firm-year observations with available 10-K filing dates. Since filing dates are unavailable for numerous firms—especially for pre-1994 years—we do not require sample firms to have 10-K filing dates.

[18] Please see supporting information, "Appendix B: Derivation of conversion from ROE forecasts to EPS forecasts" as an addition to the online article.

In addition to modifying our ROE forecasts and focusing on EPS forecasts, we also note that analysts forecast an earnings figure (i.e., I/B/E/S earnings) which is different from GAAP earnings.[19] Accordingly, if we compare analysts' forecasts of *I/B/E/S earnings* to actual *GAAP earnings*, we unfairly attribute large forecasts errors to analysts. Additionally, if we compare model-based forecasts of *GAAP earnings* to *I/B/E/S earnings*, then we unfairly attribute large forecast errors to models. To mitigate these concerns, our comparisons of model-based forecasts to analysts' forecasts use actual I/B/E/S EPS as the benchmark. Also, for these accuracy tests, we re-estimate the empirical models using I/B/E/S actual data when available so that the models forecast I/B/E/S earnings instead of GAAP earnings. We calculate the $h$-years ahead out-of-sample absolute *EPS* forecast error for firm *i* in year *t* as: $AFE_{i,t}^{l} = \left|\left(iEPS_{i,t+h} - forecast_{i,t+h}^{l}\right)/P_{i,t}\right|$, where $iEPS_{i,t+h}$ is firm *i*'s actual I/B/E/S *EPS* in fiscal-year $t + h$, and $forecast_{i,t+h}^{l}$ is either the $h$-years ahead consensus median EPS forecast or our model's $h$-years ahead out-of-sample EPS forecast. $P_{i,t}$ is split-adjusted stock price.

Table 3 compares the accuracy of our model's out-of-sample *EPS* forecasts to that of consensus analyst *EPS* forecasts and other models. We make several observations about the EPS accuracy comparisons.[20] First, across-model EPS accuracy comparisons remain qualitatively similar to across-model ROE comparisons. Second, we find that for the one-year ahead horizon, analysts significantly outperform all the models. Specifically, for the median sample firm, the absolute forecast error of consensus analyst EPS forecasts is smaller than that of the most accurate model (i.e., $\mathbf{FULL_{LAD2}}$) by 0.21 percent of the stock price, significant at the 1 percent level. Analysts outperform all other models by an even larger margin. However, for two to five year horizons, our $\mathbf{FULL_{LAD2}}$ model is significantly more accurate than consensus analyst EPS forecasts—the median AFE difference improves from 0.02 percent at two years ahead to 0.56 percent of the stock price at five years ahead. Thus, our model outperforms consensus EPS forecasts even when we use actual I/B/E/S EPS as the benchmark and ensure analysts have access to the publicly available information that we use to estimate the model. Finally, we note that only the $\mathbf{FULL_{LAD2}}$ specification outperforms analysts at two years ahead, but the other models are also able to outperform analysts over longer horizons. Consistent with Bradshaw et al (2012), we find that the accuracy of random walk forecasts compares favorably to consensus analyst forecasts at long horizons. For example, at three and four years ahead, the two forecast errors are insignificantly different; at five years ahead, random walk forecasts are more accurate than consensus analyst forecasts. This result is also

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[19] For example, I/B/E/S earnings remove many categories of special and non-recurring items that are included in GAAP earnings.

[20] Figure 2 provides a graphical representation of EPS accuracy comparisons, using $\mathbf{FULL_{LAD2}}$ as the benchmark.

consistent with findings in Harris (1999, 729), which document “extremely low” accuracy of analysts’ long-term growth estimates in forming earnings forecasts at three to five year horizons.

Taken together, our results reveal that our proposed model is more accurate than three other models’ forecasts at annual horizons ranging from one to five years, and more accurate than analysts’ forecasts at annual horizons ranging from two to five years. In addition, the greatest impact on accuracy derives from using LAD estimation, followed by decomposing earnings and incorporating mean reversion through a partial adjustment model.

## 4. Results on the economic relevance of model-based forecasts

Our previous tests document the statistical accuracy of our model relative to analysts and other models; however, thus far, we have yet to examine the extent to which forecast accuracy is economically meaningful. If forecast accuracy differences are economically meaningful, such differences should be captured by differential abilities to predict future equity returns. In this section, our analyses assess the economic relevance of forecast accuracy by examining the predictive ability of different earnings forecasts for future equity returns (Poon and Granger 2003; Lev, Li, and Sougiannis 2010). Following a long history of accounting and finance literature, we interpret expected return estimates as a proxy for cost of equity capital.

To demonstrate the differential economic relevance of profitability forecasts, we follow the approach used by Lyle, Callen, and Elliott (2013), who use asset pricing theory to develop an equilibrium returns model that estimates expected returns (cost of equity capital).

We conduct our analyses via the Lyle et al.’s equilibrium returns model for several reasons. First, their model is ideal for our research question because it includes expected future earnings as one of the determinants for expected return. Second, Lyle et al. report that the model is superior to conventional returns models (e.g., one that relies on Fama-French factors or the CAPM model).[21] Finally, the model is easy to apply because it casts expected returns solely as a linear combination of observable accounting variables and firm fundamentals. In summary, the model is empirically implementable and it enables us to directly compare the expected returns implied by model-based forecasts and analyst forecasts.

Specifically, Lyle et al. develop and validate the following model:

$$Returns_{m+1} = \alpha + \varphi_1 Inverse\ market\ value_{t,m-1} + \varphi_2 Book\ value_t / MVE_{t,m-1}$$

[21] In addition, Callen (2015) notes that Lyle et al.’s model, which estimates *both* firm value *and* cost of capital, addresses the inconsistencies present in most empirical valuation studies where one model is used to make value judgments (e.g., Ohlson-type model) and another model is used to estimate cost of capital (e.g., CAPM-type model).

$$+ \varphi_3\, Earnings_t/MVE_{t,m-1} + \varphi_4\, E_m[Earnings_{t+h}]/MVE_{t,m-1}$$
$$+ \varphi_5\, Dividends_t/MVE_{t,m-1} + \varepsilon_{m+1}, \qquad (5)$$

where the subscript $t$ indicates the most recent *fiscal* year as of *calendar* month $m$, $Returns_{t,m+1}$ is one-month ahead raw returns; $MVE_{t,m-1}$ is common shares outstanding at the end of fiscal year $t$, multiplied by the split-adjusted stock price at the end of calendar month $m$ – 1; $Inverse\ market\ value_{t,m-1}$ is 1 divided by $MVE_{t,m-1}$; $Book\ value_t$ is the book value of common equity at the end of fiscal year $t$; $Earnings_t$ is net income before extraordinary items for fiscal year $t$; and $Dividends_t$ is cash dividends for fiscal year $t$. Finally, as in Lyle et al. (2014), we measure expected future earnings during calendar month $m$, $E_m[Earnings_{t+h}]$, as the time-weighted mean of fiscal years $t$+1 and $t$+2 EPS forecasts, multiplied by number of common shares outstanding during calendar month $m$.[22]

We evaluate five proxies for $E_m(Earnings\ per\ share_{t+h})$: (1) consensus analyst forecast, (2) second-stage LAD estimation of our model (**FULL$_{\mathbf{LAD2}}$**), (3) LAD estimation of the scaled HDZ model (**sHDZ$_{\mathbf{LAD1}}$**), (4) OLS estimation of the scaled HDZ model (**sHDZ$_{\mathbf{OLS1}}$**) and (5) OLS estimation of the AR model (**AR**). All the model forecasts are out-of-sample. Following Lyle et al. (2013), we use three types of analyses to compare the expected returns implied by model forecasts, relative to analyst forecasts. First, we empirically estimate equation (5) in-sample, in order to compare the strength of association between earnings forecasts and future realized raw stock returns, controlling for other known determinants of cross-sectional variation in stock returns. However, in-sample associations may not translate into practically meaningful out-of-sample associations. Accordingly, our second set of analyses evaluate the association between out-of-sample expected return estimates from equation (5) and realized raw returns, using monthly Fama-MacBeth regressions. Finally, in our third set of analyses, we form portfolios based on the out-of-sample expected return estimates and compare portfolio-based raw returns and portfolio-based alphas of model-based and analysts' forecasts. In all of these

[22] Specifically, we measure expected future earnings as follows:

$$E_m[Earnings_{t+h}] = SHROUT_m \times \{w_d \times E_m[EPS_{t+1}] + (1 - w_d) \times E_m[EPS_{t+2}]\},$$

where $SHROUT_m$ is the number of common shares outstanding in month $m$ (from CRSP); $w_d$ is the time-weight, calculated as the number of days between the firm's $t$+1 fiscal year-end and the current forecast date, divided by 365; and $E_m[EPS_{t+1}]$ and $E_m[EPS_{t+2}]$ are either: (1) the prevailing 1 and 2-years ahead I/B/E/S consensus EPS forecast or, (2) the 1 and 2-years ahead out-of-sample EPS forecast from an empirical model. Note that while consensus analyst EPS forecasts are allowed to update, model forecasts do not update—only their weighting or the prevailing number of common shares outstanding update.

analyses, we compare the performance of our model's forecasts with analysts' consensus earnings forecasts and forecasts from the three other models described in Appendix A.

***Association between expected earnings and realized returns***

Table 4 presents results from monthly Fama-MacBeth regressions of one-month-ahead raw returns on firm fundamentals, as laid out in equation (5). All regression variables are standardized to have a mean of zero and variance of one, to make across-model coefficient comparisons easier to interpret. We make several observations based on these results. First, in column (1), we replicate Lyle et al.'s results and show that earnings expectations from analysts are positively associated with future raw returns (coefficient = 0.038, $p$-value < 0.001). Second, in column (2), we show earnings expectations derived from our full model, $\mathbf{FULL}_{\mathbf{LAD2}}$, are significantly correlated with future raw returns, after controlling for other known determinants of cross-sectional variation in returns (coefficient = 0.069, $p$-value < 0.001). Specifically, we reject the null that these two coefficient estimates are equal, at the 1 percent level ($p$-value < 0.001). We interpret this result as suggesting that, controlling for other determinants of stock returns, the out-of-sample earnings expectations from our model are at least as informative about future returns as analysts' consensus earnings expectations. Third, in columns (3) and (4), we show that earnings expectations derived from the $\mathbf{sHDZ}_{\mathbf{LAD1}}$ and $\mathbf{sHDZ}_{\mathbf{OLS1}}$ models are also positively associated with future raw returns (coefficients = 0.054 and 0.030, respectively; $p$-values < 0.001 for both). Importantly, the coefficient estimate on earnings expectations from the LAD version of **sHDZ** is almost twice as large as that of its OLS version (0.054 vs 0.030; $p$-value for the null that the two coefficients are equal is 0.013). Thus, the LAD improvement is not just statistically significant, but also economically relevant. Including additional explanatory variables, and incorporating mean reversion via stage two, provides less discernible economic relevance improvements—the coefficient estimate on EPS expectations further increases from 0.054 to 0.069, but this improvement is not statistically significant at the 10 percent level ($p$-value = 0.129).

Table 4 shows that the magnitudes of the standardized coefficient estimates for the EPS expectation derived from $\mathbf{FULL}_{\mathbf{LAD2}}$ and $\mathbf{sHDZ}_{\mathbf{LAD1}}$ models are significantly higher than the coefficient magnitude from analysts ($p$-values < 0.001 and 0.011, respectively) or any other model. Thus, while all forecasts examined (except for **AR**) are economically meaningful, forecasts from $\mathbf{FULL}_{\mathbf{LAD2}}$ and $\mathbf{sHDZ}_{\mathbf{LAD1}}$ are the most economically relevant, based on these results.[23] Additionally, we reconfirm these results in later, out-of-sample, portfolio-based tests.

***Association between expected returns and realized returns***

In this section, we evaluate whether our model generates reliable proxies for expected returns by assessing the association between expected returns (derived using earnings forecasts from our model) and future realized raw returns. Specifically, as in Lyle et al., we calculate expected returns based on analyst earnings forecasts ($\mu_{analysts}$) using out-of-sample predictions from regression (5). Analogously, we use our model's earnings forecasts as an input in regression (5) to obtain out-of-sample model-based expected returns (e.g., $\mu_{FULL.LAD2}$). Other model-based forecasts (**sHDZ** and **AR**) follow accordingly.

Table 5, panel A, presents summary statistics—expressed in percentage—for the realized raw return ($r_{t+1}$), and out-of-sample expected returns, $\mu$. For the average/median firm, the model-based expected returns are slightly smaller than the analyst-based expected returns, and the **AR** model yields the lowest expected returns. In panel B, we regress monthly realized raw returns separately on each expected return proxy. If proxies for expected return represent the "true" cost of capital, then the intercept should equal 0, and the coefficient on the expected return proxy should be significant and close to 1. Results reveal that measures for expected returns have robust associations with future realized returns (coefficients estimates range from 1.162 to 1.285), which are significantly different from zero (at the 1 percent level). We reject the null that these slope coefficient estimates are different from one, at the 5 percent level ($p$-values range from 0.0614 to 0.1852). Furthermore, we fail to reject the null that the intercept estimates in these regressions are different from zero, at 1 percent level ($p$-values range from 0.855 to 0.934). Based on this result, the analyst-based expected returns and expected returns from our models appear to be strongly associated with future realized returns, suggesting that they are viable proxies of expected returns.

***Portfolio-based time-series tests***

As in Lyle et al., we also conduct portfolio-level analyses since firm-level analyses could be inhibited by measurement error. Table 6, panel A, presents the realized raw returns of five portfolios, sorted by expected returns. Realized raw returns increase monotonically with expected returns based on analysts and models. In

[23] Earnings expectations from the AR model are insignificantly associated with expected returns (coefficient = 0.017, $p$-value = 0.235). This result, while perhaps surprising, highlights the deficiency of a simple model, estimated using OLS, when extreme values are present.

addition, the last row presents the excess of mean returns for the highest quintile of expected returns over the mean returns for the lowest quintile of expected returns. This excess is significant at the 5 percent level for all expected return proxies: 1.902 percent for analyst-based expected return, 2.192 percent for our $\mathbf{FULL_{LAD2}}$-based expected return, 1.996 percent for $\mathbf{sHDZ_{LAD1}}$, 1.880 percent for $\mathbf{sHDZ_{OLS1}}$ and 1.767 percent for **AR**, respectively. Importantly, the $\mathbf{FULL_{LAD2}}$-based excess is greater than analysts' by 29 basis points per month, and greater than other models by a range of 20 to 43 basis points per month, which is nontrivial considering that the realized monthly raw return for the median firm in our sample is 56 basis points.

In Table 6, panel B, we present the difference in returns after controlling for the three Fama-French factors and momentum. Specifically, these excess returns (alphas) are presented for five portfolios, sorted by expected returns. The high-low quintile difference in alphas is 1.673 percent for the analyst-based expected return versus 1.942 percent for our $\mathbf{FULL_{LAD2}}$-based expected return—a difference of 27 basis points. In addition, the difference based on $\mathbf{FULL_{LAD2}}$ is greater than the difference based on other models. This result suggests that the association between model-based expected returns and realized returns is robust to controlling for Fama-French factors and momentum. Taken together, these results provide robust evidence that our model's out-of-sample earnings forecasts can be used as valid proxies for expected earnings and, in turn, can be used to calculate valid proxies for expected returns. These results are important because they suggest the feasibility of using forecasts from a cross-sectional forecasting model to calculate cost of capital estimates when analyst forecasts are either unavailable or problematic.

**5. Robustness tests**

We conduct several robustness tests, largely focused on alleviating concerns about per-share effects in EPS comparisons. First, because our model predicts profitability (ROE), we examine analysts' forecasts of ROE rather than EPS. This comparison is the most direct method to assess whether our model outperforms analysts. However, analysts' ROE forecasts (obtained from I/B/E/S) are limited to the last few years.[24] Nevertheless, in unreported robustness tests, we use GAAP ROE as a benchmark and compare analyst ROE forecasts to model ROE results. The results of this comparison are qualitatively similar to the EPS results discussed above, with only one exception: at the two year horizon, the difference in accuracy between analysts' ROE forecasts and our model's ROE forecasts is statistically insignificant.

[24] To our knowledge, we are the first paper to evaluate the accuracy of analysts' *explicit* ROE forecasts—as opposed to implied ROE forecasts derived from EPS forecasts.

In addition to examining analysts' forecast of ROE, we modify our tests by using book value per share as the deflator, rather than price per share. Also, we conduct separate analyses without using a deflator for EPS. In all tests, results (unreported) are similar to the reported results. The robustness of our forecast accuracy results helps alleviate concerns about scale effects with using price as a deflator.

**6. Conclusion**

In this paper, we provide evidence suggesting that a cross-sectional profitability forecasting model which incorporates the reversion of profitability to expected levels using methods that alleviate the influence of outliers can lead to forecast accuracy improvement. We find that our model is significantly more accurate than a random walk model, an autoregressive model, and a scaled version of the cross-sectional model proposed by Hou et al. (2012) for forecast horizons of one to five years. In addition, the improvements increase with the forecast horizon. Furthermore, while consensus analyst forecasts have an accuracy advantage over our proposed model's forecasts at the one-year-ahead horizon, we show that our model has a much larger accuracy advantage over consensus forecasts from two to five years ahead. In all our accuracy tests, LAD estimation provides the greatest accuracy improvement followed by the decomposition of income variables and second stage mean reversion. In addition, we show that future realized raw returns and future abnormal returns are greater using a trading strategy based on our model's earnings forecasts, relative to strategies based on analyst-based portfolios or other model-based portfolios. Returns results emphasize that, not only are our results *statistically* significant, they are also *economically* relevant.

Our model's forecasts possess similar advantages as other cross-sectional models; however, our model's improvements, resulting in increased accuracy and economic relevance, make our forecasts potentially more desirable. For example, like extant cross-sectional forecasting model (e.g., Hou et al. 2012), our proposed model has the potential to alleviate concerns about sample selection bias. In particular, researchers can use our model to make out-of-sample forecasts for the sample of firms that are not covered by I/B/E/S analysts—but have COMPUSTAT data. Our model can also be helpful in settings where there is reason for concern regarding the quality of analyst forecasts. Nevertheless, it is important to emphasize that our results do not suggest that our model's forecasts should replace analyst forecasts. This is because we compare the model to the consensus median analyst and not to individual analysts; there are individual, or star, analysts whose average forecast accuracy is higher than our model's forecasts. In addition, numerous research questions are best answered using analyst forecasts —for example, event studies that examine short-window market surprises.

Overall, our research answers the call to incorporate more structure in researchers' forecasting frameworks (e.g., Richardson et al. 2010). Specifically, the use of alternative archival research techniques is able to provide a cross-sectional earnings forecasting model that is relatively simple to implement, in the interest of parsimony. In addition, we apply a two-stage estimation to incorporate the mean reversion of profitability into our model specification and we use a more refined estimation methodology (LAD vs. OLS) to alleviate the influence of outliers. We believe our model provides a forecasting tool to generate reliable earnings forecasts that would be potentially useful to researchers.

## Appendix 1
## Variable definitions

**Panel A:** Variables used in model-based forecasts

| | |
|---|---|
| *ROE* | Return on equity [IB/AVG_CSE] |
| *EPS* | Annual earnings per share (EPSPX / AJEX) |
| *Dividend payer* | Dummy for positive dividend payer (dummy = 1 if DVC > 0 and 0 o/w) |
| *Dividends* | Distributions to equity holders [DVC] |
| *Debt reduction* | Net distributions to debtholders [ - (ΔDLC + ΔDLTT) ] |
| *Stock split* | Dummy for stock splits (dummy equals 1 if AJEX > 1 and 0 otherwise) |
| *Market value* | Market value of equity [PRCC_F×CSHO] |
| *Log(Assets)* | Natural logarithm of lagged assets [ln(lag(AT))] |
| *Loss* | Dummy equal to 1 if IB is negative and 0 otherwise |
| *Operating income* | Operating income [OIADP] |
| *Nonoperating income* | Nonoperating income [NOPI] |
| *Interest expense* | Interest expense [XINT] |
| *Income tax expense* | Total income taxes [TXT] |
| *Special items* | Special and extraordinary items [ SPI ] |
| *Total accruals* | Accruals [(IB – (OANCF – XIDOC))/AVG_CSE] if fiscal year > 1987 |
| *Total accruals* | Accruals [(ΔWC – DP)/AVG_CSE] if fiscal year < 1988 |
| *Dev* | $\widehat{ROE_{t+1}} - ROE_t$ |
| *Below expectation* | 1 if *Dev* > 0, and 0 otherwise. |
| *Dev squared* | *Dev* × *Dev* |
| *Abs(Total accruals)* | Absolute value of *Total Accruals* |
| *Market share* | SALE/3-digit SIC industry SALE |
| *Tobins Q* | Tobin's Q [(PRCC_F×CSHO + AT – SEQ – TXDB)/AT], quintile-ranked |

**Appendix 1 (continued)**
**Variable definitions**

**Panel B:** COMPUSTAT variable definitions

| | |
|---|---|
| WC | Working capital [(ACT – CHE) – (LCT – DLC)] |
| NOA | Net operating assets [(AT – CHE) – (LT – DLC –DLTT – PSTK)] |
| AVG_CSE | Average book value of common equity [ 0.5 × (CEQ + lagCEQ) ] |
| EPSPX | Earnings per share (Basic)— Excluding extraordinary items |
| AJEX | Adjustment factor (Company—)—Cumulative by ex-date |
| AT | Assets—Total |
| CHE | Cash and short-term investments |
| LT | Liabilities—Total |
| DLC | Debt in current liabilities—Total |
| DLTT | Long-term debt—Total |
| OANCF | Net cash flow from operating activities |
| DP | Depreciation and amortization |
| PSTK | Preferred/preference stock (Capital)—Total |
| CEQ | Common equity |
| SEQ | Total parent stockholders' equity |
| IB | Income before extraordinary items |
| OIADP | Operating income after depreciation |
| NOPI | Nonoperating income |
| SPI | Special items |
| TXT | Income taxes total |
| XIDOC | Extraordinary items and discontinued operations |
| ACT | Current assets—Total |
| LCT | Current liabilities—Total |
| PRCC_F | Price Close—Annual—Fiscal |
| CSHO | Common shares outstanding |
| DVC | Dividends common/ordinary |
| TXDB | Income taxes deferred—Balance sheet |

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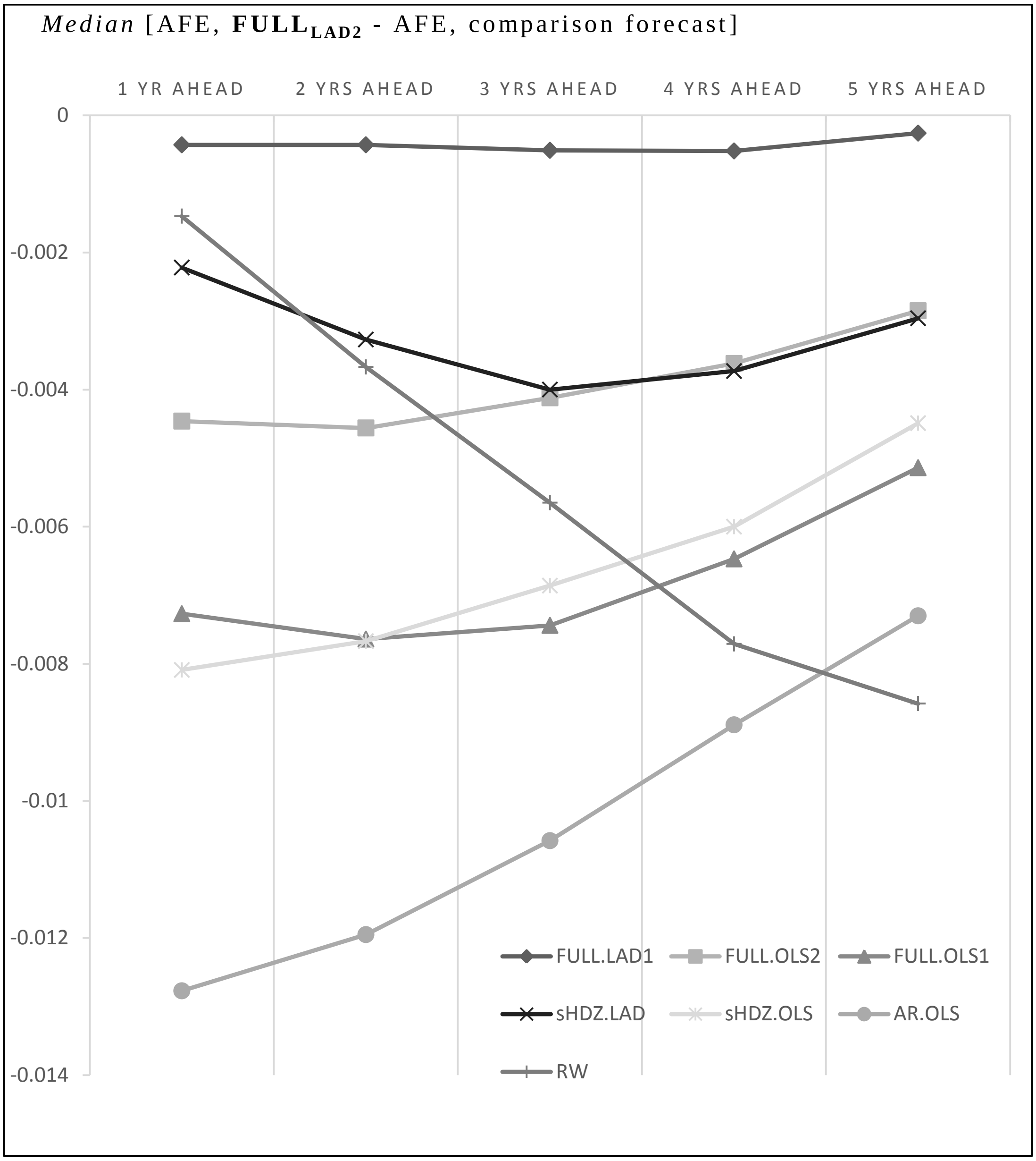
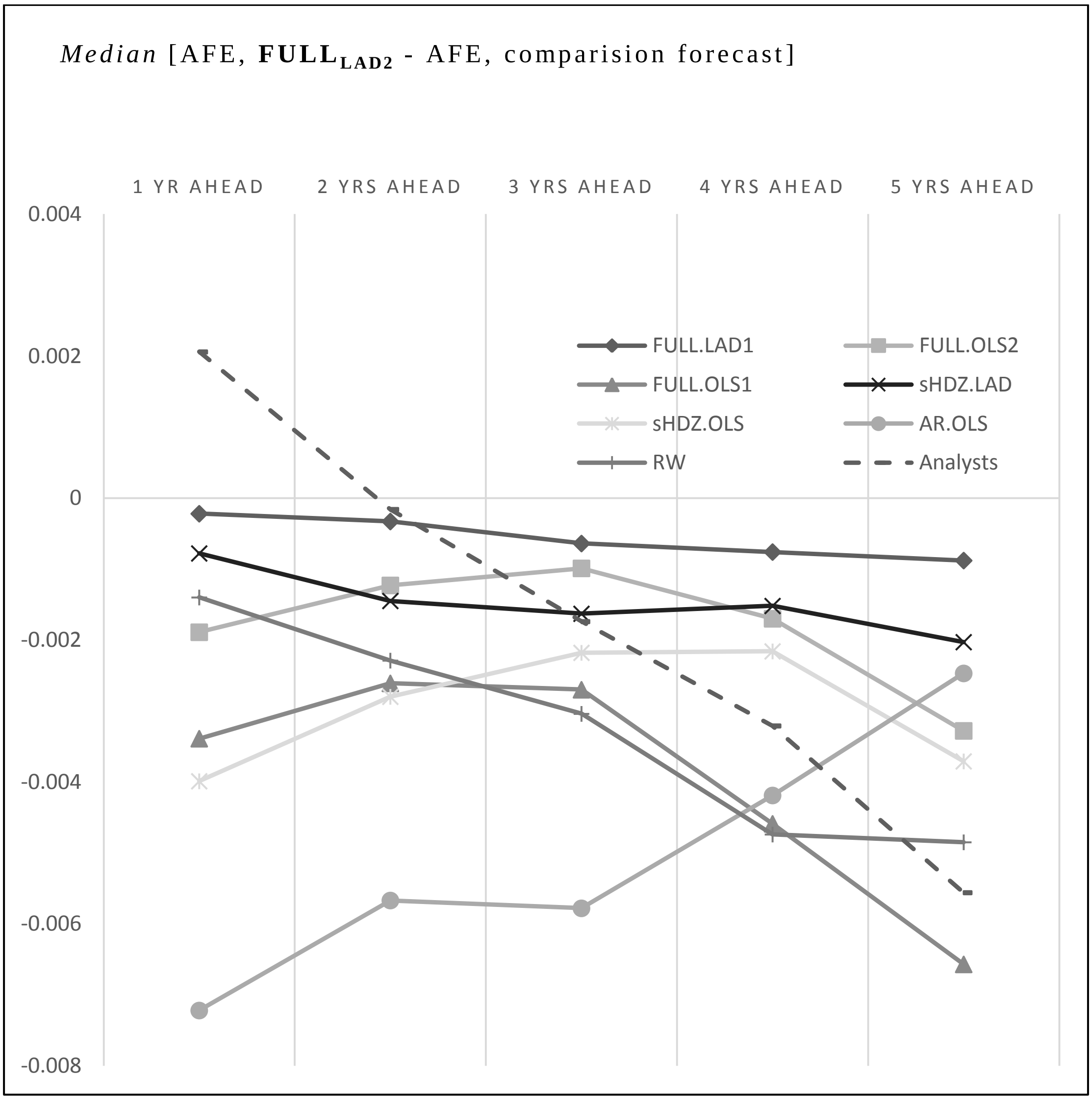
**Figure 1: Median differences in ROE absolute forecast errors relative to FULL$_{LAD2}$ (full sample)**




*Notes:* The figure presents a graphical representation of Table 2, column (1), or median differences of ROE absolute forecast errors (AFEs) between our full, benchmark model (**FULL$_{LAD2}$**) and other, comparison models. Values greater than zero indicate that comparison models are more accurate than **FULL$_{LAD2}$**. Values less than zero indicate that comparison models are less accurate than **FULL$_{LAD2}$**. All comparison models are less accurate at each horizon considered.

**Figure 2: Median differences in EPS absolute forecast errors relative to $\text{FULL}_{\text{LAD2}}$ (analyst-covered sample)**




*Notes:* The figure presents a graphical representation of Table 3, column (2) and column/row (1/2), or median differences of EPS absolute forecast errors (AFEs) between our full, benchmark model ($\mathbf{FULL_{LAD2}}$) and other, comparison forecasts. This figure differs from Figure 1 in that: (1) it evaluates EPS forecasts rather than ROE forecasts and (2) it includes consensus analysts' forecasts as additional comparisons. Values greater than zero indicate that comparison forecasts are more accurate than $\mathbf{FULL_{LAD2}}$. Values less than zero indicate that comparison forecasts are less accurate than $\mathbf{FULL_{LAD2}}$. All comparison models are less accurate for each forecast horizon considered and analysts are less accurate at horizons 2 – 5.

**TABLE 1**
**Sample description and in-sample estimation of profitability forecasting models**

**Panel A**: Descriptive statistics (*N*=181,912)

| **Variable** | **mean** | **sd** | **1%** | **Q1** | **median** | **Q3** | **99%** |
|---|---|---|---|---|---|---|---|
| *ROE* | 0.049 | 0.229 | -0.921 | 0.016 | 0.101 | 0.160 | 0.420 |
| $\widehat{ROE}$ | 0.060 | 0.174 | -0.707 | 0.033 | 0.098 | 0.148 | 0.344 |
| *Dev* | 0.010 | 0.007 | -0.125 | -0.019 | -0.002 | 0.016 | 0.340 |
| *Dev squared* | 0.005 | 0.020 | 0.000 | 0.000 | 0.000 | 0.002 | 0.117 |
| *Operating income* | 0.165 | 0.268 | -0.808 | 0.065 | 0.200 | 0.309 | 0.765 |
| *Nonoperating income* | 0.014 | 0.058 | -0.187 | 0.000 | 0.011 | 0.031 | 0.207 |
| *Interest expense* | 0.057 | 0.087 | 0.000 | 0.003 | 0.029 | 0.075 | 0.427 |
| *Special items* | -0.0147 | 0.073 | -0.370 | 0.000 | 0.000 | 0.000 | 0.115 |
| *Income tax expense* | 0.056 | 0.073 | -0.117 | 0.002 | 0.046 | 0.100 | 0.278 |
| *Dividends* | 0.028 | 0.044 | 0.000 | 0.000 | 0.008 | 0.044 | 0.202 |
| *Market to book* | 2.066 | 2.095 | 0.262 | 0.906 | 1.459 | 2.242 | 10.993 |
| *Debt reduction* | -0.075 | 0.362 | -1.513 | -0.135 | 0.000 | 0.038 | 0.805 |
| *Log(Assets)* | 5.260 | 2.225 | 0.933 | 3.597 | 5.092 | 6.798 | 10.685 |

**TABLE 1**
**Sample description and in-sample estimation of profitability forecasting models (continued)**

**Panel B**: First-stage cross-sectional profitability forecasting models: in-sample estimation; dependent variable = $ROE_{t+1}$

| | | **$AR_{OLS}$** | | **$sHDZ_{OLS}$** | | **$sHDZ_{LAD}$** | | **$FULL_{LAD1}$** | |
|---|---|---|---|---|---|---|---|---|---|
| | Predicted | Coeff. | *p*-value | Coeff. | *p*-value | Coeff. | *p*-value | Coeff. | *p*-value |
| *Dividends* | + | -- | -- | 0.135 | <0.001 | 0.080 | <0.001 | 0.129 | <0.001 |
| *Dividend payer* | + | -- | -- | 0.039 | <0.001 | 0.012 | <0.001 | 0.005 | <0.001 |
| *Market to book* | + | -- | -- | -- | -- | -- | -- | 0.003 | <0.001 |
| *Debt reduction* | + | -- | -- | -- | -- | -- | -- | 0.009 | <0.001 |
| *Stock split* | + | -- | -- | -- | -- | -- | -- | 0.018 | <0.001 |
| *ROE* | + | 0.794 | <0.001 | 0.735 | <0.001 | 0.772 | <0.001 | -- | -- |
| *Accruals* | - | -- | -- | -0.075 | <0.001 | -0.021 | <0.001 | -- | -- |
| *Operating income* | + | -- | -- | -- | -- | -- | -- | 0.620 | <0.001 |
| *Nonoperating income* | + | -- | -- | -- | -- | -- | -- | 0.546 | <0.001 |
| *Interest expense* | - | -- | -- | -- | -- | -- | -- | -0.610 | <0.001 |
| *Special items* | + | -- | -- | -- | -- | -- | -- | 0.200 | <0.001 |
| *Income tax expense* | - | -- | -- | -- | -- | -- | -- | -0.450 | <0.001 |
| *Log(Assets)* | + | -- | -- | 0.003 | <0.001 | 0.001 | <0.001 | 0.001 | <0.001 |
| *Loss* | - | -- | -- | -0.031 | <0.001 | 0.003 | <0.001 | -0.014 | |
| *Loss×Operating income* | - | -- | -- | -- | -- | -- | -- | 0.224 | <0.001 |
| *Loss×Nonoperating income* | - | -- | -- | -- | -- | -- | -- | -0.125 | <0.001 |
| *Loss×Interest expense* | - | -- | -- | -- | -- | -- | -- | -0.056 | <0.001 |
| *Loss×Special items* | - | -- | -- | -- | -- | -- | -- | -0.033 | 0.001 |
| *Loss×Income tax expense* | - | -- | -- | -- | -- | -- | -- | -0.218 | <0.001 |
| *Intercept* | | -0.010 | <0.001 | -0.048 | <0.001 | 0.003 | <0.001 | -0.002 | 0.054 |
| *N* | | 181,912 | | 181,912 | | 181,912 | | 181,912 | |
| $R^2$ (or pseudo-$R^2$ for LAD) | | 0.43 | | 0.45 | | 0.29 | | 0.32 | |

**TABLE 1**
**Sample description and in-sample estimation of profitability forecasting models (continued)**

**Panel C**: Second-stage model: **$\mathbf{FULL_{LAD2}}$** model

**STAGE 2: Dependent Variable = $\Delta ROE_{t+1}$**

| | | Predicted | Coefficient | *p*-value |
|---|---|---|---|---|
| $\widehat{ROE}$ | $\beta_1$ | + | 0.629 | <0.001 |
| *ROE* | $\beta_2$ | - | -0.627 | <0.001 |
| *Below expectation* | $\beta_3$ | - | -0.003 | <0.001 |
| *Below expectation*×$\widehat{ROE}$ | $\beta_4$ | + | 0.090 | <0.001 |
| *Below expectation*×*ROE* | $\beta_5$ | - | -0.113 | <0.001 |
| *Dev squared* | $\beta_6$ | - | -3.208 | <0.001 |
| *Below expectation*×*Dev squared* | $\beta_7$ | + | 3.456 | <0.001 |
| *Market share* | $\beta_8$ | ? | 0.000 | 0.875 |
| *Tobins Q* | $\beta_9$ | ? | 0.000 | 0.379 |
| *Abs(Total Accruals)* | $\beta_{10}$ | ? | -0.001 | <0.001 |
| *Dev*×*Market share* | $\beta_{11}$ | - | -0.005 | 0.110 |
| *Dev*×*Tobins Q* | $\beta_{12}$ | - | -0.028 | <0.001 |
| *Dev*×*Abs(Total Accruals)* | $\beta_{13}$ | + | 0.071 | <0.001 |
| *Intercept* | | | 0.004 | <0.001 |
| *N* | | | 181,912 | |
| Pseudo $R^2$ | | | 0.08 | |

*Notes:* This table presents distributional statistics for variables used in profitability forecasting models (panel A) and in-sample estimation results for profitability forecasting models (panels B and C). The sample includes 181,912 firm-year observations from the years 1966 to 2012. Results from in-sample forecasting regressions for four different models are presented. **AR**: first-order autoregressive; **sHDZ**: scaled version of Hou, van Dijk, and Zhang (2012); **FULL:** our proposed, fully-specified model. The Stage 1 model (panel B) captures cross-sectional variation in the level of one-year ahead ROE. The Stage 2 model (panel C) captures the reversion of ROE to expected values by estimating the one year change in ROE as a function of the difference between expected ROE (from Stage 1) and current ROE. In stage 1, continuous variables beyond the 1st and 99th percentiles are treated as missing. Variables and models are defined in Appendices A and B, respectively. In panels B and C, coefficients are presented alongside *p*-values.

**TABLE 2**
**Out-of-sample absolute ROE forecast errors (full sample)**

| *One Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *N=162,084* | | **MedianAFE** (0) | **FULL$_{LAD2}$** (1) | **FULL$_{LAD1}$** (2) | **FULL$_{OLS2}$** (3) | **FULL$_{OLS1}$** (4) | **sHDZ$_{LAD}$** (5) | **sHDZ$_{OLS}$** (6) | **AR$_{OLS}$** (7) |
| **FULL$_{LAD2}$** | (1) | 0.051 | | | | | | | |
| **FULL$_{LAD1}$** | (2) | 0.051 | -0.0004*** | | | | | | |
| **FULL$_{OLS2}$** | (3) | 0.063 | -0.0045*** | -0.0045*** | | | | | |
| **FULL$_{OLS1}$** | (4) | 0.067 | -0.0073*** | -0.0063*** | -0.0021*** | | | | |
| **sHDZ$_{LAD}$** | (5) | 0.055 | -0.0022*** | -0.0019*** | +0.0014*** | +0.0033*** | | | |
| **sHDZ$_{OLS}$** | (6) | 0.070 | -0.0081*** | -0.0076*** | -0.0037*** | -0.0016*** | -0.0051*** | | |
| **AR$_{OLS}$** | (7) | 0.073 | -0.0128*** | -0.0125*** | -0.0081*** | -0.0063*** | -0.0124*** | -0.0033*** | |
| **RW** | (8) | 0.056 | -0.0015*** | -0.0019*** | +0.0016*** | +0.0038*** | -0.0010*** | +0.0047*** | +0.0090*** |

| *Two Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *N=143,731* | | **MedianAFE** (0) | **FULL$_{LAD2}$** (1) | **FULL$_{LAD1}$** (2) | **FULL$_{OLS2}$** (3) | **FULL$_{OLS1}$** (4) | **sHDZ$_{LAD}$** (5) | **sHDZ$_{OLS}$** (6) | **AR$_{OLS}$** (7) |
| **FULL$_{LAD2}$** | (1) | 0.064 | | | | | | | |
| **FULL$_{LAD1}$** | (2) | 0.065 | -0.0004*** | | | | | | |
| **FULL$_{OLS2}$** | (3) | 0.079 | -0.0046*** | -0.0042*** | | | | | |
| **FULL$_{OLS1}$** | (4) | 0.082 | -0.0076*** | -0.0061*** | -0.0018*** | | | | |
| **sHDZ$_{LAD}$** | (5) | 0.068 | -0.0033*** | -0.0031*** | +0.0011*** | +0.0024*** | | | |
| **sHDZ$_{OLS}$** | (6) | 0.083 | -0.0077*** | -0.0074*** | -0.0027*** | -0.0008*** | -0.0044*** | | |
| **AR$_{OLS}$** | (7) | 0.087 | -0.0120*** | -0.0116*** | -0.0079*** | -0.0058*** | -0.0103*** | -0.0042*** | |
| **RW** | (8) | 0.075 | -0.0037*** | -0.0049*** | +0.0002*** | +0.0016*** | -0.0034*** | +0.0014*** | +0.0055*** |

**TABLE 2**
**Out-of-sample absolute ROE forecast errors (full sample; continued)**

| *Three Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *N=128,294* | | **MedianAFE** (0) | **FULL$_{LAD2}$** (1) | **FULL$_{LAD1}$** (2) | **FULL$_{OLS2}$** (3) | **FULL$_{OLS1}$** (4) | **sHDZ$_{LAD}$** (5) | **sHDZ$_{OLS}$** (6) | **AR$_{OLS}$** (7) |
| **FULL$_{LAD2}$** | (1) | 0.070 | | | | | | | |
| **FULL$_{LAD1}$** | (2) | 0.070 | -0.0005*** | | | | | | |
| **FULL$_{OLS2}$** | (3) | 0.084 | -0.0041*** | -0.0036*** | | | | | |
| **FULL$_{OLS1}$** | (4) | 0.087 | -0.0074*** | -0.0055*** | -0.0017*** | | | | |
| **sHDZ$_{LAD}$** | (5) | 0.073 | -0.0040*** | -0.0036*** | +0.0008*** | +0.0018*** | | | |
| **sHDZ$_{OLS}$** | (6) | 0.085 | -0.0069*** | -0.0066*** | -0.0024*** | -0.0008*** | -0.0033*** | | |
| **AR$_{OLS}$** | (7) | 0.090 | -0.0106*** | -0.0100*** | -0.0066*** | -0.0045*** | -0.0075*** | -0.0039*** | |
| **RW** | (8) | 0.084 | -0.0057*** | -0.0073*** | -0.0018*** | -0.0014*** | -0.0056*** | -0.0020*** | +0.0011*** |

| *Four Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *N=115,013* | | **MedianAFE** (0) | **FULL$_{LAD2}$** (1) | **FULL$_{LAD1}$** (2) | **FULL$_{OLS2}$** (3) | **FULL$_{OLS1}$** (4) | **sHDZ$_{LAD}$** (5) | **sHDZ$_{OLS}$** (6) | **AR$_{OLS}$** (7) |
| **FULL$_{LAD2}$** | (1) | 0.072 | | | | | | | |
| **FULL$_{LAD1}$** | (2) | 0.072 | -0.0005*** | | | | | | |
| **FULL$_{OLS2}$** | (3) | 0.087 | -0.0036*** | -0.0031*** | | | | | |
| **FULL$_{OLS1}$** | (4) | 0.089 | -0.0065*** | -0.0046*** | -0.0013*** | | | | |
| **sHDZ$_{LAD}$** | (5) | 0.075 | -0.0037*** | -0.0034*** | +0.0010*** | +0.0016*** | | | |
| **sHDZ$_{OLS}$** | (6) | 0.085 | -0.0060*** | -0.0057*** | -0.0016*** | -0.0001 | -0.0021*** | | |
| **AR$_{OLS}$** | (7) | 0.089 | -0.0089*** | -0.0081*** | -0.0046*** | -0.0030*** | -0.0049*** | -0.0036*** | |
| **RW** | (8) | 0.089 | -0.0077*** | -0.0094*** | -0.0040*** | -0.0041*** | -0.0078*** | -0.0051*** | -0.0033*** |

**TABLE 2**
**Out-of-sample absolute ROE forecast errors (full sample; continued)**

| *Five Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *N=103,435* | | **MedianAFE** (0) | $\mathbf{FULL_{LAD2}}$ (1) | $\mathbf{FULL_{LAD1}}$ (2) | $\mathbf{FULL_{OLS2}}$ (3) | $\mathbf{FULL_{OLS1}}$ (4) | $\mathbf{sHDZ_{LAD}}$ (5) | $\mathbf{sHDZ_{OLS}}$ (6) | $\mathbf{AR_{OLS}}$ (7) |
| $\mathbf{FULL_{LAD2}}$ | (1) | 0.073 | | | | | | | |
| $\mathbf{FULL_{LAD1}}$ | (2) | 0.073 | -0.0003*** | | | | | | |
| $\mathbf{FULL_{OLS2}}$ | (3) | 0.088 | -0.0029*** | -0.0030*** | | | | | |
| $\mathbf{FULL_{OLS1}}$ | (4) | 0.089 | -0.0051*** | -0.0038*** | -0.000*** | | | | |
| $\mathbf{sHDZ_{LAD}}$ | (5) | 0.075 | -0.0030*** | -0.0030*** | +0.001*** | +0.0020*** | | | |
| $\mathbf{sHDZ_{OLS}}$ | (6) | 0.085 | -0.0045*** | -0.0041*** | -0.000 | +0.0005*** | -0.0012*** | | |
| $\mathbf{AR_{OLS}}$ | (7) | 0.087 | -0.0073*** | -0.0068*** | -0.003*** | -0.0019*** | -0.0032*** | -0.0031*** | |
| **RW** | (8) | 0.093 | -0.0086*** | -0.0105*** | -0.005*** | -0.0056*** | -0.0089*** | -0.0068*** | -0.0061*** |

*Notes:* This table presents results comparing profitability forecasts from different models—random walk (**RW**), autoregressive (**AR**), scaled version of Hou et al. model (**sHDZ**), and our proposed model (**FULL**). Column (0) reports the median absolute forecast error for each model $k$, as: $AFE_{i,t}^{k} = |ROE_{i,t+h} - forecast_{i,t+h}|$; $ROE_{i,t+h}$ is firm $i$'s actual GAAP ROE for fiscal-year $t + h$; $forecast_{i,t}^{k}$ is the out-of-sample forecast of $ROE_{i,t+h}$ by model $k$. In columns (1) – (7), we subtract the AFE of the [row] model from the AFE of the [column] model and report the cross-sectional median of this difference. The statistical significance is based on the Wilcoxon signed-rank test. Under the null that the matched model pairs are equally accurate, the median difference should not be significantly different from zero. If this value is significantly negative (positive), then the [column] model is more (less) accurate than the [row] model. Row/columns pairs (1) – (4) reflect within-model differences while row/columns pairs (5) – (8) reflect across model differences. ***, ** or * indicate significance at the 1 percent, 5 percent or 10 percent levels.

**TABLE 3**
**Out-of-sample absolute EPS forecast errors (analyst-covered sample)**

| *One Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *N=78,662* | | **MedianAFE** (0) | **Analysts** (1) | **$FULL_{LAD2}$** (2) | **$FULL_{LAD1}$** (3) | **$FULL_{OLS2}$** (4) | **$FULL_{OLS1}$** (5) | **$sHDZ_{LAD}$** (6) | **$sHDZ_{OLS}$** (7) | **$AR_{OLS}$** (8) |
| **Analysts** | (1) | 0.014 | | | | | | | | |
| **$FULL_{LAD2}$** | (2) | 0.018 | -0.0021*** | | | | | | | |
| **$FULL_{LAD1}$** | (3) | 0.019 | -0.0024*** | -0.0002*** | | | | | | |
| **$FULL_{OLS2}$** | (4) | 0.021 | -0.0043*** | -0.0019*** | -0.0012*** | | | | | |
| **$FULL_{OLS1}$** | (5) | 0.024 | -0.0059*** | -0.0034*** | -0.0031*** | -0.0023*** | | | | |
| **$sHDZ_{LAD}$** | (6) | 0.019 | -0.0028*** | -0.0009*** | -0.0004*** | +0.0008*** | +0.0026*** | | | |
| **$sHDZ_{OLS}$** | (7) | 0.024 | -0.0065*** | -0.0040*** | -0.0036*** | -0.0024*** | -0.0007*** | -0.0034*** | | |
| **$AR_{OLS}$** | (8) | 0.028 | -0.0092*** | -0.0072*** | -0.0069*** | -0.0054*** | -0.0035*** | -0.0068*** | -0.0027*** | |
| **RW** | (9) | 0.018 | -0.0038*** | -0.0014*** | -0.0008*** | +0.0005*** | +0.0022*** | -0.0005*** | +0.0029*** | +0.0055*** |

| *Two Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *N=59,633* | | **MedianAFE** (0) | **Analysts** (1) | **$FULL_{LAD2}$** (2) | **$FULL_{LAD1}$** (3) | **$FULL_{OLS2}$** (4) | **$FULL_{OLS1}$** (5) | **$sHDZ_{LAD}$** (6) | **$sHDZ_{OLS}$** (7) | **$AR_{OLS}$** (8) |
| **Analysts** | (1) | 0.025 | | | | | | | | |
| **$FULL_{LAD2}$** | (2) | 0.026 | +0.0002*** | | | | | | | |
| **$FULL_{LAD1}$** | (3) | 0.027 | -0.0002*** | -0.0003*** | | | | | | |
| **$FULL_{OLS2}$** | (4) | 0.028 | -0.0013*** | -0.0012*** | -0.0008*** | | | | | |
| **$FULL_{OLS1}$** | (5) | 0.030 | -0.0023*** | -0.0026*** | -0.0021*** | -0.0012*** | | | | |
| **$sHDZ_{LAD}$** | (6) | 0.028 | -0.0012*** | -0.0015*** | -0.0009*** | -0.0003*** | +0.0008*** | | | |
| **$sHDZ_{OLS}$** | (7) | 0.030 | -0.0028*** | -0.0028*** | -0.0022*** | -0.0016*** | -0.0002*** | -0.0015*** | | |
| **$AR_{OLS}$** | (8) | 0.033 | -0.0047*** | -0.0057*** | -0.0053*** | -0.0044*** | -0.0033*** | -0.0043*** | -0.0024*** | |
| **RW** | (9) | 0.027 | -0.0017*** | -0.0023*** | -0.0013*** | -0.0004*** | +0.0005*** | -0.0006*** | +0.0009*** | +0.0034*** |

**TABLE 3**
**Out-of-sample absolute EPS forecast errors (analyst-covered sample; continued)**

| *Three Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *N=17,352* | | **MedianAFE** (0) | **Analysts** (1) | **$FULL_{LAD2}$** (2) | **$FULL_{LAD1}$** (3) | **$FULL_{OLS2}$** (4) | **$FULL_{OLS1}$** (5) | **$sHDZ_{LAD}$** (6) | **$sHDZ_{OLS}$** (7) | **$AR_{OLS}$** (8) |
| **Analysts** | (1) | 0.030 | | | | | | | | |
| **$FULL_{LAD2}$** | (2) | 0.029 | +0.0017*** | | | | | | | |
| **$FULL_{LAD1}$** | (3) | 0.029 | +0.0016*** | -0.0006*** | | | | | | |
| **$FULL_{OLS2}$** | (4) | 0.031 | +0.0004*** | -0.0010*** | -0.0005*** | | | | | |
| **$FULL_{OLS1}$** | (5) | 0.032 | -0.0001*** | -0.0027*** | -0.0016*** | -0.0010*** | | | | |
| **$sHDZ_{LAD}$** | (6) | 0.031 | +0.0004*** | -0.0016*** | -0.0007*** | -0.0003*** | +0.0006* | | | |
| **$sHDZ_{OLS}$** | (7) | 0.032 | -0.0004*** | -0.0022*** | -0.0011*** | -0.0010*** | +0.0003 | -0.0005*** | | |
| **$AR_{OLS}$** | (8) | 0.035 | -0.0032*** | -0.0058*** | -0.0052*** | -0.0042*** | -0.0032*** | -0.0049*** | -0.0042*** | |
| **RW** | (9) | 0.030 | -0.0009 | -0.0030*** | -0.0017*** | -0.0027*** | -0.0001*** | -0.0016*** | -0.0009*** | +0.0025*** |

| *Four Year Forecast Horizon* | | | *Median Difference in AFE: (column) – (row)* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *N=7,505* | | **MedianAFE** (0) | **Analysts** (1) | **$FULL_{LAD2}$** (2) | **$FULL_{LAD1}$** (3) | **$FULL_{OLS2}$** (4) | **$FULL_{OLS1}$** (5) | **$sHDZ_{LAD}$** (6) | **$sHDZ_{OLS}$** (7) | **$AR_{OLS}$** (8) |
| **Analysts** | (1) | 0.036 | | | | | | | | |
| **$FULL_{LAD2}$** | (2) | 0.031 | +0.0032*** | | | | | | | |
| **$FULL_{LAD1}$** | (3) | 0.032 | +0.0031*** | -0.0008*** | | | | | | |
| **$FULL_{OLS2}$** | (4) | 0.035 | +0.0008*** | -0.0017*** | -0.0017*** | | | | | |
| **$FULL_{OLS1}$** | (5) | 0.036 | -0.0006*** | -0.0046*** | -0.0032*** | -0.0013*** | | | | |
| **$sHDZ_{LAD}$** | (6) | 0.033 | +0.0027*** | -0.0015*** | -0.0003*** | +0.0012*** | +0.0028*** | | | |
| **$sHDZ_{OLS}$** | (7) | 0.033 | +0.0021*** | -0.0022*** | -0.0005*** | +0.0007*** | +0.0027*** | -0.0003*** | | |
| **$AR_{OLS}$** | (8) | 0.036 | +0.0003*** | -0.0042*** | -0.0036*** | -0.0008*** | +0.0001*** | -0.0038*** | -0.0038*** | |
| **RW** | (9) | 0.035 | -0.0014 | -0.0047*** | -0.0024*** | -0.0005*** | +0.0006*** | -0.0039*** | -0.0029*** | -0.0005 |

**TABLE 3**
**Out-of-sample absolute EPS forecast errors (analyst-covered sample; continued)**

| *Five Year Forecast Horizon* | | | | *Median Difference in AFE: (column) – (row)* | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *N=3,475* | | **MedianAFE** (0) | **Analysts** (1) | **$FULL_{LAD2}$** (2) | **$FULL_{LAD1}$** (3) | **$FULL_{OLS2}$** (4) | **$FULL_{OLS1}$** (5) | **$sHDZ_{LAD}$** (6) | **$sHDZ_{OLS}$** (7) | **$AR_{OLS}$** (8) |
| **Analysts** | (1) | 0.040 | | | | | | | | |
| **$FULL_{LAD2}$** | (2) | 0.033 | +0.0056*** | | | | | | | |
| **$FULL_{LAD1}$** | (3) | 0.034 | +0.0057*** | -0.0009*** | | | | | | |
| **$FULL_{OLS2}$** | (4) | 0.038 | +0.0019*** | -0.0033*** | -0.0032*** | | | | | |
| **$FULL_{OLS1}$** | (5) | 0.040 | +0.0011*** | -0.0066*** | -0.0050*** | -0.0012*** | | | | |
| **$sHDZ_{LAD}$** | (6) | 0.034 | +0.0059*** | -0.0020*** | 0.0004 | +0.0019*** | +0.0049*** | | | |
| **$sHDZ_{OLS}$** | (7) | 0.036 | +0.0036*** | -0.0037*** | -0.0011*** | +0.0009 | +0.0043*** | -0.0019*** | | |
| **$AR_{OLS}$** | (8) | 0.036 | +0.0040*** | -0.0025*** | -0.0021*** | +0.0007 | +0.0028*** | -0.0019*** | -0.0002*** | |
| **RW** | (9) | 0.038 | +0.0007** | -0.0049*** | -0.0028*** | +0.0030*** | +0.0018* | -0.0064*** | -0.0042*** | -0.0029*** |

*Notes:* This table presents results comparing profitability forecasts from different models—random walk (**RW**), autoregressive (**AR**), scaled version of Hou et al. model (**sHDZ**), consensus analyst forecasts (**Analysts**), and our proposed model (**FULL**). Column (0) reports the median absolute forecast error for each model *k*, as: $AFE_{i,t}^{k} = |iEPS_{i,t+h} - forecast_{i,t+h}|/Price$; $iEPS_{i,t+h}$ is firm *i*'s actual I/B/E/S *EPS* for fiscal-year $t + h$; $forecast_{i,t}^{k}$ is the out-of-sample forecast of $iEPS_{i,t+h}$ by model *k*. In columns (1) – (8), we subtract the AFE of the [row] model from the AFE of the [column] model and report the cross-sectional median of this difference. The statistical significance is based on the Wilcoxon signed-rank test. Under the null that the matched model pairs are equally accurate, the median difference should not be significantly different from zero. If this value is significantly negative (positive), then the [column] model is more (less) accurate than the [row] model. Row/columns pairs (2) – (5) reflect within-model differences while rolw/columns pairs (6) – (8) reflect across model differences. ***, ** or * indicate significance at the 1 percent, 5 percent or 10 percent levels.

**TABLE 4**
**In-sample, firm-level association between earnings forecasts and future raw realized returns (standardized coefficients presented)**

| **Dependent variable: *Returns$_{m+1}$*** | | | | | |
|---|---|---|---|---|---|
| | $E_m[Earnings_{t+h}]/MVE_{t,m-1}$ *based on:* | | | | |
| | **Analysts** | **FULL$_{LAD2}$** | **sHDZ$_{LAD}$** | **sHDZ$_{OLS}$** | **AR$_{OLS}$** |
| Intercept | 0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| *p*-value | (0.235) | (0.161) | (0.150) | (0.208) | (0.179) |
| $Inverse\ market\ value_{t,m-1}$ | 0.016 | 0.018 | 0.021 | 0.020 | 0.016 |
| *p*-value | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) |
| $Book\ value_t/MVE_{t,m-1}$ | 0.013 | 0.004 | 0.011 | 0.023 | 0.022 |
| *p*-value | (0.011) | (0.426) | (0.040) | (<0.001) | (<0.001) |
| $Earnings_t/MVE_{t,m-1}$ | -0.021 | -0.047 | -0.038 | -0.021 | -0.012 |
| *p*-value | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (0.405) |
| $E_m[Earnings_{t+h}]/MVE_{t,m-1}$ | 0.038 | 0.069 | 0.054 | 0.030 | 0.017 |
| *p*-value | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (0.235) |
| $Dividends_t/MVE_{t,m-1}$ | 0.009 | 0.004 | 0.004 | 0.004 | 0.011 |
| *p*-value | (0.056) | (0.360) | (0.446) | (0.337) | (0.028) |
| No. Observations | 644,057 | 644,057 | 644,057 | 644,057 | 644,057 |
| $R^2$ | 0.033 | 0.031 | 0.031 | 0.031 | 0.032 |

*Notes:* We present regressions results for monthly, Fama-MacBeth regressions of future monthly returns (*Return$_{m+1}$*) on firm fundamentals for the years 1980-2012. $E_m[Earnings_{t+h}]/MVE_{t,m-1}$ represents the time-weighted mean of fiscal years *t+1* and *t+2* EPS forecasts, multiplied by number of common shares outstanding during calendar month *m* at the end of the fiscal year *t*. Future earnings expectation is a time-weighted mean of either consensus analyst EPS forecast or the out-of-sample EPS forecast obtained from the **FULL$_{LAD2}$**, **sHDZ**, or **AR** models. *MVE* is split-adjusted lagged monthly price times fiscal year-end shares outstanding, per COMPUSTAT. *Book value* is the book value of equity divided by common shares outstanding. *Earnings* is calculated as income before extraordinary items divided by common shares outstanding; *Dividends* is cash dividends available for common, divided by common shares outstanding. Monthly returns are obtained from CRSP. All regression variables are standardized to have a mean of zero and standard deviation of one. The time-series means of coefficient estimates and *p*-values (below) are presented using Fama-MacBeth standard errors.

**TABLE 5**

**Construct validity test: firm-level association between expected returns and future realized returns**

**Panel A:** Summary statistics

| | *Firm-level expected returns ($\boldsymbol{\mu}$) based on EPS forecasts from:* | | | | | *Realized Returns* |
|---|---|---|---|---|---|---|
| | **Analysts** | **$\mathbf{FULL_{LAD2}}$** | **$\mathbf{sHDZ_{LAD}}$** | **$\mathbf{sHDZ_{OLS}}$** | **$\mathbf{AR_{OLS}}$** | **($r_{t+1}$)** |
| Mean | 0.953 | 0.936 | 0.932 | 0.945 | 0.810 | 1.061 |
| Standard | 0.584 | 0.657 | 0.627 | 0.597 | 0.557 | 15.840 |
| 1% | 0.093 | 0.069 | 0.047 | 0.095 | 0.069 | -38.360 |
| 5% | 0.373 | 0.347 | 0.328 | 0.364 | 0.275 | -21.372 |
| 25% | 0.667 | 0.632 | 0.634 | 0.652 | 0.544 | -6.100 |
| Median | 0.837 | 0.800 | 0.806 | 0.830 | 0.697 | 0.556 |
| 75% | 1.074 | 1.047 | 1.048 | 1.068 | 0.923 | 7.296 |
| 95% | 1.925 | 1.951 | 1.951 | 1.902 | 1.681 | 23.971 |
| 99% | 3.340 | 3.744 | 3.569 | 3.392 | 3.076 | 48.611 |

**Panel B:** Construct validity: cross-sectional regressions of realized returns on expected returns

**Dependent Variable: Realized returns ($r_{t+1}$)**

| | *Independent variable: Firm-level expected returns ($\boldsymbol{\mu}$) based on EPS forecasts from* | | | | |
|---|---|---|---|---|---|
| | **Analysts** | **$\mathbf{FULL_{LAD2}}$** | **$\mathbf{sHDZ_{LAD}}$** | **$\mathbf{sHDZ_{OLS}}$** | **$\mathbf{AR_{OLS}}$** |
| $\boldsymbol{\mu}$ | 1.162 | 1.190 | 1.221 | 1.194 | 1.285 |
| *p*-value (Ho: $\boldsymbol{\mu}$=0) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *p*-value (Ho: $\boldsymbol{\mu}$=1 ) | (0.185) | (0.068) | (0.070) | (0.151) | (0.061) |
| | | | | | |
| Intercept | -0.030 | -0.046 | -0.067 | -0.059 | 0.038 |
| *p*-value (Ho: Intercept = 0) | (0.934) | (0.898) | (0.855) | (0.877) | (0.910) |
| No. of obs | 578,007 | 578,007 | 578,007 | 578,007 | 578,007 |
| $R^2$ | 0.007 | 0.007 | 0.008 | 0.008 | 0.009 |

*Notes:* This table reports results from tests of the association between expected returns, based on out-of-sample fitted values from either analysts' earnings expectations or model-based EPS forecasts, and realized returns. Panel A presents summary statistics for expected returns ($\mu$), based on analysts or models; and realized returns ($r_{t+1}$). Panel B reports the time-series mean coefficients and *p*-values from out-of-sample Fama-MacBeth regressions of realized returns on expected returns.

**TABLE 6**
**Portfolio-based time-series tests**

**Panel A:** Portfolio-based returns

Portfolios formed based on expected return estimates

| | **Analyst-** based mean return | | **FULL$_{LAD2}$-** based mean return | | **sHDZ$_{LAD}$-** based mean return | | **sHDZ$_{OLS}$-** based mean return | | **AR$_{OLS}$-** based mean return | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Quintile | E[$r_{t+1}$ \| $\mu$] | Mean($r_{t+1}$) | E[$r_{t+1}$ \| $\mu$] | Mean($r_{t+1}$) | E[$r_{t+1}$ \| $\mu$] | Mean($r_{t+1}$) | E[$r_{t+1}$ \| $\mu$] | Mean($r_{t+1}$) | E[$r_{t+1}$ \| $\mu$] | Mean($r_{t+1}$) |
| 1 (Low) | 0.534 | 0.354 | 0.506 | 0.163 | 0.494 | 0.270 | 0.526 | 0.326 | 0.469 | 0.393 |
| *p-value* | (<0.001) | (0.412) | (<0.001) | (0.710) | (<0.001) | (0.550) | (<0.001) | (0.474) | (<0.001) | (0.274) |
| 2 | 0.696 | 0.606 | 0.662 | 0.524 | 0.668 | 0.646 | 0.688 | 0.677 | 0.577 | 0.630 |
| *p-value* | (<0.001) | (0.071) | (<0.001) | (0.125) | (<0.001) | (0.048) | (<0.001) | (0.045) | (<0.001) | (0.057) |
| 3 | 0.807 | 0.999 | 0.776 | 1.059 | 0.781 | 0.959 | 0.802 | 1.020 | 0.672 | 1.001 |
| *p-value* | (<0.001) | (0.002) | (<0.001) | (0.001) | (<0.001) | (0.002) | (<0.001) | (0.001) | (<0.001) | (0.002) |
| 4 | 0.985 | 1.331 | 0.962 | 1.445 | 0.960 | 1.406 | 0.974 | 1.317 | 0.828 | 1.364 |
| *p-value* | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) |
| 5 (High) | 1.736 | 2.256 | 1.776 | 2.355 | 1.748 | 2.266 | 1.706 | 2.206 | 1.501 | 2.159 |
| *p-value* | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) |
| High - Low | 1.202 | **1.902** | 1.270 | **2.192** | 1.254 | **1.996** | 1.180 | **1.880** | 1.032 | **1.767** |
| *p-value* | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (<0.001) |

**TABLE 6**
**Portfolio-based time-series tests (continued)**

**Panel B:** Portfolio-based alphas

Portfolios formed based on expected return estimates

| | **Analyst-** based excess return | | **$FULL_{LAD2}$-** based excess return | | **$sHDZ_{LAD}$-** based excess return | | **$sHDZ_{OLS}$-** based excess return | | **$AR_{OLS}$-** based excess return | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Quintile | $\alpha_{analysts}$ | *p*-value | $\alpha_{FULL}$ | *p*-value | $\alpha_{sHDZ.LAD}$ | *p*-value | $\alpha_{sHDZ.OLS}$ | *p*-value | $\alpha_{AR}$ | *p*-value |
| 1 (Low) | 0.169 | 0.703 | 0.000 | 0.999 | 0.100 | 0.831 | 0.150 | 0.749 | 0.173 | 0.641 |
| 2 | 0.428 | 0.217 | 0.335 | 0.342 | 0.447 | 0.186 | 0.494 | 0.158 | 0.437 | 0.203 |
| 3 | 0.832 | 0.012 | 0.870 | 0.009 | 0.772 | 0.019 | 0.833 | 0.012 | 0.834 | 0.015 |
| 4 | 1.164 | 0.001 | 1.287 | <0.001 | 1.262 | <0.001 | 1.157 | 0.001 | 1.228 | 0.001 |
| 5 (High) | 2.127 | <0.001 | 2.227 | <0.001 | 2.139 | <0.001 | 2.085 | <0.001 | 2.048 | <0.001 |
| High-Low | **1.673** | <0.001 | **1.942** | <0.001 | **1.754** | <0.001 | **1.650** | <0.001 | **1.590** | <0.001 |

*Notes:* This table presents results from portfolio-based time-series tests of the relation between expected returns and realized returns. Panel A reports monthly average excess returns, sorted by out-of-sample expected return measures. $r_{t+1}$ denotes net realized returns; $E[r_{t+1} \mid \mu]$ denotes expected returns, conditional on analysts' expectations and model-based expectations. Panel B presents results from portfolio-adjusted excess returns (alphas) for each quintile based on analysts' expectations and model-based expectations. *p*-values are presented below estimates.