THE ACCOUNTING REVIEW
Vol. 91, No. 3
May 2016
pp. 811–833

American Accounting Association
DOI: 10.2308/accr-51233

Firm-Specific Estimates of Differential Persistence and their Incremental Usefulness for Forecasting and Valuation

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ABSTRACT: Although the differential persistence of accruals and operating cash flows is a firm-specific phenomenon, research seeking to exploit the differential persistence of these earnings components typically employs cross-sectional forecasting models. We find that a model based on firm-specific estimates of the differential persistence of accruals and operating cash flows is incrementally useful for out-of-sample forecasting relative to state-of-the-art cross-sectional models. In doing so, we show that firm-specific estimates of differential persistence are particularly useful when forecasting earnings for more stable firms (e.g., more profitable, lower growth, and less levered firms). We also demonstrate that a trading strategy exploiting investors' fixation on earnings and based on firm-specific estimates of differential persistence earns statistically and economically significant excess returns that are incremental to those generated by trading strategies based on the size of accruals. These results suggest that firm-specific estimates of differential persistence are incrementally informative for forecasting and valuation.

Keywords: firm-specific estimates; differential persistence; accruals; operating cash flows.

JEL Classifications: M41.

I. INTRODUCTION

Beginning with Sloan (1996), a long line of research examines the differential persistence of accruals and operating cash flows and its implications for forecasting and valuation. The literature suggests investors fixate on bottom-line earnings (i.e., aggregate earnings) and do not incorporate the lower persistence of accruals relative to the persistence of operating cash flows. This research generally examines differential persistence using *cross-sectional* analyses, where a single accrual and a single operating cash flow persistence parameter are estimated for a large cross-section of firms (e.g., Sloan 1996; Xie 2001; Desai, Rajgopal, and Venkatachalam 2004; Richardson, Sloan, Soliman, and Tuna 2005; Dechow, Richardson, and Sloan 2008).

We thank John Campbell, Patricia Dechow, Ed deHaan, Weili Ge, Andrew Jackson, Yaniv Konchitchki, Todd Kravet, Charles Lee, Carolyn Levine, Rick Mergenthaler, Kyle Peterson, Shiva Rajgopal, Darren Roulstone, D. Shores, Richard Sloan, Mark Soliman, Steve Stubben, Mohan Venkatachalam, Peter Wysocki, and Xiao-Jun Zhang for helpful comments. We also thank workshop participants at the University of California, Berkeley, The University of Georgia, University of Miami, University of Virginia, and the Virginia Polytechnic Institute and State University, as well as participants at the 2015 Accounting and Finance Association of Australia and New Zealand Conference, 2007 American Accounting Association Annual Meeting, 2006 Brigham Young University Research Symposium, 2013 European Accounting Association Annual Congress, 2013 Financial Accounting Reporting Section Midyear Meeting, and the 2007 Universities of British Columbia, Oregon, and Washington Conference for helpful comments.

Editor's note: Accepted by Charles M. C. Lee.

Submitted: June 2013
Accepted: July 2015
Published Online: July 2015

Implicit in the cross-sectional estimation of differential persistence is the critical assumption that the differential persistence of accruals and operating cash flows is the same for all firms (e.g., Sloan 1996; Hafzalla, Lundholm, and Van Winkle 2011). In addition, cross-sectional estimation requires information about other firms' accruals and operating cash flows. In contrast, a *firm-specific* estimation procedure allows the magnitude of the differential persistence of accruals and operating cash flows to vary across firms and does not rely on information about other firms to estimate the persistence of a given firm's earnings components. Given that the cross-sectional and firm-specific estimation procedures incorporate different information, using information from both estimation approaches is likely to improve forecasts of earnings. We examine whether a firm-level analysis of differential persistence—using an individual firm's time-series of financial statement information—provides *incremental* forecasting and valuation information beyond that provided by cross-sectional analyses.

Francis and Smith (2005) highlight the importance of firm-specific analyses and argue that estimating the differential persistence of accruals and operating cash flows at the firm level is appropriate because the persistence of a firm's accruals and operating cash flows are unlikely to depend on the persistence of other firms' earnings components. However, Francis and Smith (2005) find that relatively few firms possess accruals that are significantly less persistent than operating cash flows. Therefore, the authors conclude that firm-specific estimates of differential persistence are unlikely to be useful for forecasting and valuation and that "something other than differential accruals and cash flow persistence drives the accruals anomaly" (Francis and Smith 2005, 444). Based on this conclusion, subsequent research has primarily relied on cross-sectional estimates of differential persistence for forecasting and valuation. However, Francis and Smith (2005) do not empirically test whether firm-specific estimates of differential persistence provide information for forecasting and valuation.

Our study directly considers whether firm-specific estimates of differential persistence provide incremental information to cross-sectional models for out-of-sample forecasting and valuation. We explore this issue by examining (1) all firms for which the differential persistence of accruals and operating cash flows can be estimated using a time-series of ten years of financial statement information, (2) a sample of firms for which accruals are historically less persistent than operating cash flows (57 percent of all observations with firm-specific estimates of differential persistence), and (3) a sample of firms for which accruals are historically *significantly* less persistent than operating cash flows (16 percent of all observations with firm-specific estimates of differential persistence). Using these samples, we test whether earnings forecasts based on firm-specific estimates of differential persistence provide incremental information, over and above earnings forecasts produced by cross-sectional models, for the purposes of forecasting and valuation.

We find that estimates of year-ahead earnings persistence based on firm-specific estimates of differential persistence explain the variation in the actual persistence of current earnings into year-ahead earnings. For the sample of all firms for which accruals are less persistent than operating cash flows, we find a significant range (0.115) in the persistence of current earnings into year-ahead earnings for firms in the top (0.794) versus bottom (0.679) decile of estimated earnings persistence. This range increases to 0.351 for the sample of firms for which accruals are *significantly* less persistent than operating cash flows. These results suggest that estimates of earnings persistence based on firm-specific estimates of differential persistence are informative about the actual persistence of current earnings into year-ahead earnings.

We then directly examine whether firm-specific estimates of differential persistence provide *incremental* information for out-of-sample forecasting over the cross-sectional models of Sloan (1996), Hou, van Dijk, and Zhang (2012), So (2013), and Li and Mohanram (2014). We regress year-ahead *actual* earnings on the decile ranks of earnings forecasts generated by (1) the cross-sectional forecasting models, and (2) the model based on firm-specific estimates of differential persistence. In each analysis, we find that including information about firm-specific estimates of the differential persistence of accruals and operating cash flows provides incremental information about year-ahead earnings, even relative to state-of-the-art cross-sectional models. We also examine the firm characteristics associated with the ability of the model based on firm-specific estimates of differential persistence to provide incremental information for forecasting over the cross-sectional models. We find that firm-specific estimates are more useful for relatively profitable, lower growth, and less levered firms, suggesting that firm-specific estimates of differential persistence are particularly useful for stable firms.

We next investigate whether investors fully incorporate firm-specific estimates of differential persistence into stock prices. Given that prior research suggests that investors fixate on aggregate earnings (Sloan 1996; Hirshleifer and Teoh 2003; Hewitt 2009), we develop a trading strategy that takes positions based on estimates of unexpected earnings. We measure the difference between forecasted earnings based on firm-specific estimates of differential persistence and forecasted earnings based on a firm's historical aggregate earnings. These estimates of unexpected earnings directly address the notion that the differential persistence of accruals and operating cash flows is not fully processed by "fixated" investors.

We sort firms into deciles based on the estimates of unexpected earnings, and take long (short) positions in firms with the highest (lowest) estimates of unexpected year-ahead earnings. To demonstrate the importance of excluding loss firms from tests of fixation (Kraft, Leone, and Wasley 2006), we present our findings both excluding and including loss firms. When excluding loss firms, our hedge portfolios earn statistically and economically significant *excess* returns averaging between 7.80 and 8.04 percent (11.64 and 12.60 percent) annually for all firms for which accruals are less persistent than operating cash flows (accruals are *significantly* less persistent than operating cash flows). These returns are incremental to the Fama and French (1993) factors, a momentum factor (Carhart 1997), and an accrual factor reflecting the cross-sectional accrual-based trading strategy suggested by Sloan (1996). Consistent with the fixation-based hypothesis, the trading strategy generates much larger excess returns when loss firms are excluded from the trading strategy relative to when loss firms are included.

Our study makes important contributions to financial statement analysis and valuation. Specifically, our study provides guidance to analysts and investors by demonstrating that firm-specific estimates of differential persistence can be used to improve earnings forecasts. These insights are particularly important for analysts who examine the time-series of historical earnings of individual firms as part of their financial analysis (Stickney, Brown, and Wahlen 2003; White, Sondhi, and Fried 2003; Lundholm and Sloan 2009; Penman 2013). The findings of our study are also important for investors as they seek to improve their valuations of individual firms and use these valuations to develop trading strategies based on the differential persistence of accruals and operating cash flows.

Our study also contributes to research on the differential persistence of accruals and operating cash flows. Using a firm-specific time-series methodology, Francis and Smith (2005) conclude that firm-specific estimates of differential persistence are unlikely to yield useful information. However, Francis and Smith (2005) do not empirically test whether firm-specific estimates of differential persistence provide information for forecasting and valuation. In contrast, we empirically show that firm-specific estimates of differential persistence provide incremental information for forecasting and valuation.

Finally, our study contributes to the literature on earnings fixation (Sloan 1996; Hirshleifer and Teoh 2003; Hewitt 2009). Recent research has questioned whether the profitability of trading strategies based on earnings fixation can be explained by investors' fixation on earnings (Fairfield, Whisenant, and Yohn 2003a; Kraft et al. 2006; Khan 2008; Wu, L. Zhang, and X. Zhang 2010). We use firm-specific estimates of the differential persistence of accruals and operating cash flows to directly target firms for which the effects of fixation should be the greatest. Using this new approach, we find that a trading strategy based on these firm-specific estimates of differential persistence generates abnormal excess returns. In light of our findings, future research should consider using firm-specific estimates of differential persistence to reevaluate the conclusions of studies suggesting that investors are no longer fixated on aggregate earnings (Green, Hand, and Soliman 2011).

Section II discusses research that uses either a cross-sectional or firm-specific approach to estimate differential persistence and develops our hypotheses. Section III describes our estimation of differential persistence, the samples used in this study, and preliminary evidence concerning the benefit of allowing differential persistence to vary across firms. Section IV provides evidence on the incremental usefulness of firm-specific estimates of differential persistence for forecasting. Section V considers the extent to which investors incorporate firm-specific estimates of differential persistence into stock prices. Section VI concludes.

II. BACKGROUND LITERATURE AND HYPOTHESES DEVELOPMENT

Using Firm-Specific Estimates of Differential Persistence for Forecasting

Prior research primarily relies on a cross-sectional approach to estimate the differential persistence of accruals and operating cash flows. The cross-sectional approach pools firm-year observations within a given year, and sometimes across years, to estimate a single persistence parameter for each component using all available firms in the analysis (e.g., Sloan 1996; Xie 2001; Hanlon 2005). Using this estimation approach, each parameter is meant to capture the average of the underlying firm-specific persistence parameters. This approach usually assumes—implicitly or otherwise—that the inferences stemming from cross-sectional estimation of the differential persistence of accruals and operating cash flows extend to firm-specific estimation.

However, Teets and Wasley (1996) argue that cross-sectional and firm-specific estimation procedures generally do not lead to the same inferences. They show that earnings response coefficients estimated using a cross-sectional approach are not the same as the average of the earnings response coefficients from a firm-specific approach. When there is a systematic relation between the firm-specific coefficients and the firm-specific variances of the explanatory variables, the results from a cross-sectional estimation approach do not mirror those from a firm-specific approach. In the context of earnings persistence, it is likely that the firm-specific earnings persistence parameters are systematically related to the firm-specific variance of the independent variables (i.e., accruals and operating cash flows). For example, prior research highlights how earnings persistence varies with firm characteristics, such as payout ratios, economic pressures, growth, conservatism, and book-tax differences (Dechow, Hutton, and Sloan 1999; Feltham and Ohlson 1995; Hanlon 2005; Blaylock, Shevlin, and Wilson 2012).

Following the insights of Teets and Wasley (1996), Francis and Smith (2005, 415) argue that the differential persistence of accruals and operating cash flows is "inherently firm specific," and unlikely to be related to the persistence of *other* firms' accruals and operating cash flows. However, Francis and Smith (2005, 413) suggest that firm-specific differential persistence is unlikely to be informative for forecasting because "more than 85% of firms show no evidence that accruals are less persistent than cash flows." However, Francis and Smith (2005) do not empirically test whether firm-specific estimates of the differential persistence of accruals and operating cash flows are informative for forecasting.[1] Despite this lack of evidence, subsequent research has generally relied solely on cross-sectional differential persistence models and has not examined whether firm-specific estimates of differential persistence provide information incremental to cross-sectional estimates.[2]

A firm-specific estimation approach allows the magnitude of differential persistence to vary across firms, whereas the cross-sectional approach estimates a single accrual persistence parameter and a single operating cash flow persistence parameter for all firms. In addition, unlike cross-sectional estimates of differential persistence, firm-specific estimates of differential persistence focus on a firm's own "inputs" rather than on information about other firms in the economy. Therefore, we hypothesize that incorporating firm-specific estimates of the differential persistence of accruals and operating cash flows provides incremental information for forecasting relative to using only cross-sectional estimates of differential persistence.

Our first hypothesis predicts that out-of-sample forecasts of earnings that incorporate firm-specific estimates of differential persistence are predictive of year-ahead earnings incremental to forecasts based on cross-sectional estimates of differential persistence (Sloan 1996) and to the state-of-the-art cross-sectional forecasting models proposed by Hou et al. (2012), So (2013), and Li and Mohanram (2014):

H1: Firm-specific estimates of the differential persistence of accruals and operating cash flows provide information for out-of-sample earnings forecasts that is incremental to the information provided by cross-sectional forecasting models.

Using Firm-Specific Estimates of Differential Persistence for Valuation

Research proposes that naïve investors limit their attention to aggregate earnings (Sloan 1996; Hirshleifer and Teoh 2003; Hewitt 2009), suggesting that investors fail to incorporate the differential persistence of accruals and operating cash flows into their trading decisions. Numerous studies examine investors' pricing of differentially persistent accruals and operating cash flows using a cross-sectional approach (e.g., Sloan 1996; Xie 2001; Desai et al. 2004; Richardson et al. 2005; Dechow et al. 2008) and conclude that investors do not understand the differential persistence of accruals and operating cash flows. More recently, however, research has questioned whether earnings fixation explains the cross-sectional accrual anomaly (Fairfield et al. 2003a; Kraft et al. 2006; Khan 2008; Wu et al. 2010).

In an attempt to provide insight into whether earnings fixation explains the accrual anomaly, Shi and Zhang (2012) interact estimates of firm-specific differential persistence with cross-sectional sorts of accruals and examine whether this interaction helps explain the returns to the cross-sectional accrual anomaly.[3] Although Shi and Zhang (2012) employ firm-specific estimates of differential persistence, their examination does not directly identify firms for which earnings forecasts based on firm-specific estimates of differential persistence are different from earnings forecasts based on aggregate earnings alone. We contend that directly identifying firms for which firm-specific estimates of differential persistence yield an earnings forecast that differs from an earnings forecast based on aggregate earnings is more likely to target mispricing that stems from earnings fixation. This approach exploits earnings fixation by calculating the difference between (1) a forecast of the firm's earnings based on the differential persistence of accruals and operating cash flows, and (2) a forecast of the firm's earnings based only on aggregate earnings. If investors fixate on aggregate earnings, then we argue that earnings forecasts based on firm-specific estimates of differential persistence will identify mispriced securities.

Kraft et al. (2006) argue that mispricing associated with earnings fixation is more likely to occur for firms that do not report a loss. Because firms often incur losses due to write-downs and losses on the disposal of noncurrent assets, they suggest that the earnings fixation explanation is inconsistent with investors being "fooled" by loss firms because losses are relatively salient, given both the income statement presentation of write-downs and the prominence of a bottom-line loss. Kraft et al. (2006) believe the abnormal returns generated by loss firms are due to these firms' poor past performance (Li 2011) rather than investors' fixation on aggregate earnings *per se*. That is, the earnings fixation hypothesis suggests that fixated investors do not misprice loss firms, and that their inclusion would dilute the abnormal returns generated by a fixation-based trading strategy. Our second hypothesis, based on the earnings fixation theory, predicts that a trading strategy based on forecasts of unexpected

[1] We note that Francis and Smith's (2005) conclusion is based on low-power tests of differential persistence (i.e., a 5 percent significance level using only 20 observations).

[2] Dechow and Dichev (2002) show that firm-specific estimates of accruals quality are useful for predicting earnings persistence. Their study does not—nor was it intended to—examine the informativeness of firm-specific estimates of the differential persistence of accruals and operating cash flows incremental to cross-sectional approaches.

[3] The objective of Shi and Zhang (2012) is to explain the source of the cross-sectional accrual anomaly rather than to examine whether a trading strategy based only on firm-specific information (including estimates of differential persistence) yields incremental returns beyond the cross-sectional accrual strategy.

earnings that incorporate firm-specific estimates of differential persistence yields positive returns that are incremental to the returns associated with the size of accruals and that are more pronounced when loss firms are excluded from the analysis:

H2: Trading strategies based on firm-specific estimates of the differential persistence of accruals and operating cash flows generate abnormal excess returns that are (1) incremental to the returns associated with the size of accruals, and (2) more pronounced when loss firms are excluded.

III. FIRM-SPECIFIC ESTIMATES OF DIFFERENTIAL PERSISTENCE

Estimating Firm-Specific Differential Persistence of Accruals and Operating Cash Flows

Earnings persistence can be estimated using a time-series approach. Using a firm's historical time-series of earnings, year-ahead earnings can be estimated as follows:

$$E_{t+1} = \alpha_0 + \omega_0 \cdot E_t, \quad (1)$$

where ω_0 represents the persistence of the firm's earnings, and E_t (E_{t+1}) is the earnings that the firm reports in year t (t+1).[4] Because earnings represent the sum of accruals and operating cash flows, Equation (1) can also be expressed as follows:

$$E_{t+1} = \alpha_1 + \omega_1 \cdot ACC_t + \omega_2 \cdot CASH_t, \quad (2)$$

where ω_1 (ω_2) represents the persistence of the firm's accruals (operating cash flows), and ACC_t ($CASH_t$) is the accruals (operating cash flows) that the firm reports in year t. Note that Equation (2) allows the differential persistence of accruals and operating cash flows to vary across firms, a key distinction from the cross-sectional estimation approach.

Consistent with Francis and Smith (2005), historical estimates of ω_1 and ω_2 can be derived from the following firm-specific regression:

$$E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t. \quad (3)$$

Equation (3) is estimated using rolling windows for each firm each year. Given that ACC_t, $CASH_t$, and E_t are readily observable before making forecasts for year t+1 earnings—and that ω_1 and ω_2 are both estimated using only historical firm-specific data—investors can estimate the persistence of accruals and operating cash flows using data available at the time of estimation. In this study, we directly incorporate estimates of ω_1 and ω_2 into our forecasting model to examine the incremental benefit of estimates of differential persistence for forecasting and valuation.

Samples Used to Examine the Incremental Usefulness of Firm-Specific Estimates

We begin with all firms with available data listed on Compustat between 1972 and 2010 (212,825 firm-year observations). Because we estimate ω_1 and ω_2 employing ten-year rolling windows, we require data as far back as 1962. We exclude financial institutions because the data required to calculate accruals are not available for these firms. We construct three samples to examine the incremental usefulness of firm-specific estimates of differential persistence for forecasting and valuation.

Our first sample consists of all firms for which we can derive firm-specific estimates of ω_1 and ω_2 from 1972 to 2010 (79,492 firm-year observations). We label this sample, "All observations with sufficient data to estimate ω_1 and ω_2." We estimate Equation (3) using rolling ten-year windows for each firm and each year, beginning with accruals and operating cash flows (earnings) from year t–10 (t–9) and ending with accruals and operating cash flows (earnings) from year t–1 (t). We estimate ω_1 and ω_2 using historical financial statement information and only data available at the time of the forecast. For example, to forecast earnings for 2010, one would observe the accruals and operating cash flows for 2009 and estimate the historical persistence of accruals and operating cash flows using data from 1999 through 2009. It is worth noting that the requirement to have sufficient information to derive firm-specific persistence estimates (i.e., ten years of consecutive data) restricts our sample to approximately 37 percent of the Compustat population. Therefore, one disadvantage of the firm-specific estimation approach is that a firm must have sufficient time-series information to estimate ω_1 and ω_2. However, requiring ten years of historical data results in relatively established firms being included in the "All observations with sufficient data to estimate ω_1 and ω_2" sample. In fact, over our sample period, this sample accounts for an annual average (median) of 64 (73) percent of the total market capitalization of all Compustat firms.

Francis and Smith (2005) find that some firms exhibit accruals that are more (not less) persistent than operating cash flows. Our next two samples consist of firms for which the assumption that $\omega_1 < \omega_2$ is more likely to hold. We examine a sample of

[4] This equation includes an error term; however, we assume that the expectation of the error term is zero.

TABLE 1

Descriptive Statistics
Samples Used to Examine the Incremental Usefulness of Firm-Specific Estimates

	All Observations on Compustat for the Sample Period (n = 212,825)		All Observations with Sufficient Data to Estimate ω_1 and ω_2 (n = 79,492)		All Observations with $\omega_1 < \omega_2$ (n = 44,919)		Observations with $\omega_1 < \omega_2$ at p-value < 0.10 (n = 12,481)	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
E_t	0.024	0.074	0.066	0.084	0.071	0.088	0.083	0.095
ACC_t	−0.035	−0.035	−0.041	−0.040	−0.041	−0.040	−0.038	−0.038
$CASH_t$	0.059	0.104	0.107	0.122	0.112	0.125	0.121	0.132
$ASSETS_t$	1,512.61	83.71	2,568.06	232.72	2,480.20	240.79	2,446.31	237.85
Firm-specific differential persistence:								
ω_1 (accruals)			0.437	0.452	0.230	0.298	0.054	0.140
ω_2 (operating cash flows)			0.480	0.511	0.561	0.584	0.658	0.678

ω_1 (ω_2) is a firm-specific estimate of the persistence of accruals (operating cash flows), obtained from the following firm-specific regression estimated using ten years of prior data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence. The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows. The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the difference between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less.

Variable Definitions:
E_t = operating income after depreciation scaled by average total assets;
ACC_t = operating accruals scaled by average total assets, where operating accruals are calculated as follows: (Δ current assets − Δ cash and short-term investments − Δ current liabilities + Δ debt in current liabilities + Δ in taxes payable − depreciation);
$CASH_t = E_t - ACC_t$; and
$ASSETS_t$ = total assets.

44,919 firm-year observations (57 percent of all observations with estimates of ω_1 and ω_2) where the historical estimate of ω_1 is less than the historical estimate of ω_2 (labeled "All observations with $\omega_1 < \omega_2$"). We also examine a sample of 12,481 firm-year observations (16 percent of all observations with estimates of ω_1 and ω_2) for which the historical firm-specific estimate of ω_1 is *significantly* lower than the historical firm-specific estimate of ω_2 at the 10 percent significance level (one-sided) (labeled "Observations with $\omega_1 < \omega_2$ at p-value < 0.10").[5]

Table 1 presents descriptive statistics for the three samples based on estimates of ω_1 and ω_2. In the first set of columns, we also present descriptive statistics for the population of Compustat firm-year observations. The second, third, and fourth sets of columns present the descriptive statistics for the sample of all firms for which ω_1 and ω_2 can be estimated, the sample of firms for which $\omega_1 < \omega_2$, and the sample of firms for which $\omega_1 < \omega_2$ at a significance level of 10 percent, respectively. We note that the samples based on estimates of ω_1 and ω_2 generally include larger and more profitable firm-year observations relative to the population of Compustat firm-year observations.

Comparing the results across our three samples in Table 1 highlights the usefulness of identifying firms for which the historical persistence of accruals is less than the historical persistence of operating cash flows. For the sample of all firms for which ω_1 and ω_2 can be estimated, we find only a modest difference in the mean persistence of accruals and operating cash flows (0.437 and 0.480, respectively). Yet for the "All observations with $\omega_1 < \omega_2$" sample, the mean firm-specific estimate of ω_1 is 0.230, whereas the mean firm-specific estimate of ω_2 is 0.561. Similarly, for the "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample, the mean firm-specific estimates of ω_1 and ω_2 are 0.054 and 0.658, respectively. These findings suggest that the latter two samples are more likely to consist of firms where accruals and operating cash flows are differentially persistent.[6] Importantly, the similarity of the mean values of earnings, accruals, operating cash flows, and total assets across all three

[5] If we restrict this sample to firms with differential persistence significant at the 5 percent level, then we trade off power along opposing dimensions: a smaller sample, but with greater probability that the persistence of accruals is less than the persistence of operating cash flows. *Ex ante,* we chose a 10 percent significance level to achieve a larger sample size with reasonable confidence that the persistence differs between the two earnings components.

[6] The estimates of ω_1 and ω_2 are lower than the cross-sectional estimates reported in the prior literature (Sloan 1996), but are consistent with prior research using firm-specific estimates of persistence (Francis and Smith 2005).

samples suggests that the only notable difference across the samples is the firm-specific differential persistence of accruals and operating cash flows.

Firm-Specific Estimates of Earnings Persistence Based on Differential Persistence

Based upon the estimates of ω_1 and ω_2 we generate from Equation (3), we construct firm-specific estimates of earnings persistence and test whether they are informative about year-ahead earnings persistence. Specifically, we estimate a firm's earnings persistence ($\hat{w}_0$) as the weighted-average sum of the firm's historical persistence of accruals (ω_1) and the firm's historical persistence of operating cash flows (ω_2):

$$\hat{w}_0 = \omega_1 \cdot ACC_t/E_t + \omega_2 \cdot CASH_t/E_t. \tag{4}$$

In addition to estimates of ω_1 and ω_2, estimating $\hat{w}_0$ in Equation (4) requires several inputs. Specifically, we require current measures of a firm's accruals (ACC_t), operating cash flows ($CASH_t$), and earnings (E_t). We use Sloan's (1996) definitions of ACC_t, $CASH_t$, and E_t.[7] Again, ACC_t, $CASH_t$, and E_t are all observable from a firm's reported financial statements. In estimating $\hat{w}_0$, we also assume that the intercept in Equation (3) is equal to 0. This assumption appears to be empirically valid, as only 14.6 percent (26.9 percent) of the observations used in our empirical analyses have an intercept that is significantly different from 0 at the 5 percent (10 percent) level when estimated over the prior ten years.

To provide preliminary evidence as to whether estimates of year-ahead earnings persistence based on firm-specific estimates of differential persistence explain the actual persistence of current earnings into year-ahead earnings, we substitute ACC_t, $CASH_t$, E_t, and the estimates of ω_1 and ω_2 into Equation (4). We then form ranked deciles each year based on $\hat{w}_0$, where firms with the lowest (highest) forecast of earnings persistence are assigned to Decile 1 (Decile 10). Within each decile of $\hat{w}_0$, we estimate annual cross-sectional regressions of year-ahead earnings on current earnings. If firm-specific estimates of ω_1 and ω_2 provide useful information about the persistence of current earnings into year-ahead earnings, then we should observe higher earnings persistence parameters as we increase from Decile 1 through Decile 10.

Table 2 reports the average and median annual persistence of current earnings into year-ahead earnings for each decile of firms classified according to $\hat{w}_0$. For all firms for which we estimate ω_1 and ω_2 (reported in the first set of columns), we find no statistically significant increase in earnings persistence across the $\hat{w}_0$ deciles. Specifically, the mean earnings persistence parameters range from 0.698 (lowest decile of forecasted earnings persistence) to 0.743 (highest decile of forecasted earnings persistence). This result is arguably not surprising because the analysis relies on the notion that accruals and operating cash flows are differentially persistent, and this sample of firms likely includes many firm-year observations for which the earnings components are not differentially persistent (see Table 1).

However, for the samples in Table 2 of firms where, historically, $\omega_1 < \omega_2$, we find that estimates of year-ahead earnings persistence based on firm-specific estimates of differential persistence explain the actual persistence of current earnings into year-ahead earnings. For the "All observations with $\omega_1 < \omega_2$" sample, we find that $\hat{w}_0$ is informative about the actual persistence of current earnings, in that we observe a statistically significant range in mean earnings persistence from 0.679 for the lowest decile of forecasted earnings persistence to 0.794 for the highest decile of forecasted earnings persistence (a range of 0.115). For the "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample, we find that forming deciles based on $\hat{w}_0$ results in a range in mean earnings persistence from 0.642 for the lowest decile of forecasted earnings persistence to 0.993 for the highest decile of forecasted earnings persistence (a range of 0.351). These results suggest that forecasting earnings persistence based on firm-specific estimates of differential persistence helps explain the actual persistence of current earnings into year-ahead earnings.

IV. FIRM-SPECIFIC DIFFERENTIAL PERSISTENCE AND FORECASTING

Forecasting Analyses and Benchmark Forecasting Models

In this section, we test our first hypothesis by examining whether forecasts based on firm-specific estimates of differential persistence provide incremental forecasting ability to forecasts based on cross-sectional estimates. We also examine the situations in which forecasts based on firm-specific estimates of differential persistence provide greater incremental information over forecasts based on cross-sectional estimates, and expect forecasts based on firm-specific estimates of differential persistence to provide greater incremental information when predicting earnings for relatively stable firms.

[7] Earnings is defined as operating income after depreciation. Accruals is defined as the sum of the change in current assets (ACT) minus the change in cash/cash equivalents (CHE) minus the change in current liabilities (LCT) plus the change in debt included in current liabilities (DLC) plus the change in income taxes payable (TXP) minus depreciation (DP). Operating cash flows is defined as earnings minus accruals. Earnings, accruals, and operating cash flows are scaled by current average total assets (AT).

TABLE 2

Average Annual Persistence of Current Earnings into Year-Ahead Earnings Across Deciles of Firm-Specific Estimates of Earnings Persistence Based on the Differential Persistence of Accruals and Operating Cash Flows

	All Observations with Sufficient Data to Estimate ω_1 and ω_2		All Observations with $\omega_1 < \omega_2$		Observations with $\omega_1 < \omega_2$ at p-value < 0.10	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Decile 1	0.698	0.773	0.679	0.683	0.642	0.629
Decile 2	0.779	0.811	0.810	0.817	0.780	0.819
Decile 3	0.821	0.844	0.786	0.851	0.845	0.837
Decile 4	0.818	0.834	0.838	0.850	0.826	0.802
Decile 5	0.808	0.782	0.840	0.822	0.872	0.895
Decile 6	0.829	0.811	0.818	0.820	0.879	0.864
Decile 7	0.810	0.809	0.860	0.820	0.821	0.843
Decile 8	0.805	0.831	0.831	0.826	0.868	0.866
Decile 9	0.801	0.785	0.829	0.848	0.846	0.857
Decile 10	0.743	0.752	0.794	0.817	0.993	0.858
Range (10–1)	0.045	−0.021	0.115**	0.134**	0.351***	0.229***
# of years	39	39	38	38	36	36
Average n per decile	203	203	118	118	34	34

***, ** Indicate significance at the 1 percent and 5 percent levels, respectively.

We report mean (and median) annual persistence of current earnings into year-ahead earnings by estimating the regression ($E_{t+1} = \alpha_0 + \omega_0 \cdot E_t + \varepsilon_{t+1}$) separately for each decile each year. Deciles are formed based on firm-specific forecasts of earnings persistence ($\hat{w}_0 = \omega_1 \cdot ACC_t/E_t + \omega_2 \cdot CASH_t/E_t$). Decile 1 (10) represents firm-year observations with the lowest (highest) $\hat{w}_0$. The mean (median) annual difference between Decile 10 and Decile 1 is based on a t-test (Wilcoxon signed rank test). "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence. The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows. The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the difference between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less.

We benchmark the forecasts based on firm-specific estimates of differential persistence against four cross-sectional forecasting models. Our first benchmark combines pooled cross-sectional estimates of ω_1 and ω_2 with firm-specific information (i.e., ACC_t and $CASH_t$) to forecast earnings. We refer to this model as the "Sloan (1996) forecasting model," as it incorporates annual cross-sectional estimates of ω_1 and ω_2 using pooled firm-year data.[8] These cross-sectional persistence parameters are based on the same ten-year rolling windows used to calculate firm-specific persistence parameters to ensure that both models incorporate data across the same time period when forecasting earnings. Because the Sloan (1996) forecasting model estimates a single persistence parameter for accruals and a single persistence parameter for operating cash flows for all firms, this cross-sectional model does not allow the differential persistence of the earnings components to vary across firms.

Our next three benchmark models represent state-of-the-art forecasting models in the financial statement analysis literature. Each of these benchmark models implicitly captures cross-sectional estimates of differential persistence by considering the persistence of accruals for a pooled cross-section of firms. However, these models also incorporate other financial statement information aside from earnings and its components (e.g., dividends). Specifically, Hou et al. (2012) forecast earnings using the following pooled cross-sectional regression:

$$E_{t+1} = \gamma_0 + \gamma_1 \cdot ASSETS_t + \gamma_2 \cdot DIV_t + \gamma_3 \cdot DIVDUM_t + \gamma_4 \cdot E_t + \gamma_5 \cdot LOSSDUM_t + \gamma_6 \cdot ACCRUALS_t + \varepsilon_{t+1}. \quad (5)$$

Equation (5) estimates γ_0 through γ_6 using ten years of pooled cross-sectional data and combines these estimates with firm-specific information (i.e., assets, dividends, earnings, and accruals) in year t to forecast earnings in year t+1. $ASSETS_t$, DIV_t, E_t, and $ACCRUALS_t$ represent the firm's assets, dividends, earnings, and accruals in year t, respectively. In Hou et al. (2012), these variables are unscaled (i.e., the model forecasts dollar earnings); however, Hou et al. (2012) conduct robustness tests using variables scaled by total assets and find similar results. We scale these variables by average total assets to facilitate comparison

[8] Although the purpose of Sloan (1996) was not to forecast earnings *per se*, this forecasting model is consistent with Sloan (1996) in that annual cross-sectional data are used to estimate the persistence of the earnings components.

with the earnings forecasts based on firm-specific estimates of differential persistence. $DIVDUM_t$ and $LOSSDUM_t$ are dummy variables that identify firms that pay dividends and report losses in year *t*, respectively.

We also evaluate the forecasting ability of the model based on firm-specific estimates of differential persistence relative to So (2013). So (2013) incorporates financial statement information and market information (e.g., book-to-market and stock price) using the following cross-sectional regression:

$$E_{t+1} = \beta_0 + \beta_1 \cdot E\_POS_t + \beta_2 \cdot LOSSDUM_t + \beta_3 \cdot ACCRUALS\_NEG_t + \beta_4 \cdot ACCRUALS\_POS_t + \beta_5 \cdot AG_t + \beta_6 \cdot DIVDUM_t + \beta_7 \cdot DIVSHARE_t + \beta_8 \cdot BTM_t + \beta_9 \cdot PRICE_t + \varepsilon_{t+1}. \quad (6)$$

Equation (6) estimates β_0 through β_9 using cross-sectional data from the prior year and combines these estimates with firm-specific information in year *t*. E_POS_t represents earnings before extraordinary items adjusted for special items with values left-truncated at 1. $ACCRUALS\_NEG_t$ ($ACCRUALS\_POS_t$) represents accruals per share when accruals are negative (positive), and is set to 0 for all other accrual values. AG_t represents asset growth as a percentage of lagged assets; $DIVSHARE_t$ represents dividends per share; BTM_t is the firm's book-to-market ratio; and $PRICE_t$ is the firm's year-end stock price. Whereas So (2013) estimates the coefficients β_0 through β_9 using only one year of cross-sectional data, we estimate these coefficients using ten years of prior data to ensure that the So (2013) forecasting model uses the equivalent data as the other models.[9] Note that So (2013) incorporates stock prices and other market data, in addition to financial statement information, when forecasting earnings.

The final benchmark model is the "persistence in earnings" forecasting model presented by Li and Mohanram (2014) as a parsimonious alternative to the Hou et al. (2012) model.[10] Li and Mohanram (2014) use the following cross-sectional regression to forecast earnings:

$$E_{t+1} = \mu_0 + \mu_1 \cdot LOSSDUM_t + \mu_2 \cdot E_t + \mu_3 \cdot LOSSDUM_t \times E_t + \varepsilon_{t+1}. \quad (7)$$

Equation (7) estimates μ_0 through μ_3 using ten years of pooled cross-sectional data to forecast earnings in year t+1. Li and Mohanram (2014) scale the variables by the number of shares outstanding; however, we scale these variables by average total assets to facilitate comparison with the earnings forecasts based on firm-specific estimates of differential persistence. All models are based only on information available at the time of the forecast and all models use information covering the same time period (i.e., ten years) to derive earnings forecasts.[11]

The Incremental Usefulness of Firm-Specific Estimates of Differential Persistence

Table 3 reports the descriptive statistics for the forecasting model based on firm-specific estimates of differential persistence and the cross-sectional forecasting models (Sloan 1996; Hou et al. 2012; So 2013; Li and Mohanram 2014). Panel A reports the descriptive statistics for all observations for which we can estimate ω_1 and ω_2. Panel B reports the descriptive statistics for all observations where $\omega_1 < \omega_2$, and Panel C reports the descriptive statistics for the sample requiring $\omega_1 < \omega_2$ at the 10 percent significance level (one-sided).

In each panel of Table 3, the cross-sectional forecasting models outperform the forecasting model based on firm-specific estimates of differential persistence, as indicated by the median forecast improvement being significantly negative in each comparison. However, in each comparison, the forecasting model based on firm-specific estimates of differential persistence outperforms its cross-sectional counterparts for at least 40 percent of the observations. Therefore, although the forecasting model based on firm-specific estimates of differential persistence does not dominate its cross-sectional counterparts, firm-specific estimates of differential persistence are clearly useful in many instances. These findings suggest that, contrary to Francis and Smith's (2005) conclusion, firm-specific estimates of differential persistence are useful, *in isolation,* when forecasting earnings for a substantial number of firms.[12]

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[9] The incremental usefulness of the forecasting model based on firm-specific estimates of differential persistence is not an artifact of these design choices. Estimating the So (2013) model using one year of cross-sectional data does not improve its performance relative to using ten years of data to estimate the model.

[10] Li and Mohanram (2014) propose another model that adds book value and accruals (as defined by Richardson et al. [2005]) to Equation (7). Our findings are inferentially the same when we replace the model reflected in Equation (7) with this alternative model. We choose to report the forecasting model reflected in Equation (7) because the alternative model's data requirements further restrict the number of firms for which earnings can be forecasted.

[11] Again, our firm-specific estimates of differential persistence are based on ten years of information, and firms without this time-series of information are excluded from our analyses. An important caveat to our study is that our findings may not generalize to firms with insufficient information to estimate firm-specific differential persistence.

[12] Similar to the findings of Li and Mohanram (2014), in untabulated analyses, we also find that a random walk forecasting model performs favorably relative to both firm-specific and cross-sectional forecasting models.

TABLE 3

Descriptive Statistics
Forecasting Models Based on Firm-Specific and Cross-Sectional Estimates

Panel A: All Observations with Sufficient Data to Estimate ω_1 and ω_2

	Forecast		Forecast Error		Absolute Forecast Error		Median Forecasting Improvement	% Observations where Firm-Specific Model is Superior
	Mean	Median	Mean	Median	Mean	Median		
Forecasts based on firm-specific estimates	0.067	0.084	0.006	0.002	0.064	0.032		
Cross-sectional models								
Sloan (1996)	0.067	0.080	0.006	−0.004	0.053	0.028	−0.003***	45.0
Hou et al. (2012)	0.067	0.083	0.006	−0.002	0.053	0.028	−0.003***	44.3
So (2013)	0.061	0.078	0.001	−0.005	0.063	0.032	−0.001***	48.3
Li and Mohanram (2014)	0.060	0.077	0.000	−0.008	0.054	0.030	−0.003***	45.2

Panel B: All Observations with $\omega_1 < \omega_2$

	Forecast		Forecast Error		Absolute Forecast Error		Median Forecasting Improvement	% Observations where Firm-Specific Model is Superior
	Mean	Median	Mean	Median	Mean	Median		
Forecasts based on firm-specific estimates	0.073	0.089	0.007	0.003	0.061	0.031		
Cross-sectional models								
Sloan (1996)	0.071	0.083	0.005	−0.005	0.052	0.028	−0.002***	45.5
Hou et al. (2012)	0.071	0.086	0.005	−0.002	0.052	0.028	−0.003***	44.9
So (2013)	0.065	0.081	0.001	−0.005	0.062	0.031	−0.001***	48.9
Li and Mohanram (2014)	0.065	0.080	0.000	−0.008	0.053	0.029	−0.002***	46.1

Panel C: Observations with $\omega_1 < \omega_2$ at p-value < 0.10

	Forecast		Forecast Error		Absolute Forecast Error		Median Forecasting Improvement	% Observations where Firm-Specific Model is Superior
	Mean	Median	Mean	Median	Mean	Median		
Forecasts based on firm-specific estimates	0.084	0.097	0.006	0.004	0.064	0.033		
Cross-sectional models								
Sloan (1996)	0.080	0.089	0.003	−0.006	0.050	0.028	−0.004***	43.2
Hou et al. (2012)	0.080	0.091	0.003	−0.004	0.050	0.028	−0.004***	42.9
So (2013)	0.075	0.088	−0.001	−0.006	0.058	0.031	−0.002***	46.4
Li and Mohanram (2014)	0.075	0.086	−0.002	−0.008	0.050	0.029	−0.004***	43.6

*** Indicates significance at the 1 percent level.

We report mean and median forecasts, forecast errors (forecasted earnings − actual earnings), and absolute forecast errors for the forecasting models. "Median Forecasting Improvement" reports the median difference in absolute forecast errors for the forecast using firm-specific estimates of differential persistence and the forecast based on the cross-sectional forecasting model in question. Positive (negative) values are consistent with the forecasting model based on firm-specific estimates of differential persistence being more (less) accurate than the cross-sectional forecasting model in question. "% Observations where Firm-Specific Model is Superior" reports the percentage of firm-year observations for which the forecasting model based on firm-specific estimates of differential persistence yields a smaller absolute forecast error than the cross-sectional forecasting model in question. The forecasting model based on firm-specific estimates of differential persistence forecast is the firm-specific estimate of earnings, calculated as the fitted value from the following firm-specific model using ten years of prior data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Sloan (1996) forecast is the fitted value from the following cross-sectional model using ten years of pooled data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Hou et al. (2012), So (2013), and Li and Mohanram (2014) forecasts are fitted values based on the cross-sectional forecasting models outlined by Hou et al. (2012), So (2013), and Li and Mohanram (2014), and are estimated using ten years of pooled cross-sectional data. Because the forecasting model based on firm-specific estimates of differential persistence requires ten years of prior data for each firm, we impose the same restriction in the estimation of all cross-sectional forecasts. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence (Panel A). The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows (Panel B). The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the inequality between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less (Panel C).

Table 4 reports the primary test of our first hypothesis, where we examine whether the forecasting model based on firm-specific estimates of differential persistence provides incremental information for out-of-sample forecasting when combined with cross-sectional forecasting models. In Columns (1) through (5), we regress actual year-ahead earnings (i.e., earnings in year $t+1$) on decile ranks of each of the cross-sectional forecasts and the forecasts based on firm-specific estimates of differential persistence. We then add the decile ranks of earnings forecasts based on firm-specific estimates of differential persistence to the decile ranks based on the Sloan (1996) forecasts (Column (6)), the decile ranks based on the Hou et al. (2012) forecasts (Column (7)), the decile ranks based on the So (2013) forecasts (Column (8)), and the decile ranks based on the Li and Mohanram (2014) forecasts (Column (9)). These tests allow us to examine whether firm-specific estimates of differential persistence provide incremental information for forecasting relative to the cross-sectional forecasting models.

We find in Table 4 that forecasts based on firm-specific estimates of differential persistence provide incremental information relative to every benchmark cross-sectional forecasting model we examine. First, the coefficients for forecasts based on firm-specific estimates of differential persistence provide information incremental to the cross-sectional Sloan (1996) forecasts (Column (6)) across all three samples. This comparison is important because both the firm-specific forecasting model and the Sloan (1996) forecasting model consider only the persistence of accruals and operating cash flows, and differ only in the adopted estimation approach (i.e., firm-specific versus cross-sectional). Similarly, incremental to the cross-sectional forecasting models suggested by Hou et al. (2012) (Column (7)), So (2013) (Column (8)), and Li and Mohanram (2014) (Column (9)), the coefficients on the deciles of the forecasts based on firm-specific estimates of differential persistence are significantly positive across all three samples.

In summary, our findings suggest that the forecasts based on firm-specific estimates of differential persistence provide information about year-ahead actual earnings that is incremental to the state-of-the-art cross-sectional forecasting models. These findings are even more noteworthy as the three state-of-the-art cross-sectional forecasting models also incorporate varying amounts of additional financial statement information (e.g., book-to-market, price, dividends, and whether the firm made a loss), whereas the model based on firm-specific estimates of differential persistence incorporates only accruals and operating cash flows. Thus, firm-specific estimates of differential persistence provide incremental information for forecasting despite the cross-sectional models incorporating more financial statement variables.

One concern with these analyses is the possibility that the forecasting model based on firm-specific estimates of differential persistence and the cross-sectional forecasting models produce earnings forecasts that are highly correlated. Accordingly, multicollinearity potentially affects the models presented in Table 4. However, we note that multicollinearity inflates standard errors, thereby reducing the statistical significance of the coefficients. In spite of this feature, we find statistically significant incremental explanatory power for the forecasts based on firm-specific estimates of differential persistence. In addition, the variance inflation factors in the regressions examining the incremental information provided by the forecasts based on firm-specific estimates of differential persistence (i.e., for Columns (6) through (9) in each panel of Table 4) are well below the threshold of 10 suggested by Marquardt (1970). Specifically, for each cross-sectional forecast, the average annual variance inflation factor never exceeds 4.01, and the maximum variance inflation factor in any one year never exceeds 6.75 for any of the cross-sectional forecasts.[13]

As a final test to ensure that multicollinearity is not driving our results, in Table 5, we examine whether the model based on firm-specific estimates of differential persistence provides incremental information for forecasting across quintiles of each cross-sectional forecast. We sort firms into quintiles each year based on the cross-sectional forecast in question, with Quintile 1 (Quintile 5) representing the smallest (largest) forecasts of earnings from the cross-sectional model. Within each quintile, we then sort firms into deciles based on the earnings forecast generated by the cross-sectional and firm-specific models, respectively. In almost every quintile based on the cross-sectional forecast (i.e., 92 percent of the quintiles analyzed), the model based on firm-specific estimates of differential persistence provides incremental information for out-of-sample forecasting. Further, we observe that the forecasting model based on firm-specific estimates of differential persistence is most incrementally informative relative to the cross-sectional models for extreme forecasts of these cross-sectional models (i.e., Quintiles 1 and 5). These additional forecasting analyses further bolster our primary analyses and strongly support our first hypothesis that firm-specific estimates of differential persistence provide incremental information for out-of-sample forecasting.

Firm Characteristics When Firm-Specific Estimates of Differential Persistence are Useful

As an exploratory analysis, we now consider the firm characteristics that explain when firm-specific estimates of differential persistence are likely to be incrementally useful for forecasting. Given that the firm-specific estimates of differential persistence are calculated using ten years of historical data, we argue that the performance of the forecasting model based on

[13] Note that we estimate each cross-sectional forecasting model separately for each year during our sample period. Also, note that because each model outlined in Columns (6) through (9) in Table 4 includes only two independent variables, the variance inflation factor for both coefficients is identical.

TABLE 4

Incremental Informativeness of Firm-Specific Estimates of Differential Persistence for Forecasting

Panel A: All Observations with Sufficient Data to Estimate ω_1 and ω_2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	−0.071**	−0.072***	−0.071***	−0.071***	−0.058***	−0.077***	−0.077***	−0.080***	−0.077***
Sloan (1996) $Decile_t$	0.285***					0.228***			
Hou et al. (2012) $Decile_t$		0.285***					0.229***		
So (2013) Decile_t			0.282***					0.202***	
Li and Mohanram (2014) $Decile_t$				0.284***					0.227***
$Decile_t$ of forecasts based on firm-specific estimates					0.259***	0.067***	0.068***	0.098***	0.069***
Adjusted R^2	42.2%	42.3%	41.6%	42.1%	34.4%	42.8%	42.9%	43.3%	42.8%

Panel B: All Observations with $\omega_1 < \omega_2$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	−0.068**	−0.068***	−0.069***	−0.068***	−0.057***	−0.072***	−0.073***	−0.077***	−0.074***
Sloan (1996) $Decile_t$	0.284***					0.228***			
Hou et al. (2012) $Decile_t$		0.285***					0.227***		
So (2013) $Decile_t$			0.284***					0.199***	
Li and Mohanram (2014) $Decile_t$				0.284***					0.219***
$Decile_t$ of forecasts based on firm-specific estimates					0.262***	0.065***	0.068***	0.102***	0.077***
Adjusted R^2	43.3%	43.4%	42.7%	43.1%	36.0%	43.9%	44.1%	44.7%	44.0%

Panel C: Observations with $\omega_1 < \omega_2$ at p-value < 0.10

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	−0.057*	−0.057***	−0.058***	−0.056***	−0.042***	−0.062***	−0.063***	−0.067***	−0.065***
Sloan (1996) $Decile_t$	0.282***					0.237***			
Hou et al. (2012) $Decile_t$		0.282***					0.231***		
So (2013) $Decile_t$			0.284***					0.215***	
Li and Mohanram (2014) $Decile_t$				0.282***					0.223***
$Decile_t$ of forecasts based on firm-specific estimates					0.253***	0.075***	0.062***	0.087***	0.075***
Adjusted R^2	46.2%	46.2%	45.8%	46.0%	36.2%	47.6%	47.6%	47.7%	47.6%

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

We report average annual coefficient estimates where the dependent variable is year-ahead earnings (E_{t+1}) and the explanatory variables are the decile rank of the forecast of year-ahead earnings using the forecasts generated by the benchmark model based on cross-sectional estimates of differential persistence and/or the forecasting model based on firm-specific estimates of differential persistence. The forecast based on firm-specific estimates of differential persistence is calculated as the fitted value from the following firm-specific model using ten years of prior data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Sloan (1996) forecast is the fitted value from the following cross-sectional model using ten years of pooled data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Hou et al. (2012), So (2013), and Li and Mohanram (2014) forecasts are fitted values based on the cross-sectional forecasting models outlined by Hou et al. (2012), So (2013), and Li and Mohanram (2014), and are estimated using ten years of pooled cross-sectional data. Because the forecasting model based on firm-specific estimates of differential persistence requires ten years of prior data for each firm, we impose the same restriction in the estimation of all cross-sectional forecasts. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence (Panel A). The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows (Panel B). The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the inequality between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less (Panel C).

TABLE 5

Incremental Informativeness of Firm-Specific Estimates of Differential Persistence for Forecasting Conditioned on the Cross-Sectional Forecast
(Quintiles Based on Sorted Forecast from the Named Forecast Model in the First Column)

Panel A: All Observations with Sufficient Data to Estimate ω_1 and ω_2

		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Sloan (1996)	Intercept	−0.244***	0.021***	0.069***	0.095***	0.107***
	Sloan (1996) *Decile$_t$*	0.239***	0.035***	0.024***	0.028***	0.093***
	Decile$_t$ of firm-specific forecasts	0.080***	0.017***	0.007**	0.015***	0.073***
	Adjusted R^2	22.4%	4.9%	3.2%	5.7%	24.4%
Hou et al. (2012)	Intercept	−0.243***	0.020***	0.067***	0.095***	0.107***
	Hou et al. (2012) *Decile$_t$*	0.237***	0.034***	0.023***	0.027***	0.099***
	Decile$_t$ of firm-specific forecasts	0.081***	0.021***	0.010***	0.016***	0.067***
	Adjusted R^2	22.2%	4.7%	3.3%	5.6%	25.1%
So (2013)	Intercept	−0.229***	−0.011	0.063***	0.091***	0.109***
	So (2013) *Decile$_t$*	0.070***	0.050***	0.019***	0.028***	0.098***
	Decile$_t$ of firm-specific forecasts	0.226***	0.049***	0.021***	0.023***	0.065***
	Adjusted R^2	17.8%	8.8%	4.4%	7.1%	28.2%
Li and Mohanram (2014)	Intercept	−0.243***	0.020***	0.068***	0.096***	0.106***
	Li and Mohanram (2014) *Decile$_t$*	0.236***	0.036***	0.024***	0.028***	0.090***
	Decile$_t$ of firm-specific forecasts	0.083***	0.019***	0.008***	0.015***	0.077***
	Adjusted R^2	22.5%	5.0%	3.2%	6.2%	24.4%

Panel B: All Observations with $\omega_1 < \omega_2$

		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Sloan (1996)	Intercept	−0.241***	0.026***	0.073***	0.097***	0.112***
	Sloan (1996) *Decile$_t$*	0.229***	0.038***	0.026***	0.031***	0.092***
	Decile$_t$ of firm-specific forecasts	0.092***	0.012***	0.001	0.015***	0.072***
	Adjusted R^2	23.6%	5.4%	4.3%	6.7%	25.9%
Hou et al. (2012)	Intercept	−0.242***	0.026***	0.070***	0.097***	0.112***
	Hou et al. (2012) *Decile$_t$*	0.226***	0.036***	0.023***	0.026***	0.098***
	Decile$_t$ of firm-specific forecasts	0.095***	0.016***	0.008**	0.017***	0.066***
	Adjusted R^2	23.1%	4.7%	4.7%	6.0%	26.4%
So (2013)	Intercept	−0.233***	0.003	0.063***	0.093***	0.114***
	So (2013) *Decile$_t$*	0.075***	0.041***	0.019***	0.029***	0.096***
	Decile$_t$ of firm-specific forecasts	0.232***	0.042***	0.028***	0.025***	0.068***
	Adjusted R^2	18.9%	7.7%	6.3%	8.6%	29.2%

(continued on next page)

TABLE 5 (continued)

		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Li and Mohanram (2014)	Intercept	−0.243***	0.025***	0.068***	0.095***	0.109***
	Li and Mohanram (2014) $Decile_t$	0.224***	0.034***	0.024***	0.028***	0.083***
	$Decile_t$ of firm-specific forecasts	0.100***	0.020***	0.011***	0.021***	0.085***
	Adjusted R^2	23.3%	5.4%	4.1%	7.8%	26.3%

Panel C: Observations with $\omega_1 < \omega_2$ at p-value < 0.10

		Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Sloan (1996)	Intercept	−0.215***	0.037***	0.075***	0.103***	0.126***
	Sloan (1996) $Decile_t$	0.223***	0.038***	0.036***	0.032***	0.118***
	$Decile_t$ of firm-specific forecasts	0.071***	−0.002	−0.005*	0.017**	0.045***
	Adjusted R^2	23.1%	4.5%	7.6%	10.5%	27.9%
Hou et al. (2012)	Intercept	−0.218***	0.035***	0.073***	0.102***	0.124***
	Hou et al. (2012) $Decile_t$	0.225***	0.037***	0.029***	0.034***	0.124***
	$Decile_t$ of firm-specific forecasts	0.075***	0.002	0.006	0.018***	0.043***
	Adjusted R^2	23.3%	5.0%	5.7%	11.8%	29.2%
So (2013)	Intercept	−0.214***	0.023**	0.067***	0.102***	0.125***
	So (2013) $Decile_t$	0.091***	0.043***	0.021***	0.029***	0.102***
	$Decile_t$ of firm-specific forecasts	0.204***	0.019**	0.026***	0.028***	0.062***
	Adjusted R^2	19.4%	7.6%	8.1%	11.6%	31.7%
Li and Mohanram (2014)	Intercept	−0.218***	0.031***	0.071***	0.102***	0.120***
	Li and Mohanram (2014) $Decile_t$	0.206***	0.033***	0.025***	0.026***	0.106***
	$Decile_t$ of firm-specific forecasts	0.095***	0.013**	0.016*	0.026***	0.067***
	Adjusted R^2	23.3%	5.4%	6.7%	11.9%	28.8%

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

We report average annual coefficients from regressions where the dependent variable is year-ahead earnings (E_{t+1}) and the explanatory variables are the decile rank of the forecast of year-ahead earnings using the forecasts generated by the benchmark model based on cross-sectional estimates of differential persistence and the forecasting model based on firm-specific estimates of differential persistence. We sort firms into quintiles each year based on the cross-sectional forecasting model in question, with Quintile 1 (Quintile 5) representing the smallest (largest) forecasts of year-ahead earnings. Within each quintile, we then sort firms into deciles based on the earnings forecast generated by the benchmark and firm-specific models, respectively. The forecast based on firm-specific estimates of differential persistence is calculated as the fitted value from the following firm-specific model using ten years of prior data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Sloan (1996) forecast is the fitted value from the following cross-sectional model using ten years of pooled data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Hou et al. (2012), So (2013), and Li and Mohanram (2014) forecasts are fitted values based on the cross-sectional forecasting models outlined by Hou et al. (2012), So (2013), and Li and Mohanram (2014), and are estimated using ten years of pooled cross-sectional data. Because the forecasting model based on firm-specific estimates of differential persistence requires ten years of prior data for each firm, we impose the same restriction in the estimation of all cross-sectional forecasts. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence (Panel A). The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows (Panel B). The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the inequality between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less (Panel C).

this information is likely to be dependent on the stability of the firm (i.e., firms where firm-specific differential persistence is stable across time). We identify four firm characteristics, firm size (*SIZE*), market-to-book ratio (*MTB*), leverage (*LEV*), and operating income after depreciation scaled by average total assets (*NI*), that likely capture the stability of the firm. We expect that earnings forecasts based on firm-specific information are more likely to provide incremental information for out-of-sample forecasting relative to cross-sectional forecasts of earnings for larger, lower growth, less levered, and more profitable firms.

To explore this issue, we regress actual year-ahead earnings on decile ranks of each of the cross-sectional forecasts, decile ranks of the forecasts based on firm-specific estimates of differential persistence, and the decile ranks of the forecasts based on firm-specific estimates of differential persistence interacted with quintile ranks of each of the four firm characteristics. Table 6 reports our findings. We generally find that the model based on firm-specific estimates of differential persistence provides greater incremental information for forecasting for more profitable, lower growth, and less levered firms. We note that our findings with respect to *SIZE* are mixed, arguably due to the fact that all three samples already consist of large firms with ten years of prior data.[14]

V. FIRM-SPECIFIC DIFFERENTIAL PERSISTENCE AND VALUATION

A Trading Strategy Based on Firm-Specific Estimates of Differential Persistence

Our second hypothesis predicts that a trading strategy based on firm-specific estimates of differential persistence generates abnormal returns. We argue that a trading strategy based on firm-specific estimates of differential persistence directly exploits investors' fixation on earnings because it takes advantage of the variation in differential persistence across firms and identifies the information fixated investors ignore when only considering aggregate earnings. Therefore, we take positions in firms based on estimates of unexpected earnings, measured as the difference between the forecast of earnings based on firm-specific estimates of differential persistence and a forecast of earnings only based on aggregate earnings information (i.e., the information investors potentially ignore when fixating on a firm's time-series of aggregate earnings).

To test our second hypothesis, we employ the portfolio regression approach described by Fama and French (1993). We assign firms to deciles and take long (short) positions in firms in the largest (smallest) decile of unexpected earnings. We then calculate returns for the 12 months beginning at the start of the fourth month after the end of the fiscal year (when financial statement information becomes available). For example, for a firm with a fiscal year-end of December 31, 2009, we calculate returns for the period of April 1, 2010 through March 31, 2011. To ensure that there is no look-ahead bias when considering firms with different fiscal year-ends, we use observable decile cutoffs from the prior year when assigning firms to deciles.[15] We present our findings first, when loss firms are included in the trading strategy, and second, when loss firms are excluded from the trading strategy. Consistent with Kraft et al. (2006), we argue that fixated investors are unlikely to be "fooled" by firms incurring losses because losses are relatively salient. Therefore, we expect the excess abnormal returns to be greater when loss firms are excluded from the trading strategy.

We form hedge portfolios based on the difference between forecasted earnings using firm-specific estimates of differential persistence and forecasted earnings using aggregate (i.e., bottom-line) earnings, and regress the returns to these portfolios of unexpected earnings on market, size, book-to-market, and momentum factors, as follows:

$$R_{pt} - R_{ft} = \alpha_p + b_p \cdot (R_{mt} - R_{ft}) + s_p \cdot SMB_t + h_p \cdot HML_t + d_p \cdot UMD_t + \varepsilon_{pt}. \tag{8}$$

$R_{pt} - R_{ft}$ is the monthly return on the portfolio in excess of the Treasury bill rate in month *t;* $R_{mt} - R_{ft}$ is the excess return on the CRSP equally weighted market index; SMB_t and HML_t are the returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively; and UMD_t is the difference between returns on portfolios of past winners and losers (Carhart 1997). In additional specifications, we also add an accrual factor ($ACCRUALS_t$) based on the size of accruals, which mimics the accrual-based trading strategy proposed by Sloan (1996), and test whether the returns to a strategy based on firm-specific estimates of differential persistence is independent to the returns to an accrual-based strategy. The estimate of the intercept (α_p) tests our second hypothesis.

[14] Our results are inferentially similar when we supplement the cross-sectional models with these firm characteristics. Specifically, if we modify the cross-sectional forecasting models by including *SIZE*, *MTB*, *LEV*, and *NI*, then the model based on firm-specific estimates of differential persistence provides incremental information for out-of-sample forecasting. We thank an anonymous referee for suggesting this analysis. Note that all of the cross-sectional forecasting models—with the exception of Sloan (1996)—already have some version of *NI* in their model, and that the So (2013) model incorporates *MTB*.

[15] Our findings are robust to restricting the analyses to calendar year-end firms, consistent with prior research (Fairfield, Whisenant, and Yohn 2003b; Sloan 1996; Mashruwala, Rajgopal, and Shevlin 2006). However, this approach further restricts the sample due to the calendar year-end requirement.

TABLE 6

Firm Characteristics Explaining When Firm-Specific Estimates of Differential Persistence are Useful

Panel A: All Observations with Sufficient Data to Estimate ω_1 and ω_2

	Sloan (1996)	Hou et al. (2012)	So (2013)	Li and Mohanram (2014)
Intercept	−0.068***	−0.068***	−0.069***	−0.068***
$Decile_t$ of forecasts based on cross-sectional estimates	0.212***	0.215***	0.191***	0.210***
$Decile_t$ of forecasts based on firm-specific estimates	0.058***	0.058***	0.088***	0.059***
$Decile_t$ of forecasts based on firm-specific estimates × $SIZE_t$	0.006	−0.004	−0.013***	0.009*
$Decile_t$ of forecasts based on firm-specific estimates × MTB_t	−0.018**	−0.014	−0.014	−0.018**
$Decile_t$ of forecasts based on firm-specific estimates × LEV_t	−0.007*	−0.005	−0.008**	−0.007*
$Decile_t$ of forecasts based on firm-specific estimates × NI_t	0.036***	0.037***	0.037***	0.034***
Adjusted R^2	45.9%	46.0%	45.0%	45.8%

Panel B: All Observations with $\omega_1 < \omega_2$

	Sloan (1996)	Hou et al. (2012)	So (2013)	Li and Mohanram (2014)
Intercept	−0.063***	−0.064***	−0.065***	−0.065***
$Decile_t$ of forecasts based on cross-sectional estimates	0.207***	0.210***	0.189***	0.200***
$Decile_t$ of forecasts based on firm-specific estimates	0.061***	0.063***	0.092***	0.072***
$Decile_t$ of forecasts based on firm-specific estimates × $SIZE_t$	0.003	−0.006	−0.016***	0.005
$Decile_t$ of forecasts based on firm-specific estimates × MTB_t	−0.021**	−0.018*	−0.014	−0.023**
$Decile_t$ of forecasts based on firm-specific estimates × LEV_t	−0.009**	−0.007*	−0.010***	−0.009**
$Decile_t$ of forecasts based on firm-specific estimates × NI_t	0.047***	0.049***	0.040***	0.047***
Adjusted R^2	46.9%	47.1%	46.4%	47.1%

Panel C: Observations with $\omega_1 < \omega_2$ at p-value < 0.10

	Sloan (1996)	Hou et al. (2012)	So (2013)	Li and Mohanram (2014)
Intercept	−0.056***	−0.058***	−0.059***	−0.059***
$Decile_t$ of forecasts based on cross-sectional estimates	0.218***	0.216***	0.200***	0.202***
$Decile_t$ of forecasts based on firm-specific estimates	0.053***	0.062***	0.084***	0.075***
$Decile_t$ of forecasts based on firm-specific estimates × $SIZE_t$	0.009	−0.001	−0.011**	0.009
$Decile_t$ of forecasts based on firm-specific estimates × MTB_t	−0.008	−0.008	0.011	−0.008
$Decile_t$ of forecasts based on firm-specific estimates × LEV_t	−0.009**	−0.006	−0.006	−0.007*
$Decile_t$ of forecasts based on firm-specific estimates × NI_t	0.023*	0.025**	0.008	0.020*
Adjusted R^2	50.2%	50.3%	49.6%	50.3%

(continued on next page)

TABLE 6 (continued)

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

We report average annual coefficients from regressions where the dependent variable is year-ahead earnings (E_{t+1}) and the explanatory variables are the decile rank of the forecast of year-ahead earnings using the forecasts generated by the benchmark model based on cross-sectional estimates of differential persistence and the forecasting model based on firm-specific estimates of differential persistence, as well as the interaction of the quintile ranks of each firm characteristic ($SIZE_t$, MTB_t, LEV_t, NI_t), and the decile rank of the forecasting model based on firm-specific estimates of differential persistence. $SIZE_t$ is the quintile rank of the natural log of the market value of equity as of the end of year t. MTB_t is the quintile rank of the market value of equity scaled by the firm's book value as of year t. LEV_t is the quintile rank of long-term debt scaled by total assets as of year t. NI_t is the quintile rank of the operating income after depreciation scaled by average total assets as of year t. The forecasting model based on firm-specific estimates of differential persistence forecast is the firm-specific estimate of earnings, calculated as the fitted value from the following firm-specific model using ten years of prior data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Sloan (1996) forecast is the fitted value from the following cross-sectional model using ten years of pooled data: $E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$. The Hou et al. (2012), So (2013), and Li and Mohanram (2014) forecasts are fitted values based on the cross-sectional forecasting models outlined by Hou et al. (2012), So (2013), and Li and Mohanram (2014), and are estimated using ten years of pooled cross-sectional data. Because the forecasting model based on firm-specific estimates of differential persistence requires ten years of prior data for each firm, we impose the same restriction in the estimation of all cross-sectional forecasts. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence (Panel A). The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows (Panel B). The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the inequality between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less (Panel C).

The Incremental Usefulness of Firm-Specific Estimates of Differential Persistence

Table 7 reports the returns to the portfolios based on estimates of unexpected earnings. When excluding loss firms, we document that this trading strategy generates significant abnormal returns in excess of the Fama and French (1993) and momentum factors across all three samples. For the "All observations with sufficient data to estimate ω_1 and ω_2" sample, we document significant excess returns of 2.16 percent annually (0.0018×12). These excess returns are considerably larger, and become economically significant, when we restrict the trading strategy based on the extent of the differential persistence of accruals and operating cash flows. Specifically, for the "All observations with $\omega_1 < \omega_2$" sample, we document significant excess returns of 8.04 percent annually, and for the "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample, we document significant excess returns of 11.64 percent annually.[16] Consistent with the fixation hypothesis, these significant excess returns disappear when loss firms are included in the trading strategy.

As shown in Table 8, these findings are robust to supplementing Equation (8) with an accruals factor.[17,18] When excluding loss firms, for the "All observations with sufficient data to estimate ω_1 and ω_2" sample, we document significant excess returns of 2.16 percent annually. Again, these excess returns become considerably larger and economically significant when we restrict the trading strategy based on the extent of the differential persistence of accruals and operating cash flows. Specifically, for the "All observations with $\omega_1 < \omega_2$" sample, we document significant excess returns of 7.80 percent annually, and for the "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample, we document significant excess returns of 12.60 percent annually. Again, consistent with the fixation hypothesis, these significant excess returns are substantially reduced when loss firms are included in the trading strategy. Overall, our analyses provide strong support for our second hypothesis that firm-specific estimates of differential persistence can be used to generate abnormal excess returns.

Table 9 reports the descriptive statistics for the firms in the long and short positions of our trading strategy when loss firms are excluded (i.e., when the fixation hypothesis predicts abnormal excess returns). In order to assess the similarity of the firms included in this trading strategy to the population of firms, we also provide descriptive statistics for the universe of firms covered in Compustat during our sample period, as well as significance tests examining differences between the firms in the long or short side of our strategy and the Compustat universe, respectively. Across all three samples, we find that firms in the long and firms in the short positions are significantly larger and generally have lower market-to-book ratios. They also are more highly levered and experience greater return momentum compared with observations in the Compustat population. Overall,

[16] For the "All observations with $\omega_1 < \omega_2$" sample, these returns are positive in 23 of the 32 years (72 percent), whereas for the "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample, these returns are positive in 27 of the 32 years (84 percent).

[17] Including a monthly factor based on the returns to a portfolio based on the strategy suggested by Hafzalla et al. (2011) also yields significant excess returns for the trading strategy based on estimates of unexpected earnings.

[18] The estimated coefficient on the accruals factor is an estimate of the sensitivity of the returns to our hedge strategy to the accrual factor returns, and is not an estimate of the profitability of an accrual-based trading strategy itself.

TABLE 7

Returns to the Unexpected Earnings Trading Strategy Excluding Accruals Factor

Model: $R_{pt} - R_{ft} = \alpha_p + b_p \cdot (R_{mt} - R_{ft}) + s_p \cdot SMB_t + h_p \cdot HML_t + d_p \cdot UMD_t + \varepsilon_{pt}$

Panel A: All Observations with Sufficient Data to Estimate ω_1 and ω_2

	Including Loss Firms			Excluding Loss Firms		
	Long	Short	Hedge	Long	Short	Hedge
Intercept	0.0028*	0.0018	0.0010	0.0024**	0.0006	0.0018*
$R_m - R_f$	0.9969***	0.9830***	0.0139	0.9755***	0.9594***	0.0160
SMB	0.9812***	1.0267***	−0.0455	0.7819***	0.7867***	−0.0048
HML	0.1405***	0.0923*	0.0483	0.2114***	0.1784***	0.0030
UMD	−0.1099	−0.1515***	0.0416	−0.0359	−0.0228	−0.0130
Adjusted R^2	84.71%	85.47%	0.15%	89.24%	88.97%	−0.05%
Average firms per year	189	185	374	156	153	309

Panel B: All Observations with $\omega_1 < \omega_2$

	Including Loss Firms			Excluding Loss Firms		
	Long	Short	Hedge	Long	Short	Hedge
Intercept	0.0029*	0.0001	0.0028*	0.0048***	−0.0018	0.0067***
$R_m - R_f$	1.0018***	0.9959***	0.0058	0.9785***	0.9887***	−0.0102
SMB	0.9733***	1.0352***	−0.0619	0.7992***	0.7821***	0.0170
HML	0.1658***	0.0849	0.0809	0.2372***	0.1908***	0.0464
UMD	−0.0766*	−0.2480***	0.1715***	−0.0127	−0.0576*	0.0448
Adjusted R^2	82.90%	82.71%	4.73%	84.20%	87.13%	−0.47%
Average firms per year	109	106	215	91	87	178

Panel C: Observations with $\omega_1 < \omega_2$ at p-value < 0.10

	Including Loss Firms			Excluding Loss Firms		
	Long	Short	Hedge	Long	Short	Hedge
Intercept	0.0017	−0.0014	0.0030	0.0078***	−0.0019	0.0097***
$R_m - R_f$	1.0444***	0.9957***	0.0487	0.9570***	1.0659***	−0.1089*
SMB	1.1602***	1.1464***	0.0138	0.7920***	0.8122***	−0.0203
HML	0.0622	0.0283	0.0339	0.1561**	0.1458**	0.0103
UMD	−0.1530**	−0.1968***	0.0439	−0.1528***	−0.1083*	−0.0445
Adjusted R^2	73.06%	66.79%	−0.91%	69.40%	74.11%	0.21%
Average firms per year	31	29	60	26	24	50

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

We take a long (short) position in firms with estimates of unexpected earnings in the highest (lowest) decile. Estimates of unexpected earnings are calculated as the difference between the forecast of earnings based on firm-specific estimates of differential persistence and the forecast of earnings based on aggregate earnings. To ensure that there is no look-ahead bias, we use observable decile cutoffs from the prior year when assigning firms to deciles and take long (short) positions in firms in the largest (smallest) decile. We then calculate returns for the 12 months beginning at the start of the fourth month after the end of the fiscal year (when financial statement information becomes available). For example, for a firm with a fiscal year-end of December 31, 2009, we calculate returns for the period of April 1, 2010 through March 31, 2011. $R_{pt} - R_{ft}$ is the monthly return on the portfolio in excess of the Treasury bill rate in month t; $R_{mt} - R_{ft}$ is the excess return on the CRSP equally weighted market index; SMB_t and HML_t are the returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively. UMD_t is the difference between returns on portfolios of past winners and losers. Each regression is estimated using monthly returns. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence (Panel A). The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows (Panel B). The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the inequality between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less (Panel C).

TABLE 8

Returns to the Unexpected Earnings Trading Strategy Including Accruals Factor

Model: $R_{pt} - R_{ft} = \alpha_p + b_p \cdot (R_{mt} - R_{ft}) + s_p \cdot SMB_t + h_p \cdot HML_t + d_p \cdot UMD_t + g_p \cdot ACCRUALS_t + \varepsilon_{pt}$

Panel A: All Observations with Sufficient Data to Estimate ω_1 and ω_2

	Including Loss Firms			Excluding Loss Firms		
	Long	**Short**	**Hedge**	**Long**	**Short**	**Hedge**
Intercept	0.0017	0.0007	0.0010	0.0023**	0.0006	0.0018*
$R_m - R_f$	0.9946***	0.9806***	0.0140	0.9753***	0.9594***	0.0159
SMB	0.9451***	0.9893***	−0.0443	0.7797***	0.7864***	−0.0067
HML	0.1316***	0.0831*	0.0486	0.2108***	0.1783***	0.0325
UMD	−0.1101***	−0.1518***	0.0417	−0.0359	−0.0228	−0.0131
ACCRUALS	0.2118***	0.2190***	−0.0072	0.0132	0.0022	0.0109
Adjusted R^2	89.21%	86.42%	−0.11%	89.21%	88.94%	−0.29%
Average firms per year	189	185	374	156	153	309

Panel B: All Observations with $\omega_1 < \omega_2$

	Including Loss Firms			Excluding Loss Firms		
	Long	**Short**	**Hedge**	**Long**	**Short**	**Hedge**
Intercept	0.0020	−0.0010	0.0030*	0.0048***	−0.0017	0.0065***
$R_m - R_f$	0.9999***	0.9936***	0.0063	0.9785***	0.9890***	−0.0106
SMB	0.9436***	0.9981***	−0.0546	0.7984***	0.7868***	0.0116
HML	0.1585***	0.0758	0.0827	0.2370***	0.1920***	0.0451
UMD	−0.0768*	−0.2483***	0.1715***	−0.0127	−0.0575*	0.0448
ACCRUALS	0.1743***	0.2173***	−0.0430	0.0047	−0.0271	0.0318
Adjusted R^2	83.50%	83.55%	4.66%	84.16%	87.11%	−0.58%
Average firms per year	109	106	215	91	87	178

Panel C: Observations with $\omega_1 < \omega_2$ at p-value < 0.10

	Including Loss Firms			Excluding Loss Firms		
	Long	**Short**	**Hedge**	**Long**	**Short**	**Hedge**
Intercept	0.0005	−0.0027	0.0032	0.0082***	−0.0023	0.0105***
$R_m - R_f$	1.0423***	0.9933***	0.0490	0.9577***	1.0652***	−0.1075*
SMB	1.1221***	1.1026***	0.0195	0.8051***	0.8001***	0.0049
HML	0.0533	0.0180	0.0353	0.1592**	0.1430**	0.0162
UMD	−0.1534**	−0.1973***	0.0439	−0.1527***	−0.1084**	−0.0442
ACCRUALS	0.2247***	0.2580***	−0.0333	−0.0771	0.0711	−0.1482*
Adjusted R^2	73.76%	67.67%	−1.15%	69.44%	74.13%	0.85%
Average firms per year	31	29	60	26	24	50

(continued on next page)

TABLE 8 (continued)

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
We take a long (short) position in firms with estimates of unexpected earnings in the highest (lowest) decile. Estimates of unexpected earnings are calculated as the difference between the forecast of earnings based on firm-specific estimates of differential persistence and the forecast of earnings based on aggregate earnings. To ensure that there is no look-ahead bias, we use observable decile cutoffs from the prior year when assigning firms to deciles and take long (short) positions in firms in the largest (smallest) decile. We then calculate returns for the 12 months beginning at the start of the fourth month after the end of the fiscal year (when financial statement information becomes available). For example, for a firm with a fiscal year-end of December 31, 2009, we calculate returns for the period of April 1, 2010 through March 31, 2011. $R_{pt} - R_{ft}$ is the monthly return on the portfolio in excess of the Treasury bill rate in month t; $R_{mt} - R_{ft}$ is the excess return on the CRSP equally weighted market index; SMB_t and HML_t are the returns on the Fama and French (1993) factor-mimicking portfolios for size and book-to-market, respectively. UMD_t is the difference between returns on portfolios of past winners and losers. Each regression is estimated using monthly returns. $ACCRUALS_t$ is an accrual factor based on the size of accruals, which mimics the accrual-based trading strategy proposed by Sloan (1996) to test whether the returns to a strategy based on firm-specific estimates of differential persistence are independent to the returns to an accrual-based strategy. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence (Panel A). The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows (Panel B). The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the inequality between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less (Panel C).

these findings suggest this trading strategy is not identifying small firms, illiquid stocks, or those associated with unusually high transaction costs.

VI. CONCLUSIONS

A long line of research examines the differential persistence of accruals and operating cash flows and its implications for forecasting and valuation. In doing so, this research generally relies on cross-sectional analyses (e.g., Sloan 1996; Xie 2001; Desai et al. 2004; Richardson et al. 2005; Dechow et al. 2008). Although the cross-sectional analysis of differential persistence captures the size of accruals and operating cash flows relative to other firms in the economy, it does not directly capture firm-specific differential persistence. As a result, cross-sectional estimates of the differential persistence of accruals and operating cash flows ignore variation in the magnitude of differential persistence across firms.

We argue that differential persistence is a firm-specific phenomenon that can be exploited for both forecasting and valuation purposes. We empirically investigate whether firm-specific estimates of differential persistence provide incremental information over cross-sectional models for forecasting and valuation. In doing so, we consider three samples of firms: (1) all firms with sufficient information to estimate firm-specific differential persistence, (2) all firms with less persistent accruals than operating cash flows, and (3) all firms with *significantly* less persistent accruals than operating cash flows. We find that a model based on firm-specific estimates of differential persistence provides incremental information for out-of-sample forecasting relative to the state-of-the-art cross-sectional models (i.e., Sloan 1996; Hou et al. 2012; So 2013; Li and Mohanram 2014) across all three samples. This finding highlights the usefulness of firm-specific estimates of differential persistence for forecasting.

We also investigate whether investors correctly incorporate firm-specific estimates of differential persistence into stock prices. We construct hedge portfolios that exploit investors' fixation on aggregate earnings. We find that hedge portfolios based on estimates of unexpected earnings earn statistically significant excess returns averaging between 2.16 and 12.60 percent annually. These returns are incremental to the Fama and French (1993) factors, a momentum factor (Carhart 1997), as well as an accrual factor that reflects the cross-sectional accrual-based trading strategy suggested by Sloan (1996).

Our study provides important contributions to the financial statement analysis literature and to practice. For example, our results provide guidance to analysts and investors as to the benefits of using firm-specific estimates of differential persistence to improve forecasts and valuation, as well as the types of firms for which firm-specific information is most likely to be informative. We demonstrate that supplementing models based on cross-sectional estimates with firm-specific information about the differential persistence of accruals and operating cash flows provides incremental information for forecasting and valuation.

Our study also contributes to research on the differential persistence of accruals and operating cash flows. Francis and Smith (2005) find that relatively few firms possess accruals that are significantly less persistent than operating cash flows, and conclude that firm-specific estimates of differential persistence are unlikely to be useful for forecasting and valuation. Based on this conclusion, subsequent research primarily relies on cross-sectional estimates of differential persistence. Our study demonstrates that firm-specific estimates of the differential persistence of accruals and operating cash flows can be exploited to

TABLE 9

Descriptive Statistics for Firms in Long and Short Positions of Trading Strategy (Excluding Loss Firms)

Panel A: All Observations with Sufficient Data to Estimate ω_1 and ω_2

	Compustat		Long		Short	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
SIZE	4.681	4.562	5.049***	4.893***	5.069***	4.912***
MTB	3.267	1.767	2.729***	1.784	2.617***	1.726
LEV	0.164	0.119	0.168	0.129***	0.168	0.132***
MOMENTUM	0.205	0.000	0.287***	0.090***	0.214	0.040***
Maximum n	162,446		4,640		4,549	

Panel B: Observations with $\omega_1 < \omega_2$

	Compustat		Long		Short	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
SIZE	4.681	4.562	4.951***	4.799***	5.151***	4.987***
MTB	3.267	1.767	2.700***	1.740	2.539***	1.697**
LEV	0.164	0.119	0.166	0.124*	0.175***	0.143***
MOMENTUM	0.205	0.000	0.283***	0.093***	0.189	0.026***
Maximum n	162,446		2,719		2,583	

Panel C: All Observations with $\omega_1 < \omega_2$ at p-value < 0.10

	Compustat		Long		Short	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
SIZE	4.681	4.562	4.891***	4.730**	5.027***	4.828***
MTB	3.267	1.767	2.714***	1.752	2.555***	1.679
LEV	0.164	0.119	0.170	0.120*	0.165	0.135
MOMENTUM	0.205	0.000	0.309***	0.111***	0.175	0.000
Maximum n	162,446		777		712	

***, **, * Indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.
We report mean and median statistics for firms included in the long and short positions of the trading strategy based on estimates of unexpected earnings. Estimates of unexpected earnings are calculated as the difference between the forecast of earnings based on firm-specific estimates of differential persistence and the forecast of earnings based on aggregate earnings. *SIZE* is the natural log of the market capitalization of the firm at the end of the fiscal year (CSHO * PRCC_F). *MTB* is the firm's market capitalization divided by the book value of common equity (CEQ) at the end of the year. *LEV* is long-term debt (DLTT) divided by total assets (AT) at the end of the year. *MOMENTUM* is the change in share prices (PRCC_F) from the beginning to the end of the year. All variables are winsorized at the 1 percent and 99 percent levels. "All Observations with Sufficient Data to Estimate ω_1 and ω_2" reflects all observations with required data to estimate firm-specific differential persistence (Panel A). The "All Observations with $\omega_1 < \omega_2$" sample includes observations where ω_1 is less than ω_2 in the firm-specific regression ($E_t = \alpha_0 + \omega_1 \cdot ACC_{t-1} + \omega_2 \cdot CASH_{t-1} + \varepsilon_t$) using ten years of prior data, indicating that accruals are less persistent than operating cash flows (Panel B). The "Observations with $\omega_1 < \omega_2$ at p-value < 0.10" sample includes observations where the F-statistic on the inequality between ω_1 and ω_2 is significant with a p-value of 0.10 (one-sided) or less (Panel C). The Compustat columns represent all firm-year observations with available data for all variables over the period 1980–2010. We test for differences in means and medians relative to the Compustat population of firms based on a t-test and the Wilcoxon signed rank test, respectively.

improve forecasts of earnings and to earn abnormal returns. Therefore, we empirically document that firm-specific estimates of differential persistence provide useful information for forecasting and valuation.

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