Pricing and Mispricing in the Cross-Section

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Abstract

This study examines the extent to which parsimonious and general cross-sectional valuation models, restricted to include only publicly-available historical accounting information, can be used to explain share pricing in the cross-section and identify mispriced stocks. A base model that includes historical book value, earnings, dividends and growth in operating income explains a fairly large proportion of the cross-sectional variation in share prices, with an average adjusted R-square of 56.3 percent in annual estimations across the 21-year study period, 1988-2008. A more refined valuation model that decomposes book value and earnings increases the average R-square to 57.9 percent. We find surprising variation in explanatory power across time, with R-squares ranging from roughly 20 percent in 'bubble' years like 1999 to roughly 70 percent in 2006. We also find these valuation models explain greater proportions of the variation in share prices for firms with less developed information environments (firms *not* covered by analysts), confirming analyst coverage impounds additional information in share prices beyond these accounting fundamental variables. We also examine whether the residuals from these cross-sectional valuation models indicate model misspecification or mispricing. Our fundamental analysis approach works well in identifying mispriced shares when we estimate the models by industry-year among firms not covered by analysts. Portfolios based on the lowest (highest) quintile of value residuals each year generate an average annual size-adjusted return of 18.6 percent (-8.1 percent). A hedge-portfolio strategy, controlling for other firm characteristics that explain returns, including size, market-to-book, accruals, and lagged returns generates an average annual abnormal return of 16.0 percent.

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Extensive research literatures in both accounting and finance test models utilizing accounting information to explain share prices in the capital markets. In simplest form, valuation methods using accounting-based market multiples, such as price-earnings or market-to-book value ratios, are widely used in practice, teaching, and research. Slightly more elaborate approaches, such as cross-sectional regressions of share prices on book value per share and earnings per share have been shown to explain the majority of cross-sectional variation in share prices (Bernard 1994). However, even well-specified cross-sectional valuation models with relatively high R-squares cannot explain all of the observed variation. The errors from such models represent a blend of model misspecifications and market mispricing, if any. In this study, we examine the extent to which parsimonious and general cross-sectional valuation models, restricted to include only publicly-available historical accounting information, explain share prices and identify mispriced stocks.

A large body of research develops and tests models of the role of historical accounting information in share pricing (the so-called "value-relevance" literature, such as Collins, Maydew and Weiss 1997, among others). Another extensive stream of research (the anomalies literature) develops approaches to predict future returns to hedge portfolios using specific accounting characteristics, such as unexpected quarterly earnings (Bernard and Thomas, 1989 and 1990), accruals (Sloan 1996), and others. A third substantial stream of research (the analysts' forecasts and recommendations literature) examines accounting information together with analysts' earnings forecasts to develop valuation models and identify mispriced stocks (e.g., Frankel and Lee 1998, and others). But very little research evaluates whether parsimonious cross-sectional valuation models based simply on reported accounting numbers identify mispriced stocks. This study takes a first step to fill this void.

We consider this an important step because it provides a baseline for fundamental analysis of financial statement information for valuation purposes. Parsimonious cross-sectional valuation models

provide insights into how financial statement information maps into share prices. Accounting scholars, practitioners, financial statement users, and standards setters can gain a deeper understanding of the determinants of the role of accounting information in the capital markets by understanding this mapping, and how it varies across time, firms, industries, information environments, economic conditions, and accounting regimes. In this study, we contribute a baseline understanding of how accounting fundamentals map into share prices across time and industries, and compare this mapping across firms in different information environments (with versus without analyst coverage).

Studying the errors from accounting-based cross-sectional valuation models—examining components of share prices that appear orthogonal to accounting fundamentals—is also an important step forward in this literature. A better understanding of conditions when market prices seem out of line with accounting fundamentals provides a foundation for examining (a) how to improve the specification and fit of the valuation models themselves, (b) how to improve the accounting information variables that help explain prices, and (c) how to identify potential market mispricing of accounting fundamentals. We examine whether residuals from accounting-based cross-sectional valuation models identify mispriced shares, and whether analyst coverage reduces the potential for mispricing.

We conduct our empirical analysis using a broad cross-section of calendar year-end firms over the 21-year period from 1988 to 2008. Each sample year we estimate a base cross-sectional regression of price per share on book value per share, trailing annual earnings per share, trailing annual dividends per share, and trailing annual growth in operating income. The results indicate that historical accounting amounts for book value, earnings, dividends, and growth explain cross-sectional variation in share prices quite well. The average adjusted R-square is 56.3 percent. The adjusted R-squares exhibit considerable variation across time, seemingly driven by the degree to which the capital markets focus on (or neglect) accounting fundamentals. The adjusted R-squares were at their lowest during the tech

stock bubble years (1998 to 2001), falling to a low of 22.2 percent during 1999, after which they reveal a striking return to fundamentals during 2004 to 2008, reaching 66.2 percent in 2006.

The difference between observed share price and the predicted value from the model is the value residual, the component of share price unexplained by the fundamental accounting variable regressors and the market-based parameter estimates. Some of the value residuals may simply represent shares for which the parsimonious cross-sectional valuation model is incomplete. Simple valuation models that only rely on historical book value, earnings, dividends, and operating income growth will be misspecified for a wide array of firms, including those with substantial amounts of share price based on expected future earnings growth and/or off-balance sheet book value (such as intangible and intellectual property-based firms), as well as firms with unusually low or high risk. Other residuals may represent the amount of pricing error in over- or under-priced shares.

We take three steps to improve the specification of the models for two purposes: to tailor a better fit between accounting fundamentals and share prices, and to sharpen the value residuals as indicators of mispricing. First, we estimate the annual cross-sectional valuation models across differing information environments based on analyst coverage. Financial analysts presumably develop forecasts, value estimates, and trade recommendations using more elaborate and dimensional models than the simple models used in this study. In addition, analysts' forecasts and recommendations can incorporate more information than that to which we constrain our parsimonious models. Insofar as capital market participants utilize analysts' forecasts and recommendations, share prices for firms covered by analysts should incorporate much more information than share prices for firms not covered. We therefore predict that simple cross-sectional value models will explain *less* of the cross-sectional variation in share prices for covered firms than firms not covered. Indeed, we find that the basic cross-sectional value model has an average adjusted R-square of 51.9 percent for covered firms, and 66.0 percent for firms without coverage.

Second, we refine the model by decomposing book value and earnings into components that likely have different valuation implications. We decompose book value into net operating assets minus net financial liabilities. If firms create shareholder value through net operating assets, and if net financial liabilities are more likely to be value neutral, then this decomposition allows the valuation parameters to vary accordingly (Feltham and Ohlson 1995). In addition, this decomposition allows valuation parameters to vary in order to capture differences in share values if balance sheets recognize net operating assets at conservative values and net financial liabilities at market (or fair) values (Penman and Zhang, 2002). We also decompose net income into three parts: accruals, cash flows from operations, and other income. Accruals and cash flows have different implications for future earnings persistence and differential explanatory power for share prices (Lipe, 1986; Dechow, 1994; Sloan, 1996; many others). Other income items tend to be transitory, with less information about future earnings persistence and lower valuation implications (Elliott and Hanna, 1996). Decomposing the valuation model increases the average adjusted R-square, but only marginally, from 51.9 percent to 53.9 percent for firms covered by analysts, and from 66.0 percent to 66.8 percent for firms without coverage.

Third, we examine whether the fit of the valuation models improves by grouping all sample firms into one of the 12 Fama-French industries each year.[1] Within each industry-year, we estimate the basic and decomposed cross-sectional valuation models. Pooled versus industry-specific estimations will differ in power because of differences in sample sizes, noise from classifying firms into industries, and other factors. It is therefore not entirely appropriate to simply compare adjusted R-squares across pooled versus industry samples; nonetheless, these comparisons are descriptive. Among the firms covered by analysts, estimating the value models by industry-year improves the fit of the models. For example, the average adjusted R-square in the decomposed model increases considerably, from 53.9

[1] Barth, et al. (2005) show that valuation model parameter estimates vary across the 17 industries in their study. Fama-French estimate varying risk premia across 12 industries that are economically homogeneous and sufficiently large to produce meaningful annual valuation parameter estimates.

percent to 61.3 percent. We speculate that the incremental improvement in model fit among covered firms may be attributable, in part, to analysts' specializing in particular industries. For firms without analyst coverage, estimating the value models by industry also increases the average adjusted R-square of the decomposed model from 66.8 percent to 71.8 percent. In general, the annual industry valuation models explain observed share prices very well for firms with or without analyst coverage.

We take a portfolio-based approach to test the degree to which the valuation model residuals represent mispricing. Each year we form portfolios by taking long positions in the quintile of firms with the most negative value residuals (potentially under-priced shares), and short positions in the quintile of firms with the highest positive value residuals (potentially over-priced shares). We hold the portfolios for twelve months and measure cumulative size-adjusted abnormal returns. If this fundamental cross-sectional valuation approach identifies mispriced shares, then we should observe positive abnormal returns to the long portfolios and negative abnormal returns to the short portfolios. If the residuals to the cross-sectional valuation models simply represent shares for which the valuation models are misspecified, then we should not observe consistent abnormal returns to either the long or short portfolios. If analyst coverage improves the information environment and share pricing for the firms they follow, our approach should be less successful in identifying mispriced stocks among firms that are covered compared to firms not covered. In addition, given that the decomposed model improves the fit of the cross-sectional valuation estimation, it should be less susceptible to misspecification error and more likely to identify mispriced stocks.

The portfolio test results show that our approach is more consistently successful in identifying under-priced shares and earning subsequent positive abnormal returns from long positions than identifying over-priced shares.[2] Our approach is also more successful in identifying mispriced shares among firms not covered by analysts than among covered firms. Our results suggest that analyst

[2] We acknowledge that this result is conditional on our choice of size portfolio returns as our expected return model. However, Berk (1995) suggests that firm size is a catchall risk proxy.

coverage appears to increase the efficiency of share prices with respect to historical accounting information to the point where basic fundamental analysis approaches like those in this paper are not successful in identifying substantially mispriced shares.

Among firms without analyst coverage, however, this basic fundamental analysis approach works quite well in identifying mispriced shares. Again, the approach is better at identifying under-priced shares than over-priced shares; the long position portfolios with negative value-residual stocks earn positive abnormal returns that range from 16.8 percent to 18.7 percent. Hedge strategy returns (long in negative value residual firms and short in positive value residual firms) are on average significant, ranging from 23.8 percent to 27.0 percent. The approach works best among firms without analyst coverage when we estimate the value models by industry-year. A hedge-portfolio strategy that controls for other firm characteristics that explain returns, including beta, size, market-to-book, accruals, and lagged returns, generates an average annual abnormal return of 16.0 percent, which is significant. Over the entire sample period, annual hedge portfolios based on value residuals estimated using decomposed, industry-specific value models generate positive abnormal returns in 17 of 21 years, and only generate significant negative returns in 2 of 21 years.

Like prior studies, we demonstrate that parsimonious valuation models, restricted to include only historical accounting information, explain the majority of the cross-sectional variation in share prices in the capital markets. Our study contributes new evidence by showing that accounting-based models explain more of the cross-sectional variation in prices among firms not covered by analysts. This is consistent with analysts enhancing the information environment of the firm and thereby reducing the ability of historical accounting variables to explain share prices. We also show that the decomposed models provide more explanatory power for prices than the basic model, and that estimating the value models within industries increases the explanatory power considerably. We also contribute new evidence by predicting and finding that our fundamental cross-sectional valuation approach identifies

mispriced shares, but only among firms without analyst coverage. Our approach and findings should be of interest to accountants, analysts, investors, researchers, and teachers interested in financial statement analysis and the relations between accounting information and share prices.

We organize the remainder of the paper as follows. In section 2 we describe the research design, methods, and samples, including the cross-sectional valuation models. In section 3, we describe the results from the various cross-sectional value model estimates and the portfolio tests. Section 4 provides concluding remarks.

2. Research Design and Sample

In this section we describe our research design, beginning with the basic cross-sectional valuation model we estimate to explain share prices and estimate value residuals. We then introduce several refinements to the model to improve the explanatory power. We also describe the model residuals and the abnormal returns tests we use to distinguish whether the residuals represent model misspecification or market mispricing. We also describe the sample.

2.1 Cross-Sectional Value Models and Residuals

Our research design is guided by three objectives pertinent to our research questions: parsimony, generality, and availability. We seek to test the extent to which parsimonious and general valuation models using available historical accounting data (i.e., not analysts' forecasts) can explain pricing and identify mispricing in the broad cross-section of firms.

We begin by estimating parameters from the following annual cross-sectional pricing model that includes available historical data on book value, earnings, dividends, and earnings growth:

(1) $$P_{i,t} = \alpha + \beta_1 BV_{i,t} + \beta_2 NI_{i,t} + \beta_3 DIV_{i,t} + \beta_4 OIGR_{i,t} + \varepsilon_{i,t}$$

P is share price measured at the end of the third-month following the fiscal year-end; BV is total common shareholders' equity per share; NI is net income per share;[3] DIV is all-inclusive dividends per share; and OIGR denotes trailing year growth in operating income per share.[4] We apply the coefficient estimates to the independent variables to project share value estimates, as follows:

$$Value_{i,t} = \hat{\alpha} + \hat{\beta}_1 BV_{i,t} + \hat{\beta}_2 NI_{i,t} + \hat{\beta}_3 DIV_{i,t} + \hat{\beta}_4 OIGR_{i,t} \quad (2)$$

We subtract Value from Price to obtain the residual, denoted VRES, which we deflate by Price.

The valuation model residuals, VRES, reflect a combination of model misspecifications and/or market mispricing, if any. Value residuals will arise from model misspecification when the model does not capture all of the value-relevant information impounded in price. While potential misspecification can arise for many reasons, some obvious sources in the cross-section include when (a) a firm's current period earnings differ from the persistent future stream of earnings the market expects (e.g., because of transitory gains or losses in current period earnings), (b) the market expects a firm's future earnings growth to differ from that in current period earnings growth, (c) a firm's share price reflects asset values not reflected in book value (such as off-balance sheet intangible assets), and (d) a firm's share price reflects an abnormally high or low level of risk. Value residuals can also arise from market mispricing. If the market has temporarily over- or under-priced a firm's shares, relative to the fundamentals included in the model, then VRES will be positive or negative, respectively. We do not attempt to discriminate between residuals that reflect model misspecification or mispricing. Instead, we attempt to maximize the fit of the valuation models in order to reduce misspecification, thereby increasing the likelihood that the residuals reflect mispricing.

[3] In supplemental tests we also include a dummy variable for firm-years with losses, interacted with the net income per share variable, to allow for differential pricing of positive versus negative income. After including this interaction, the results from the valuation model estimations and the returns tests are equivalent to those reported here in the paper.

[4] We measure price at the end of the third month to allow the market time to incorporate the financial statement information into their pricing models. We measure all-inclusive dividends using clean surplus accounting, as lagged BV plus NI minus current BV.

The base valuation model in equation (1) restricts the valuation parameters to be equal across all components of BV and NI. We know from prior research that different components of BV and NI can have different valuation implications. Therefore, we seek to increase the fit of the valuation model by decomposing book value of shareholders' equity and net income into components with potentially different valuation implications. First, we decompose shareholders' equity into net operating assets and net financial liabilities (i.e., BV = NOA – NFL). If firms create value for shareholders through net operating assets, and if net financial liabilities are more likely to be value neutral, then this decomposition allows the valuation parameters to vary accordingly. In addition, this decomposition allows valuation parameters to capture differences arising from historical cost for net operating assets and market or fair value (when interest rates are stable) for net financial liabilities (Penman and Zhang, 2002).

We also decompose net income into accruals, cash flows from operations, and other income items (i.e., NI = ACC + CFO + NIoth). Components of earnings, such as accruals and cash flows, have different implications for future earnings persistence and differential explanatory power for share value (Lipe, 1986; Dechow, 1994; Sloan, 1996). In addition, accruals and cash flows provide explanatory power for market value incremental to book value and abnormal earnings (Barth et al, 1999).[5] Other income includes transitory elements, such as extraordinary items and income from discontinued segments, which typically provide less information about future earnings and are therefore likely to have lower explanatory power for share value. By decomposing net income, we allow the valuation parameters to vary across components based on their differential implications for future earnings and share prices. We estimate the following yearly cross-sectional model:

(3) $$P_{i,t} = \alpha + \gamma_1 NOA_{i,t} + \gamma_2 NFL_{i,t} + \gamma_3 ACC_{i,t} + \gamma_4 CFO_{i,t} + \gamma_5 NIoth_{i,t} + \gamma_6 DIV_{i,t} + \gamma_7 OIGR_{i,t} + \varepsilon$$

P is share price measured at the end of the third-month following the fiscal year-end; NOA is net operating assets per share; NFL is net financial liabilities per share; ACC income before extraordinary

[5] Barth et al. (2005) decompose net income into accruals and cash flows and find smaller equity value prediction errors relative to a base model.

items less CFO per share; CFO is cash flow from operations per share; NIoth is net income less income before extraordinary items per share. We apply the coefficient estimates to the current values of these independent variables to project a share value estimate as follows:

(4) $$Value_D_{i,t} = \hat{\alpha} + \hat{\gamma}_1 NOA_{i,t} + \hat{\gamma}_2 NFL_{i,t} + \hat{\gamma}_3 ACC_{i,t} + \hat{\gamma}_4 CFO_{i,t} + \hat{\gamma}_5 NIoth_{i,t} + \hat{\gamma}_6 DIV_{i,t} + \hat{\gamma}_7 OIGR_{i,t}$$

We subtract Value_D from Price to obtain the residual, denoted VRES_D, which we deflate by price. As with the base model, the decomposed valuation model residuals, VRES_D, reflect either model misspecifications or market mispricing. If the decomposed model provides more explanatory power for share prices than the base model, then positive or negative VRES_D values will more likely indicate overpriced or underpriced securities, respectively.

We estimate the cross-sectional valuation model parameters using two methods: (a) yearly and (b) yearly by industry using 11 of the 12 industries in the Fama-French classification system (excluding firms in the financial services industry). Annual estimation of the base and the decomposed value models by industry permits the valuation parameters to vary by industry and year insofar as they differ in levels of profitability, risk, growth, combinations of accruals and cash flows, levels of investments in assets, use of net financial leverage, accounting conservatism, cost of capital, dividend payout policies, and other value determinants.[6]

We further refine the analysis and valuation model by analyzing two sub-samples with differing information environments: the set of firms covered by analysts and the set of firms not covered. Firms that are covered by analysts have richer information sets and market prices likely incorporate greater amounts of information from outside the financial statements that have implications for future earnings. We therefore expect our models to explain less of the variation in share prices of covered firms than for firms that are not covered by analysts. Further, if analyst coverage improves the relative degree of market efficiency by incorporating more information into share prices, we expect the residuals

[6] Barth et al. (1999) finds the valuation of accruals and equity book value vary across industries.

from the value models for covered firms to reflect less mispricing and more model misspecification, relative to firms that are not covered.

To examine whether the value residuals identify mispriced stocks, we calculate abnormal returns for each firm-year by compounding the firm's raw return over a one-year holding period and then subtracting the return on the CRSP size-based decile portfolio to which the firm belongs at the beginning of the holding period. We begin the return accumulation period on the first day of the fourth month following fiscal year-end (i.e., immediately after estimating the value model, projecting value, and calculating the residuals, VRES and VRES_D). This allows the market time to incorporate the financial statement information into share prices. We end the accumulation period one year later, on the last day of the third month following the subsequent fiscal year end, and thereby capture price movements caused by investors reacting to information and events during the year that confirm or refute their beliefs about the firm's value. If a firm delists, we include the delisting return in the calculation of returns, place the funds available after delisting into the size-based decile, and continue cumulating returns through the end of the period.

We examine the abnormal returns to portfolios based on the quintile ranks of the residuals. For each portfolio, we compute equal-weighted average abnormal returns. If the models identify mispriced stocks then we expect to find larger positive abnormal returns to firms in the bottom quintile (the most negative value residuals), and more negative abnormal returns to firms in the top quintile (the most positive value residuals).

2.2. Sample Selection

Our sample includes all calendar-year end firms with information available on the CRSP/Compustat merged database during 1988-2008. We remove firms in the financial services industry (SIC codes between 6000 and 6999). We merge this file with I/B/E/S to identify which firm-years had at least one outstanding analyst forecast for the next period. Our sample consists of 53,331 firm-year

observations, of which 36,664 have analyst coverage and 16,667 do not. We mitigate the effects of outliers in the parameter estimation procedure by winsorizing the variables in the models at the top and bottom percentile. To mitigate the effects of outliers, we delete observations in the top and bottom percentile based on VRES. We require at least 15 observations per industry-year to estimate model coefficients and we delete observations when the model indicates projected share value is negative.[7]

2.3. Sample Description

We report sample descriptive statistics in Table 1. Panel A describes the full sample. The average share price is $17.76, while the average book value per share is $8.54. Thus, for the typical firm in our sample, price consists of roughly equal parts book value and present value of future residual income. In decomposing book value, we find that the typical sample firm has net operating assets of $13.14 per share and net financial liabilities of $4.56 per share. On average, net operating assets are approximately three times net financial liabilities. Average earnings per share equals $0.51, consisting of $1.65 per share in cash from operations, $-1.14 per share in accruals, and $-0.03 per share in other income items.

Panels B and C report descriptive statistics for firms with versus without analyst coverage, respectively. Firms covered by analysts have higher prices on average ($22.08) than firms with no coverage ($8.25).. Covered firms have book value per share of $9.94 while firms not covered have book value per share of $5.46. Overall, these statistics suggest that firms covered by analysts derive a slightly greater portion of value from expected future residual income than do firms without coverage.[8] Firms covered by analysts finance a greater proportion of their net operating assets using net financial liabilities. In particular, covered firms have net operating assets of $15.52 and net financial liabilities of $5.56 (a multiple of less than 3). In contrast, firms without coverage have net operating assets of $7.90 and net financial liabilities of $2.38 (a multiple greater than 3). Surprisingly, firms in the analyst

[7] The results reported in the paper hold (a) without deleting observations with negative projected share values, and (b) withholding from the analysis firms with share price less than $5.

[8] This is consistent with analysts promoting the information environment, greater expected future earnings streams, and/or less risk inherent in the future earnings streams of firms covered by analysts.

coverage sample have greater standard deviation in earnings (1.99) and cash flows (2.83) than firms without analyst coverage (standard deviations of 1.52 and 2.13, respectively). These differences highlight the importance of understanding how well valuation models based on historical accounting measures explain share prices and identify mispriced stocks for firms with or without analyst coverage. We address this question in the next section.

3. Empirical Results

In this section we describe the results from our cross-sectional value estimations and our portfolio tests. We first describe the results for the base and decomposed models across the samples of firms followed versus not followed by analysts. We then describe the results based on industry-year valuation model estimations. We also report the results from robustness checks.

3.1 Broad Cross-Sectional Value Model Estimation

Table 2 presents coefficients from the yearly estimations of our base model (Panel A) and decomposed model (Panel B). The results in Panel A show that book values, earnings, dividends, and operating income growth explain on average 56.3 percent of the cross-sectional variation in share prices. However, the base model did a relatively poor job of explaining share prices during the bubble years from 1997 to 2000, with the poorest explanatory power occurring in 1999. For firms covered by analysts, the adjusted R-square was only 17.1 percent in 1999. However, share prices for firms not covered by analysts exhibited a much shorter and less dramatic departure from fundamentals during the bubble years. In particular, the adjusted R-squares reached a low of only 29.8 percent during 1999 for firms without analyst coverage. These adjusted R-squares indicate that during the bubble years market pricing made a more severe and prolonged departure from accounting fundamentals among firms followed by analysts. In recent years, particularly 2004 to 2008, the market prices made a striking return

to fundamentals, with accounting information exhibiting a surge in value relevance. During this period the adjusted R-squares were much higher than average for covered firms and for firms not covered.[9]

For the analyst coverage sample in Panel A, the mean coefficient on net income per share (3.25) is considerably higher than the coefficient for the sample without coverage (1.80), but the mean adjusted R-square is lower (51.9 percent versus 66.0 percent). We believe the effect of analyst coverage on the information environment is associated with both findings, at least to some extent. The lower coefficient on earnings likely stems from the higher uncertainty about future prospects and persistence surrounding firms without coverage (for example, a much higher proportion of these firms experience losses). The higher adjusted R-square indicates that accounting fundamentals such as earnings, book values, and dividends do a better job of summarizing the available value-relevant information for firms without analyst coverage than for those with analyst coverage, indicating coverage enables market prices to incorporate more information than that contained in summary historical accounting variables.

We present coefficients from yearly estimations of our decomposed model in Table 2 Panel B. The results confirm that our decomposition improves the explanatory power of the model for the full sample, with the adjusted R-square increasing from 56.3 percent to 57.9 percent. For firms with analyst coverage, the average adjusted R-square increases from 51.9 percent in the base model to 53.9 percent in the decomposed model. For firms without coverage, the average adjusted R-square is 66.0 percent in the base model and 66.8 percent in the decomposed version. The coefficient estimates reveal the source of the improved explanatory power. Net operating assets and net financial liabilities have substantially different implications for value, yet the base model constrains the coefficient on those variables to be same. Similarly, accruals, operating cash flows, and other items of net income differ in their consequences for value, but the base model constrains them to have the same coefficient.

[9] Differences in R-square across samples or over time could also result from differential scale effects in the cross-section or in time-series (Brown, Lo, and Lys 1999). Later, we report analyses to alleviate the concern that the R-square differences we observe are simply the result of scale effects.

In Table 3, we report returns to ranked VRES and VRES_D quintiles. We find consistently significant spreads in returns across positive value residuals (long positions) and negative value residuals (short positions) particularly among firms without analyst coverage.

The portfolios based on the lowest quintile of VRES and VRES_D are associated with positive future abnormal returns, and the portfolios based on the highest quintile of VRES and VRES_D are associated with negative future abnormal returns for each of the samples, but are strongest among firms not covered by analysts. For example, in the no analyst coverage sample: the spread in returns across extreme VRES_D quintiles equals 24.7 percent, the great majority of which arises from the lowest negative VRES_D portfolios (18.7 percent). [In Appendix A, we report Pearson and Spearman correlations between share price, value estimates, value residuals and abnormal returns. These correlations are consistent with the results reported in the tables, and are presented for completeness.]

3.2 Results from Industry-Specific Value Model Estimation

As noted earlier, our pooled yearly regressions constrain coefficients to be the same across all industries, despite substantial differences in economic characteristics, competitive structure, accounting conventions, composition of the asset base, risk, and growth. To refine our analysis, we next report results for our base and decomposed value models estimated within industry each year in Table 4. We classify companies into industries based on the Fama-French 12 industry classification (and exclude the financial services industry from our analyses). We report industry mean (averaged across the 21 years in our sample) coefficient estimates from the base model in Panel A. For the full sample, we observe substantial variation in parameter estimates across industries. For example, the coefficient on book value per share ranges from 0.75 for utilities to 2.36 for the healthcare industry. The coefficient on earnings per share ranges from 1.09 for the telephone and television industry to 4.20 for the healthcare industry. We also find substantial variation in the coefficients from the decomposed model reported in Panel B. The improvement in fit from decomposing our base model is apparent in comparing adjusted R-

square from Panel A and Panel B. For firms covered by analysts, the adjusted R-square increases from 51.7 percent in the base model to 57.7 percent in the decomposed model. Estimating the decomposed model by industry/year provides the best fit among firms covered by analysts (average adjusted R-square of 61.3 percent versus 53.9 percent without industry-specific estimation), perhaps because analysts typically specialize within industries. For firms without analyst coverage, the average adjusted R-square increases from 66.8 percent to 71.8 percent.

If industry-specific annual regressions explain share prices better than broad cross-sectional annual regressions, the residuals should be better predictors of valuation errors reflected in price. In Table 5, we examine whether VRES from our yearly industry regressions for the base and decomposed model predict future returns. We classify VRES_Ind into quintiles for both the base model and the decomposed model. The results for the full sample and the analyst coverage sample are similar. We find that the quintile portfolios with the most negative VRES_Ind experience positive abnormal returns, ranging from 8.1 percent to 11.7 percent; however, the quintile portfolios with the most positive VRES_Ind do not experience significant negative abnormal returns.

The results reveal quite a different story for the sample without analyst coverage. Using the base model, firms in the lowest VRES_Ind quintile generate positive abnormal returns of 18.4 percent, and firms in the highest VRES_Ind quintile generate negative abnormal returns of -8.6 percent. The returns decline nearly monotonically across quintiles. The spread in returns across the highest and lowest quintiles is 27.0 percent, and is statistically significant. The decomposed model with industry-specific estimationalso works very well in predicting future abnormal returns among firms without analyst coverage. Firms in the quintile with the most negative VRES_D,Ind generate positive abnormal returns of 18.6 percent, and firms in the quintile with the most positive VRES_D,Ind generate negative abnormal returns of -8.1 percent. The returns again decline monotonically across quintiles. The spread in returns across the highest and lowest quintiles is 26.7 percent, and is statistically significant.

Overall, the results suggest that book values, earnings, dividends, and growth do a good job of explaining share prices. In addition, when we refine the model to distinguish the components of book value and earnings that likely have different implications for value, the model does a better job of explaining price. The models provide the most explanatory power for share prices of firms without analyst coverage, consistent with analysts enhancing the information environment and share pricing through their research activities. When we estimate the decomposed model on relatively homogeneous groups of firms sorted by industry and year, we find that residuals indicate valuation errors, and are therefore associated with future abnormal returns, particularly for firms not covered by analysts.

3.3 Robustness Checks

3.3.1 Controlling for other predictors of future returns

Because we decompose earnings into operating cash flows, accruals, and other income components, the relation between VRES_D,Ind and future returns in Table 5 could simply reflect the accrual anomaly among relatively neglected stocks that have no analyst coverage. In Table 6, we examine whether our results for the sample firms without coverage using the decomposed, industry model (VRES_D,Ind) are distinct from the accruals anomaly as well as other firm characteristics that predict returns, such as size and book-to-market. We use an approach similar to Bernard and Thomas (1990) by estimating the following regression to simulate a zero-investment portfolio:

(5) $AR_{i,t+1} = \propto + \beta_1 rVRES_D, Ind_{i,t} + \beta_2 rMVE_{i,t} + \beta_3 rBTM_{i,t} + \beta_4 rACC_{i,t} + \beta_4 rAR_{LAG\,i,t} + \beta_5 rBETA_{i,t} + \varepsilon_{i,t+1}$

$AR_{i,t+1}$ represents one-year-ahead abnormal returns measured as the raw return less the size-adjusted market return. $rVRES_D,Ind_{i,t}$ equals the VRES_D,Ind quintile ranking standardized to range between zero and one, equaling one (zero) when VRES_D,Ind falls in the bottom (top) decile. We control for the effects of other factors associated with future returns by creating quintiles based on ranks of the following four characteristics: (1) size (MVE); (2) the book-to-market ratio (BTM); (3) accruals (ACC), measured as operating income less cash flow from operations, deflated by total assets, (4) prior size-

adjusted abnormal returns (AR_LAG), and (5) BETA. We scale all quintiles to range from 0 to 1, so the coefficients can be interpreted as the spread in returns across extreme portfolios on each characteristic after controlling for the return implications of the other characteristic portfolios. In particular, given that rVRES_D,Ind is standardized to range between zero and one, the slope coefficient, β_1, represents the return to a zero-investment hedge portfolio after controlling for the effects of the other factors. We estimate the regressions in each annual period, and report the time-series mean coefficients. We report t-statistics based on the time-series distribution of the coefficient estimates.

The coefficient on VRES_D,Ind equals 0.160 in Table 6 and is statistically significant. This coefficient suggests a spread in returns of 16.0 percent across extreme VRES_D,Ind quintiles (in contrast to the 26.7 percent spread in the portfolio results in Table 5). This suggests that the returns remain after controlling for other firm characteristics, alleviating the concern that our results merely reflect the accrual anomaly or risk premia in disguise. Overall, the results confirm our findings in Table 5, and suggest that VRES_D,Ind predicts returns and is distinct from other factors that predict returns.

To shed additional light on the relation between our VRES_D,Ind variable and accruals, we plot returns to both strategies by year in Figure 1 . Both strategies appear to predict returns through 2002. After 2002 however, the effectiveness of the accrual strategy decreases. The accrual strategy produces negative returns in 5 of the 6 years from 2003 to 2008. In contrast, VRES_D,Ind is only marginally negative in 1 of the 6 years during that span. Over the entire sample period, VRES_D,Ind predicts positive returns in 17 out of 21 years, and generates significant negative returns in only two of our sample years. Overall, Figure 1 supports our conclusion in Table 6 that VRES_D,Ind predicts returns and is distinct from the accruals result.

In addition, we examine whether price converges to value during the quarterly earnings announcements made within the holding period. We measure 3-day size-adjusted abnormal returns centered on each of the quarterly earnings announcement dates from Compustat that fall within the

one-year holding period. We calculate the percentage of abnormal returns that accumulate during future earnings announcements by dividing the absolute value of the sum of the 3-day earnings announcement returns by the absolute value of the one-year-ahead size-adjusted abnormal return. The average percentage equals 67.3%, 67.3%, 63.2%, 59.3%, and 59.1% moving from the top VRES_D,Ind quintile to the bottom VRES_D,Ind quintile, respectively. This provides further evidence that the market learns more about the value of the company at future financial statement information release dates.

3.3.2 Role of scale effects

In this section, we evaluate the role scale effects play in our comparison of R-square across models estimated in samples with and without analyst coverage. Barth and Kallapur (1996) show that scale effects can bias parameter estimates in price-level regressions such as ours. We acknowledge that our value residuals reflect model misspecifications, and bias induced by scale effects should simply make it more difficult to document a relation between VRES and future returns. However, Brown, et al. (1999) show that scale effects can also result in biased values of R-square, and this bias can potentially explain the differences in R-square we observe.[10]

Brown, et al. (1999) show that R-square will be high when the coefficient of variation in the scale factor across the sample observations is high. For price per share regressions such as ours, they suggest measures of size or resources per share as proxies for the true scale factor. We follow Brown, et al. (1999) in using the coefficients of variation for price per share (PRICE_CV) and book value per share (BVPS_CV) as our proxies for the true scale factor. The descriptive statistics in table 1 confirm that scale

[10] To illustrate, consider the following simple example offered by Brown, Lo, and Lys (1999). A researcher estimates the R-square in a regression of stock prices on EPS in one period. For simplicity, assume that all firms are of similar size and have the same number of shares in the first period. Further, assume that share prices are independent of EPS. As a result, that regression will yield an R-square that is approximately zero. Now suppose one half of the firms arbitrarily undertake a 100:1 split in the second period, resulting in prices and EPS that are 1/100th what they were previously, while the other half do not. A regression of price on EPS in the second period will yield an R-square that is greater than zero. The researcher would conclude that EPS explained prices better in the second regression than the first, but the variation explained in the second regression is not the variation of interest to the researcher. Although this is an extreme example, Brown, Lo, and Lys (1999) point out that similar effects can occur for any reason that causes share sizes to vary across firms, such as different rates of return and different dividend policies.

effects could be at play in our analysis; for firms followed by analysts, PRICE_CV (BVPS_CV) is only 0.86 (0.88), while firms without analyst following have PRICE_CV (BVPS_CV) of 1.50 (1.46). Thus, to the extent these coefficients of variation reflect differences in scale across observations in the respective samples, R-square should be higher for the sample of firms without analyst following. Because this is what we predict and find regarding the differential role of accounting fundamentals across the two samples, scale effects represent a possible alternative explanation.

To address the concern, we estimate the following regression:

6) $$R^2_{\mathrm{s,t}} = \alpha + \beta_1 DNAF_{\mathrm{s,t}} + \beta_2 Price_CV_{\mathrm{s,t}} + \beta_3 BVPS_CV_{\mathrm{s,t}} + \beta_4 TIME + \varepsilon_{\mathrm{s,t}}$$

DNAF equals one if the observation is from the non-analyst-followed sample, 0 otherwise; PRICE_CV and BVPS_CV denote the coefficients of variation for price per share and book value per share, respectively; and TIME denotes a time trend. We include a time trend because we observe increases in R-square over time, especially for our firms without analyst following. Collins, et al. (1997) and Francis and Schipper (1999) estimate similar regressions to ours and also show increases in R-square over time, while Brown, et al. (1999) show corresponding increases in PRICE_CV and BVPS_CV over time.

In Table 7, Panel A, we report results for the base and decomposed models for the sample pooled across industries. DNAF is not significant in either model. Once we partition our sample firms on industry in Panel B, DNAF is significant for both the base and decomposed models. PRICE_CV is not significant in the base model but is significant in the decomposed model. BVPS_CV is significantly positive in the base model but not significant in the decomposed model. These results are similar to Brown, et al. (1999) who also find significantly positive BVPS_CV but insignificant PRICE_CV. The time trend is significant in the pooled models but not the industry models.[11] Overall, to the extent PRICE_CV and BVPS_CV capture the effects of scale on our regression R-squares, the results in table 7 confirm that

[11] In contrast, Brown, et al. (1999) find a negative coefficient on the time trend, suggesting declines in the value relevance of book values and earnings. One possibility for the differences in our findings is a change in the proportion of firms followed by analysts over time. In particular, if analysts cover an increasing percentage of the population over time and this change is not controlled for in the regressions, the coefficient on TIME could be significantly negative.

the differences in R-square across firms with and without analyst coverage cannot be attributed simply to scale effects.

4. Conclusions

This paper provides empirical evidence on the extent to which parsimonious cross-sectional valuation models using historical accounting data explain share prices in the capital markets, and identify mispriced shares. We find that even the most basic model, using historical book value, earnings, dividends, and operating income growth, explains the majority of the cross-sectional variation in share prices. Relatively simple improvements in the valuation model specification, including estimating models with book value and earnings decomposed into components, estimating models in differing information environments based on whether firms are covered by analysts, and estimating models within industries, generally provide substantial increases in explanatory power.

We also find that our cross-sectional valuation approach identifies mispriced shares, especially among firms not covered by analysts. Our results suggest that analyst coverage seemingly increases the capital market efficiency in pricing historical accounting information, reducing the usefulness of basic fundamental analysis approaches like those in this paper. However, among firms not covered by analysts, this basic approach works well in identifying mispriced shares, particularly when the value models are estimated by industry-year. Portfolio tests based on the extreme quintiles of residuals from decomposed, industry-specific value models each year appear to generate significant and consistent abnormal returns over our 21-year sample period.

Our study provides insights into how parsimonious cross-sectional valuation models map fundamental financial statement information into share prices across time, information environments, and industries. In addition, by studying the errors from these accounting-based valuation models, we provide new insight into market mispricing of accounting fundamentals. These observations should be

helpful to accounting researchers and teachers, practitioners, and financial statement users, and they establish a baseline for future research to examine other determinants of the role of fundamental accounting information in the capital markets

References

Barth, M., W. Beaver, J. Hand, and W. Landsman. (1999). "Accruals, Cash Flows, and Equity Values." *Review of Accounting Studies* 3, 205-229.

Barth, M., W. Beaver, J. Hand, and W. Landsman. (2005). "Accruals, Accounting-Based Valuation Models, and the Prediction of Equity Values." *Journal of Accounting, Auditing Finance* 20, 311-345.

Barth, M. and S. Kallapur. (1996). "The Effects of Cross-Sectional Scale Differences on Regression Results in Empirical Accounting Research," *Contemporary Accounting Research* 12, 527-567.

Berk, J. (1995). "A Critique of Size-Related Anomalies," *The Review of Financial Studies*, Vol. 8, No. 2, 275-286.

Bernard, V. (1994). "Accounting-Based Valuation Methods, Determinants of Market-to-Book Ratios, and Implications for Financial Statement Analysis," Working Paper, University of Michigan.

Bernard, V.L.. (1995). "The Feltham-Ohlson Framework: Implications for Empiricists," *Contemporary Accounting Research* April: 733-747.

Bernard, V., and J. Thomas (1989). "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?" *Journal of Accounting Research* 27, 1-36.

Bernard, V., and J. Thomas (1990). "Evidence that Stock Prices do not Fully Reflect the Implications of Current Earnings for Future Earnings." *Journal of Accounting and Economics* 13, 305-340.

Brown, S., K. Lo, and T. Lys (1999). "Use of R2 in accounting research: measuring changes in value relevance over the last four decades," *Journal of Accounting and Economics*, December 1999, 28: 83-115.

Collins, D., E. Maydew, and I. Weiss. (1997). "Changes in the value-relevance of earnings and book values over the past forty years," *Journal of Accounting and Economics* (Vol. 24, Issue 1):39-67.

Dechow, P., (1994) "Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals," *Journal of Accounting and Economics* 18, 3-24.

Elliott, J., and J. Hanna. (1996). "Repeated Accounting Write-offs and the Information Content of Earnings," *Journal of Accounting Research* 34, 135-155.

Feltham, G. and J. Ohlson. (1995). "Valuation and Clean Surplus Accounting for Operating and Financial Activities," *Contemporary Accounting Research* (Volume 11, Issue 2): 689-731.

Francis, J., and K. Schipper. (1999). "Have financial statements lost their relevance?" *Journal of Accounting Research* 37, 319-352.

Frankel, R., and C. Lee (1998), "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns" *Journal of Accounting and Economics* 25, 283-319.

Lipe, R. (1986). “The Information Contained in the Components of Earnings,” *Journal of Accounting Research* 24, 37-64.

Penman, S. and X. Zhang (2002), “Accounting Conservatism, the Quality of Earnings, and Stock Returns” *The Accounting Review* 77, 237–264

Sloan, R. G. (1996). “Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?” *The Accounting Review* 71, 289–315

Table 1
Descriptive Statistics

Panel A – Full Sample

Variable[a]	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
Price	53,331	17.760	18.353	4.125	11.563	25.625
BV	53,331	8.542	8.784	2.216	5.774	11.799
NOA	53,331	13.138	16.712	1.588	6.688	18.253
NFL	53,331	-4.561	10.506	-6.848	-0.722	0.891
NI	53,331	0.511	1.885	-0.306	0.333	1.330
ACC	53,331	-1.136	2.146	-1.630	-0.510	-0.045
CFO	53,331	1.654	2.701	-0.034	0.822	2.608
NIoth	53,331	-0.029	0.403	0.000	0.000	0.000
DIV	53,331	-0.071	1.943	-0.367	-0.020	0.368
OIGR	53,331	0.113	1.151	-0.233	0.093	0.481
AR	53,331	0.031	0.996	-0.382	-0.082	0.214
MTB	53,330	4.416	47.512	1.179	1.955	3.485
MVE	53,331	2,242.620	11,845.680	41.273	182.737	911.254
Value	51,392	18.383	13.498	8.700	14.670	23.988
VRES	51,392	-1.127	2.667	-1.302	-0.291	0.166
Value_D	51,477	18.358	13.677	8.628	14.631	24.078
VRES_D	51,477	-1.131	2.773	-1.270	-0.275	0.165
Value_Ind	51,160	18.493	14.307	8.161	14.738	24.583
VRES_Ind	51,160	-0.930	2.210	-1.113	-0.240	0.167
Value_D,Ind	51,152	18.503	14.652	7.917	14.605	24.780
VRES_D,Ind	51,152	-0.880	2.164	-1.029	-0.215	0.169

Panel B – Analyst Coverage Sample

Variable[a]	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
Price	36,664	22.082	18.975	7.625	17.125	30.684
BV	36,664	9.942	8.789	3.650	7.436	13.572
NOA	36,664	15.517	17.512	2.798	9.386	22.068
NFL	36,664	-5.555	11.283	-9.033	-1.519	1.191
NI	36,664	0.721	1.993	-0.196	0.656	1.645
ACC	36,664	-1.320	2.261	-1.935	-0.716	-0.099
CFO	36,664	2.054	2.834	0.167	1.330	3.205
NIoth	36,664	-0.034	0.436	0.000	0.000	0.000
DIV	36,664	-0.075	2.173	-0.482	-0.029	0.587
OIGR	36,664	0.147	1.214	-0.248	0.158	0.561
AR	36,664	0.032	0.876	-0.338	-0.062	0.210
MTB	36,664	4.288	50.996	1.332	2.129	3.598
MVE	36,664	3,080.650	14,060.640	117.084	406.348	1512.320
Value	35,537	22.678	13.292	13.402	19.840	28.780
VRES	35,537	-0.629	1.438	-0.860	-0.203	0.177
Value_D	35,558	22.673	13.539	13.312	19.794	28.857
VRES_D	35,558	-0.610	1.396	-0.835	-0.188	0.171
Value_Ind	35,421	22.781	14.381	12.687	19.735	29.205
VRES_Ind	35,421	-0.517	1.230	-0.742	-0.149	0.173
Value_D,Ind	35,397	22.802	14.796	12.413	19.680	29.475
VRES_D,Ind	35,397	-0.472	1.140	-0.686	-0.130	0.171

Table 1 (continued)

Panel C – Without Analyst Coverage Sample

Variable[a]	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
Price	16,667	8.252	12.418	1.600	3.813	9.190
BV	16,667	5.462	7.947	0.793	2.358	6.613
NOA	16,667	7.904	13.390	0.608	2.654	9.070
NFL	16,667	-2.376	8.137	-2.477	-0.193	0.436
NI	16,667	0.049	1.523	-0.424	-0.015	0.417
ACC	16,667	-0.731	1.801	-0.903	-0.223	-0.005
CFO	16,667	0.774	2.131	-0.172	0.113	0.977
NIoth	16,667	-0.016	0.318	0.000	0.000	0.000
DIV	16,667	-0.061	1.299	-0.200	-0.013	0.074
OIGR	16,667	0.038	0.993	-0.210	0.015	0.272
AR	16,667	0.028	1.220	-0.477	-0.141	0.226
MTB	16,666	4.697	38.761	0.883	1.553	3.174
MVE	16,667	399.135	3,025.400	10.959	28.260	84.061
Value	15,973	8.592	10.176	2.790	4.870	10.024
VRES	15,973	-0.904	1.833	-1.278	-0.357	0.169
Value_D	16,006	8.568	10.268	2.936	4.892	9.964
VRES_D	16,006	-0.964	1.959	-1.313	-0.368	0.158
Value_Ind	15,621	8.610	10.571	2.564	4.822	10.080
VRES_Ind	15,621	-0.764	1.624	-1.108	-0.264	0.188
Value_D,Ind	15,610	8.623	10.919	2.549	4.750	9.969
VRES_D,Ind	15,610	-0.737	1.600	-1.076	-0.235	0.185

[a]Variable Definitions

Price	=	Price as of the last day of the third month following the fiscal year-end (e.g. March 31);
BV	=	Shareholders' equity divided by common shares outstanding;
NOA	=	Common Equity (ceq)+Debt in current liabilities (dlc)+Total long-term debt (dltt)+Preferred Stock (pstk)-Cash and short-term investments (che)-Investments and advances-other(ivao)+Minority Interest (mib) divided by common shares outstanding;
NFL	=	BV -NOA ;
NI	=	Net Income divided by common shares outstanding;
ACC	=	(Income before extraordinary items less Cash flow from operations) divided by common shares outstanding;
CFO	=	Cash flow from operations divided by common shares outstanding;
NIoth	=	(Net Income less Income before extraordinary items) divided by common shares outstanding;
DIV	=	(Lagged shareholders' equity-shareholders' equity + net income) divided by common shares outstanding;
OIGR	=	Operating Income less prior year operating Income divided by common shares outstanding;
AR	=	One-year-ahead size-adjusted abnormal returns;
MTB	=	Market value of equity divided by book value of shareholders' equity;
MVE	=	Price multiplied by common shares outstanding;
Value	=	Fitted value derived from applying yearly coefficients to firm values in the base model;
VRES	=	(Price – Value) divided by price;
Value_D	=	Fitted value derived from applying yearly coefficients to firm values in the decomposed model;
VRES_D	=	(Price – Value_D) divided by price;
Value_Ind	=	Fitted value derived from applying yearly-industry coefficients to firm values in the base model;
VRES_Ind	=	(Price – Value_Ind) divided by price;
Value_D,Ind	=	Fitted value derived from applying yearly-industry coefficients to firm values in the decomposed model;
VRES_D,Ind	=	(Price – Value_D,Ind) divided by price.

Table 2
Yearly Model Estimations

Panel A, Base model [a]

$$P_{i,t} = \alpha + \beta_1 BV_{i,t} + \beta_2 NI_{i,t} + \beta_3 DIV_{i,t} + \beta_4 OIGR_{i,t} + \varepsilon_{i,t}$$

	Full Sample						Analyst Coverage						No Analyst Coverage					
Year	Int.	BV	NI	DIV	OIGR	Adj. R2	Int.	BV	NI	DIV	OIGR	Adj. R2	Int.	BV	NI	DIV	OIGR	Adj. R2
1988	5.27	0.74	2.91	0.51	-0.34	0.701	8.53	0.59	3.37	0.56	-0.57	0.642	2.08	0.89	1.12	0.48	0.45	0.743
1989	5.60	0.72	3.23	0.31	0.65	0.676	9.34	0.56	3.61	0.37	0.89	0.619	1.84	0.86	1.45	-0.64	0.04	0.727
1990	5.58	0.73	4.24	-0.04	0.59	0.628	9.27	0.64	4.25	0.14	1.05	0.548	1.94	0.76	2.22	-0.20	-0.12	0.693
1991	5.85	0.99	3.02	-0.52	-0.47	0.594	9.79	0.90	2.97	-0.20	-0.48	0.514	2.54	0.83	1.75	-0.46	-0.19	0.639
1992	5.27	1.26	0.82	0.96	1.74	0.581	8.38	1.25	0.58	1.27	2.56	0.548	2.45	0.92	0.80	0.10	0.73	0.600
1993	5.94	1.10	2.01	0.52	1.64	0.603	9.17	1.01	1.84	0.77	2.27	0.555	2.54	0.93	1.43	0.25	-0.40	0.681
1994	6.36	0.85	3.85	-0.10	0.74	0.595	9.37	0.67	4.67	0.06	0.67	0.553	1.95	1.01	0.59	-0.46	1.15	0.688
1995	7.45	1.09	3.01	-0.73	0.65	0.502	10.75	1.01	2.75	-0.43	1.00	0.429	3.09	0.99	2.02	-0.90	0.76	0.625
1996	6.55	1.00	3.73	-0.38	0.93	0.600	9.08	0.90	4.01	-0.21	1.09	0.570	2.34	1.05	1.98	-0.68	0.54	0.675
1997	8.47	1.35	3.25	-0.14	2.14	0.526	12.03	1.22	3.58	0.03	1.86	0.475	2.32	1.34	1.10	0.01	2.30	0.676
1998	6.91	1.10	3.15	-0.74	-0.52	0.345	9.73	1.01	3.17	-0.62	-0.12	0.288	2.09	1.01	1.65	-0.62	-1.70	0.530
1999	11.61	0.86	3.92	-3.27	-0.67	0.222	16.80	0.58	4.27	-3.33	-0.48	0.171	4.32	0.98	1.59	-1.45	-1.22	0.298
2000	6.22	0.90	2.46	-0.35	1.25	0.493	8.72	0.86	2.64	-0.28	1.45	0.464	1.81	0.87	1.20	-0.23	0.59	0.631
2001	6.56	1.24	2.13	-0.29	-0.15	0.516	9.89	1.18	2.46	0.01	-0.10	0.505	2.03	1.05	1.02	0.09	0.12	0.577
2002	4.46	1.03	1.81	0.53	0.57	0.541	6.67	0.99	2.08	0.69	0.75	0.508	1.29	0.90	1.01	0.36	0.16	0.685
2003	8.62	1.05	3.57	-0.43	1.10	0.592	11.46	0.97	4.09	-0.34	0.59	0.561	3.31	1.09	1.48	0.12	1.76	0.743
2004	7.72	1.11	4.25	0.19	0.48	0.655	10.11	1.02	4.58	0.23	0.23	0.625	3.16	1.16	2.55	0.60	1.64	0.739
2005	9.63	1.14	3.67	0.57	3.04	0.633	12.52	1.02	3.58	0.74	3.39	0.591	3.60	1.30	3.80	0.27	1.52	0.774
2006	8.89	1.21	4.00	0.80	2.58	0.662	11.25	1.12	3.83	0.89	2.92	0.628	3.18	1.36	4.42	0.33	1.23	0.780
2007	6.74	1.07	4.39	0.09	2.65	0.633	8.28	0.98	4.53	0.09	2.79	0.606	2.40	1.37	3.41	0.01	1.47	0.708
2008	4.31	0.80	1.40	0.69	0.16	0.532	5.60	0.75	1.44	0.62	0.20	0.492	1.36	0.88	1.19	1.02	0.10	0.647
Mean	6.86	1.02	3.09	-0.09	0.89	0.563	9.84	0.92	3.25	0.05	1.05	0.519	2.46	1.03	1.80	-0.10	0.52	0.660
T-stat.	20.22	30.95	16.67	-0.21	3.44		20.52	21.48	13.96	0.66	3.28		7.65	27.00	7.68	-0.34	1.58	

Table 2 (continued)

Panel B, Decomposed model $P_{i,t} = \alpha + \gamma_1 NOA_{i,t} + \gamma_2 NFL_{i,t} + \gamma_3 ACC_{i,t} + \gamma_4 CFO_{i,t} + \gamma_5 NIoth_{i,t} + \gamma_6 DIV_{i,t} + \gamma_7 OIGR_{i,t} + \varepsilon$

	Full Sample									Analyst Coverage									No Analyst Coverage								
Year	Int.	NOA	NFL	ACC	CFO	NIoth	DIV	OIGR	Adj. R^2	Int.	NOA	NFL	ACC	CFO	NIoth	DIV	OIGR	Adj. R^2	Int.	NOA	NFL	ACC	CFO	NIoth	DIV	OIGR	Adj. R^2
1988	5.23	0.74	0.78	2.02	2.54	1.11	0.74	-0.10	0.690	8.81	0.57	0.65	2.40	3.06	1.46	0.81	-0.30	0.630	1.83	0.96	0.95	0.69	0.63	-0.26	0.74	0.62	0.746
1989	5.99	0.67	0.74	2.37	3.03	1.39	0.34	0.52	0.659	10.23	0.51	0.62	2.52	3.32	2.20	0.50	0.86	0.601	1.82	0.83	0.80	1.10	1.30	0.35	-0.82	-0.11	0.736
1990	6.29	0.59	0.75	2.76	4.11	-0.08	0.25	0.91	0.618	10.12	0.65	0.93	2.28	3.59	0.45	0.41	1.57	0.547	2.28	0.59	0.61	1.68	2.34	-0.40	0.20	0.06	0.724
1991	6.23	0.69	0.88	2.27	4.28	-1.09	-0.95	-0.01	0.614	9.81	0.70	0.98	2.30	4.17	-0.44	-0.60	-0.02	0.553	2.84	0.63	0.69	1.12	2.27	-0.76	-0.81	-0.01	0.638
1992	6.47	0.64	0.68	2.85	4.72	-1.60	0.01	-0.01	0.657	9.54	0.63	0.73	3.13	4.84	-1.64	0.22	0.64	0.640	2.96	0.66	0.66	1.03	2.16	-0.62	0.04	-0.32	0.619
1993	6.08	0.81	0.97	2.26	4.03	-1.76	-0.01	1.09	0.657	8.92	0.77	0.99	2.09	3.83	-1.95	0.23	1.68	0.621	2.75	0.79	0.84	1.41	2.40	0.12	0.07	-0.61	0.705
1994	6.48	0.73	0.95	3.22	4.75	-0.22	-0.41	0.41	0.620	9.26	0.62	0.91	3.84	5.33	-1.62	-0.18	0.59	0.584	2.19	0.86	1.02	0.38	1.44	-0.57	-0.57	0.59	0.721
1995	7.58	0.88	1.03	2.65	4.17	-1.32	-1.15	0.17	0.518	10.78	0.86	1.10	2.65	4.05	-2.30	-0.78	0.44	0.455	3.00	0.90	0.94	1.29	2.34	0.02	-1.28	0.42	0.622
1996	6.58	0.80	0.89	3.04	4.58	1.16	-0.68	0.55	0.604	8.97	0.76	0.91	2.98	4.55	0.71	-0.41	1.01	0.571	2.45	0.88	0.84	2.23	3.07	1.00	-1.29	-0.36	0.679
1997	8.88	0.99	1.06	2.70	4.80	-0.48	-0.70	1.36	0.531	12.17	0.95	1.08	2.77	4.80	-0.86	-0.42	1.25	0.479	2.76	1.03	1.07	0.66	2.30	-0.72	-0.69	1.92	0.684
1998	7.23	0.84	1.01	1.90	4.13	3.08	-1.08	-0.07	0.359	9.88	0.82	1.06	1.63	3.93	3.90	-0.89	0.56	0.306	2.23	0.80	0.76	1.01	2.18	0.04	-0.96	-1.39	0.555
1999	11.38	0.90	1.25	2.38	4.25	5.25	-3.38	-0.67	0.233	15.91	0.76	1.23	2.09	4.34	2.08	-3.38	-0.18	0.195	4.45	0.98	0.97	1.81	1.50	4.68	-1.46	-1.31	0.294
2000	6.18	0.74	0.80	2.10	3.49	0.31	-0.56	0.89	0.496	8.54	0.74	0.83	2.20	3.49	-0.20	-0.42	1.12	0.466	2.01	0.75	0.75	1.19	2.01	1.50	-0.45	0.34	0.597
2001	6.69	0.96	1.07	1.41	3.02	0.67	-0.57	0.03	0.517	9.43	1.00	1.15	1.50	3.09	0.92	-0.25	0.08	0.508	2.56	0.80	0.85	0.84	1.81	-0.35	0.03	0.35	0.566
2002	4.76	0.72	0.82	1.93	3.31	0.39	0.15	0.43	0.563	6.80	0.67	0.82	2.08	3.65	0.67	0.18	0.64	0.539	1.51	0.75	0.75	1.08	1.62	-0.03	0.57	0.00	0.675
2003	8.47	0.96	1.17	3.26	4.34	0.57	-0.79	0.75	0.601	11.07	0.95	1.20	3.74	4.61	-0.42	-0.51	0.42	0.569	3.51	0.90	0.99	1.12	2.36	3.29	-0.54	1.41	0.733
2004	7.56	0.95	1.13	2.91	4.69	0.33	-0.07	0.58	0.665	9.90	0.86	1.05	3.13	5.02	-0.17	0.03	0.35	0.638	2.91	1.07	1.15	1.57	2.60	2.78	0.16	2.10	0.741
2005	9.60	0.99	1.18	2.81	4.46	0.50	0.44	2.52	0.647	12.24	0.90	1.11	2.80	4.41	0.39	0.49	2.89	0.607	4.11	1.04	1.12	2.93	4.37	2.23	0.95	0.55	0.781
2006	9.18	0.99	1.15	3.05	4.75	-0.60	0.58	2.33	0.678	11.31	0.96	1.13	2.83	4.38	-0.20	0.79	2.79	0.645	3.64	1.06	1.15	3.79	5.38	-0.62	-0.50	0.85	0.803
2007	6.71	0.77	0.92	3.08	5.42	1.24	-0.14	2.63	0.656	7.90	0.76	0.93	3.41	5.49	0.93	-0.07	2.71	0.629	3.19	0.73	0.91	1.43	5.03	1.00	-0.80	1.51	0.751
2008	4.51	0.57	0.77	1.06	2.48	-1.23	0.51	0.30	0.565	5.57	0.56	0.77	1.16	2.51	-0.79	0.50	0.33	0.532	1.89	0.56	0.70	0.65	2.16	-2.96	0.50	0.06	0.662
Mean	7.05	0.81	0.95	2.48	4.06	0.36	-0.36	0.70	0.579	9.86	0.76	0.96	2.55	4.12	0.15	-0.18	0.92	0.539	2.71	0.84	0.88	1.38	2.44	0.46	-0.33	0.32	0.668
T-stat	21.48	20.73	18.34	12.94	20.98	-0.10	-2.13	2.78		21.10	14.73	13.94	10.61	16.96	-0.19	-0.70	3.01		8.65	20.01	15.54	5.65	9.66	0.25	-1.50	0.92	

[a] See Table 1 for variable definitions.

Table 3

One-Year-Ahead Abnormal Returns to Yearly Model Estimations

VRES and VRES_D Quintiles

		Base			Decomposed		
Sample	**Quintile**	**N**	**VRES**	**AR**	**N**	**VRES_D**	**AR**
Full	1	10,271	-4.772	0.111	10,289	-4.829	0.104
	2	10,281	-1.075	0.023	10,299	-1.048	0.029
	3	10,282	-0.324	0.026	10,298	-0.308	0.026
	4	10,281	0.078	-0.009	10,299	0.080	-0.011
	5	10,277	0.456	-0.013	10,292	0.445	-0.015
			Q1-Q5:	0.124**		*Q1-Q5:*	0.119**
Analyst Coverage	1	7,100	-2.714	0.082	7,105	-2.642	0.091
	2	7,112	-0.745	0.056	7,114	-0.721	0.052
	3	7,111	-0.225	0.009	7,118	-0.213	0.010
	4	7,112	0.103	-0.003	7,114	0.101	0.001
	5	7,102	0.436	-0.009	7,107	0.424	-0.018
			Q1-Q5:	0.091		*Q1-Q5:*	0.109**
No Analyst Coverage	1	3,187	-3.639	0.168	3,193	-3.868	0.187
	2	3,197	-1.081	0.066	3,206	-1.122	0.053
	3	3,201	-0.376	-0.015	3,204	-0.386	0.002
	4	3,197	0.067	-0.009	3,206	0.058	-0.035
	5	3,191	0.504	-0.070	3,197	0.493	-0.060
			Q1-Q5:	0.238***		*Q1-Q5:*	0.247***

***, **, and * signify two-tailed significance at the 1%, 5%, and 10% levels, respectively. We calculate p-values using two-way clustering by year and industry.

Table 4

Yearly Industry Model Estimations

Panel A, Base model [a]

$$P_{i,t} = \alpha + \beta_1 BV_{i,t} + \beta_2 NI_{i,t} + \beta_3 DIV_{i,t} + \beta_4 OIGR_{i,t} + \varepsilon_{i,t}$$

	Full Sample							Analyst Coverage							No Analyst Coverage						
FFSIC[b]	N	Int.	BV	NI	DIV	OIGR	Adj. R^2	N	Int.	BV	NI	DIV	OIGR	Adj. R^2	N[c]	Int.	BV	NI	DIV	OIGR	Adj. R^2
1	21	7.16	0.88	4.78	1.57	0.33	0.637	21	10.81	0.66	5.53	1.52	0.61	0.604	21	1.09	1.18	2.52	-0.09	-0.39	0.784
2	21	7.02	0.84	3.70	0.87	0.64	0.694	21	7.40	0.94	3.72	0.79	0.73	0.671	16	3.83	0.75	2.90	1.32	-0.39	0.767
3	21	6.31	0.96	3.12	0.98	1.16	0.588	21	9.44	0.91	3.25	1.04	1.26	0.551	21	2.08	0.90	1.55	0.75	0.65	0.680
4	21	5.04	1.25	2.66	0.60	0.04	0.727	21	6.82	1.26	2.58	0.80	0.04	0.707	21	2.28	1.05	2.90	0.24	-0.39	0.825
5	21	7.75	0.97	4.03	1.80	1.15	0.605	21	11.88	0.84	4.01	1.89	1.81	0.551	21	2.65	0.95	2.04	0.87	1.23	0.684
6	21	4.87	1.41	3.51	-1.12	1.32	0.604	21	6.89	1.31	3.84	-0.87	1.68	0.587	21	1.73	1.20	1.53	-1.62	0.57	0.579
7	21	9.71	1.28	1.09	-0.13	2.26	0.558	21	12.50	1.16	1.33	-0.03	2.79	0.547	21	3.56	1.79	0.25	-0.39	3.61	0.606
8	21	8.36	0.75	2.96	0.14	0.62	0.580	21	9.18	0.74	2.87	0.17	0.58	0.557	14	5.62	0.68	3.42	-0.10	-0.28	0.658
9	21	5.42	0.86	4.05	-0.31	0.50	0.548	21	8.33	0.78	4.18	-0.15	1.00	0.470	21	2.23	0.79	2.47	0.37	-0.06	0.698
10	21	6.80	2.36	4.20	-0.59	0.56	0.621	21	9.90	2.17	4.36	-0.33	0.82	0.606	21	2.45	1.63	1.35	-1.49	0.75	0.460
12	21	6.18	1.02	2.95	-0.34	1.18	0.544	21	9.25	0.89	3.26	-0.12	1.45	0.491	21	2.23	1.06	1.75	-0.14	0.71	0.667
Mean	231	6.78	1.14	3.37	0.31	0.89	0.610		9.31	1.06	3.54	0.43	1.16	0.577		2.71	1.09	2.06	-0.03	0.55	0.673
T stat.		5.39	9.40	5.14	0.42	0.91			5.38	6.76	4.33	0.58	0.90			2.28	7.17	2.26	-0.12	0.37	

Table 4 (continued)

Panel B, Decomposed model $P_{i,t} = \alpha + \gamma_1 NOA_{i,t} + \gamma_2 NFL_{i,t} + \gamma_3 ACC_{i,t} + \gamma_4 CFO_{i,t} + \gamma_5 NIoth_{i,t} + \gamma_6 DIV_{i,t} + \gamma_7 OIGR_{i,t} + \varepsilon$

	Full Sample									Analyst Coverage									No Analyst Coverage								
FFSIC	Int.	NOA	NFL	ACC	CFO	NIoth	DIV	OIGR	Adj. R^2	Int.	NOA	NFL	ACC	CFO	NIoth	DIV	OIGR	Adj. R^2	Int.	NOA	NFL	ACC	CFO	NIoth	DIV	OIGR	Adj. R^2
1	7.45	0.37	0.28	4.44	6.71	3.27	1.08	0.01	0.663	10.43	0.21	0.21	4.77	7.51	3.41	0.94	0.23	0.640	1.79	0.79	0.69	1.33	2.47	11.52	0.42	-0.07	0.858
2	6.70	0.66	0.83	3.65	5.05	0.17	0.72	0.48	0.737	6.93	0.79	1.09	3.42	5.06	0.55	0.75	0.50	0.715	3.78	0.78	1.17	1.85	3.24	1.75	0.54	-0.25	0.818
3	6.18	0.70	0.62	2.95	4.37	0.63	0.58	0.62	0.614	9.08	0.67	0.64	2.92	4.38	0.77	0.75	0.94	0.581	2.24	0.74	0.65	1.63	2.45	0.85	0.05	0.33	0.687
4	4.61	0.97	0.94	2.53	3.69	-0.21	0.32	-0.10	0.749	6.38	1.09	1.15	2.46	3.37	-0.01	0.54	-0.04	0.727	2.21	0.84	0.75	3.06	4.03	-3.44	0.30	-0.91	0.848
5	7.14	0.55	0.54	4.00	6.29	-3.13	1.04	0.38	0.654	10.75	0.44	0.54	3.88	6.41	-2.92	1.14	1.00	0.609	2.67	0.74	0.54	2.62	3.43	-8.21	-0.09	0.73	0.744
6	4.78	1.06	1.35	2.08	5.05	0.39	-1.38	1.06	0.640	6.67	0.96	1.20	2.44	5.44	0.48	-1.16	1.40	0.628	1.62	1.12	1.29	0.98	2.28	1.46	-1.67	0.29	0.625
7	9.26	0.97	1.04	0.98	2.82	1.15	-0.50	1.45	0.593	12.16	0.82	0.90	1.02	3.02	0.03	-0.44	2.18	0.585	3.12	1.69	1.70	0.43	0.88	3.03	-0.84	3.55	0.644
8	7.26	0.64	0.68	3.41	4.27	-0.14	-0.10	0.01	0.620	8.05	0.65	0.70	3.20	4.07	-0.24	-0.09	0.12	0.599	6.16	0.37	0.31	6.06	5.78	-10.44	-0.26	-0.87	0.712
9	5.19	0.80	1.00	3.64	4.73	-0.08	-0.54	1.02	0.569	7.59	0.84	1.09	3.32	4.43	-0.04	-0.26	1.78	0.504	2.44	0.71	0.93	2.27	3.06	0.73	-0.03	0.06	0.713
10	6.66	2.02	2.47	1.38	5.37	7.44	-0.79	1.62	0.653	9.79	1.70	2.23	1.80	6.14	2.31	-0.71	1.26	0.644	2.24	1.71	1.72	0.94	1.10	-0.71	-1.44	0.64	0.520
12	6.32	0.88	1.08	2.53	3.82	0.41	-0.61	0.98	0.562	9.21	0.80	1.03	2.97	4.09	0.27	-0.33	1.39	0.509	2.18	0.98	1.20	0.90	2.08	-0.85	-0.44	0.57	0.728
Mean	6.50	0.87	0.98	2.87	4.74	0.90	-0.02	0.68	0.641	8.82	0.82	0.98	2.93	4.90	0.42	0.10	0.98	0.613	2.77	0.95	1.00	2.01	2.80	-0.39	-0.32	0.37	0.718
T stat.	5.39	6.16	5.16	4.00	6.56	0.07	-0.26	0.66		5.22	4.44	3.89	3.22	5.38	0.09	0.03	0.77		2.42	5.24	4.30	1.67	2.73	0.07	-0.44	0.23	

[a] See Table 1 for variable definitions.

[b] Fama-French industry descriptions

FFSIC	Industry Description
1	Consumer Nondurables
2	Consumer Durables
3	Manufacturing
4	Oil, Gas, Coal
5	Chemicals and Allied Products
6	Business Equipment
7	Telephone and Television Transmission
8	Utilities
9	Wholesale, Retail, Retail Services
10	Healthcare, Medical Equipment, Drugs
11	Financial Services (omitted from the empirical analyses)
12	Other

[c] We require at least 15 observations to estimate the valuation parameters.

Table 5

One-Year-Ahead Abnormal Returns to Yearly Industry Model Estimations

VRES_Ind and VRES_D,Ind Quintiles

		Base			Decomposed		
Sample	**Quintile**	**N**	**VRES_Ind**	**AR**	**N**	**VRES_D,Ind**	**AR**
Full	1	10,223	-4.008	0.117	10,222	-3.846	0.116
	2	10,236	-0.915	0.021	10,236	-0.849	0.032
	3	10,236	-0.261	0.017	10,234	-0.238	0.012
	4	10,236	0.091	-0.003	10,236	0.097	-0.002
	5	10,229	0.439	-0.015	10,224	0.435	-0.017
			Q1-Q5:	0.132**		*Q1-Q5:*	0.133**
Analyst Coverage	1	7,075	-2.309	0.085	7,071	-2.147	0.081
	2	7,089	-0.631	0.038	7,083	-0.584	0.035
	3	7,087	-0.173	0.015	7,084	-0.153	0.025
	4	7,089	0.111	-0.004	7,083	0.112	-0.011
	5	7,081	0.416	-0.001	7,076	0.408	0.002
			Q1-Q5:	0.086		*Q1-Q5:*	0.079*
No Analyst Coverage	1	3,115	-3.232	0.184	3,114	-3.157	0.186
	2	3,130	-0.927	0.062	3,125	-0.892	0.058
	3	3,125	-0.280	-0.004	3,129	-0.256	-0.001
	4	3,130	0.103	-0.014	3,125	0.105	-0.024
	5	3,121	0.509	-0.086	3,117	0.509	-0.081
			Q1-Q5:	0.270***		*Q1-Q5:*	0.267***

***, **, and * signify two-tailed significance at the 1%, 5%, and 10% levels, respectively. We calculate p-values using two-way clustering by year and industry.

Table 6
Hedge Strategy Portfolio Returns

$$AR_{i,t+1} = \propto + \beta_1 rVRES_D, Ind_{i,t} + \beta_2 rMVE_{i,t} + \beta_3 rBTM_{i,t} + \beta_4 rACC_{i,t} + \beta_4 rAR_LAG_{i,t} + \beta_5 rBETA_{i,t} + \varepsilon_{i,t+1}$$

Parameter [a]	Estimate	Standard Error	t value	p value
Intercept	-0.127	0.037	-3.48	0.001
rVRES_D,Ind	0.160	0.036	4.44	<.0001
rMVE	-0.031	0.028	-1.13	0.261
rBTM	0.161	0.033	4.88	<.0001
rACC	-0.072	0.029	-2.50	0.013
rAR_LAG	0.026	0.030	0.88	0.377
rBETA	0.065	0.031	2.11	0.035

Average adjusted R-square = 0.0069

[a] Variable definitions.

$AR_{i,t+1}$	=	One-year-ahead size-adjusted abnormal returns;
$rVRES_D,Ind_{i,t}$	=	descending quintile ranking of VRES_D,Ind standardized to range between 0 and 1;
$rMVE_{i,t}$	=	quintile ranking of market value of equity defined as price multiplied by shares outstanding, standardized to range between 0 and 1;
$rBTM_{i,t}$	=	quintile ranking of book-to-market defined as shareholders' equity divided by market value of equity, standardized to range between 0 and 1;
$rACC_{i,t}$	=	quintile ranking of accruals deflated by total assets, standardized to range between 0 and 1;
rAR_LAG	=	quintile ranking of prior year size-adjusted abnormal returns, standardized to range between 0 and 1;
rBETA	=	quintile ranking of BETA (the slope coefficient of the regression of the firm's return on the return to the equally-weighted CRSP index, estimated using daily returns over calendar year t (approximately 250 trading days)), standardized to range between 0 and 1.

Table 7
R-Square regressions

$$R^2_{s,t} = \alpha + \beta_1 DNAF_{s,t} + \beta_2 Price_CV_{s,t} + \beta_3 BVPS_CV_{s,t} + \beta_4 TIME + \varepsilon_{s,t}$$

Panel A. Pooled base and decomposed models

	Base Model			Decomposed Model		
Parameter[a]	**Estimate**	**t value**	**p value**	**Estimate**	**t value**	**p value**
Intercept	0.315	1.50	0.143	0.341	1.56	0.126
DNAF	0.084	0.60	0.555	0.074	0.50	0.618
PRICE_CV	-0.005	-3.01	0.005	-0.004	-2.80	0.008
BVPS_CV	0.006	2.63	0.012	0.006	2.45	0.019
TIME	0.006	2.08	0.044	0.006	1.93	0.062
Adj. R-Square	0.421			0.363		

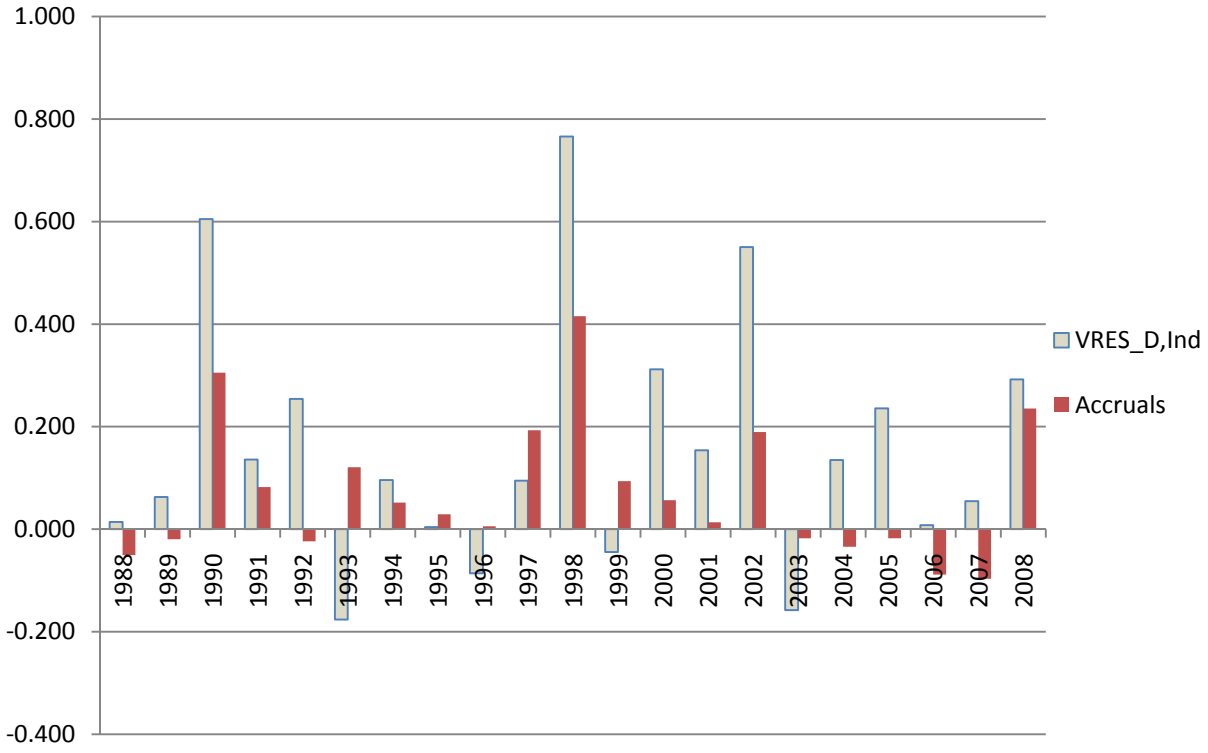
Panel B. Industry base and decomposed models

	Base Model			Decomposed Model		
Parameter	**Estimate**	**t value**	**p value**	**Estimate**	**t value**	**p value**
INTERCEPT	0.505	25.68	<.0001	0.580	30.49	<.0001
DNAF	0.037	2.24	0.0256	0.048	2.99	0.0030
PRICE_CV	0.000	-0.59	0.5526	0.000	-0.62	0.5369
BVPS_CV	0.001	7.62	<.0001	0.001	6.65	<.0001
TIME	0.000	-0.07	0.9448	0.000	-0.09	0.9263
Adj. R-Square	0.111			0.124		

[a] Variable definitions.

$R^2_{s,t}$	=	R-square from cross-sectional regression of price on accounting fundamentals for sample s (s = analyst covered, non-analyst covered) in period t;
$DNAF_{s,t}$	=	Indicator variable equal to 1 non-analyst followed, 0 otherwise;
$Price_CV_{s,t}$	=	Coefficient of variation for price per share;
$BVPS_CV_{i,t}$	=	Coefficient of variation for book value per share;
TIME	=	Time trend.

Figure 1
Hedge Strategy Portfolio Returns by Year



Appendix A: Correlations Among Value Residuals

Table A reports correlations for the full sample (Panel A), the analyst coverage sample (Panel B), and the no analyst coverage sample (Panel C). The tables report Pearson correlations above the diagonal and Spearman correlations below the diagonal. The Pearson correlations show that our refinements to the base model are effective; for the full sample, the correlation between price and value rises from .856 for the base yearly estimations (Value), to .873 for the yearly decomposed estimation (Value_D), to .889 for the yearly industry estimations (Value_Ind), and further to .905 for the decomposed yearly industry estimations (Value_D, Ind). Similar patterns exist for the analyst coverage and no analyst coverage subsamples, though the correlations are higher for the no coverage sample. The rising correlations are generally similar for the Spearman correlations for the full sample and the two subsamples.

The full sample reveals significant correlations between abnormal returns and our value residuals. In particular, the table reports full sample negative Pearson correlations between abnormal returns and VRES (-0.028), VRES_D (-0.031), VRES_Ind (-0.032), and VRES_D, Ind (-0.032). These negative correlations are consistent with our predictions; VRES should be high (low) when the stock is overpriced (underpriced). Consequently, high VRES should be associated with low future returns. However, the Pearson correlations are not supported by the Spearman correlations. In particular, the Spearman correlations for the full sample are positive and significant. For the analyst following sample, abnormal returns are significantly negatively correlated with our two industry-based measures of VRES, but again only for the Pearson correlations. For the sample without analyst coverage, we find significantly negative Pearson correlations between abnormal returns and the decomposed, industry-based VRES measure (VRES_D,Ind). These correlations confirm the result in the paper that indicate the yearly, industry-based estimations of our decomposed model appear to be useful in identifying valuation errors for firms that are not covered by analysts.

Table A

Correlations

Pearson above / Spearman below the diagonal [a]

Panel A – Full Sample[b]

	Price	Value	VRES	Value_D	VRES_D	Value_Ind	VRES_Ind	Value_D,Ind	VRES_D,Ind	AR
Price		0.765 ***	0.409 ***	0.775 ***	0.395 ***	0.804 ***	0.408 ***	0.821 ***	0.395 ***	-0.028 ***
Value	0.813 ***		0.260 ***	0.957 ***	0.270 ***	0.944 ***	0.262 ***	0.904 ***	0.263 ***	-0.021 ***
VRES	0.790 ***	0.322 ***		0.274 ***	0.980 ***	0.304 ***	0.922 ***	0.318 ***	0.891 ***	-0.065 ***
Value_D	0.823 ***	0.971 ***	0.376 ***		0.252 ***	0.913 ***	0.273 ***	0.936 ***	0.250 ***	-0.017 ***
VRES_D	0.787 ***	0.360 ***	0.962 ***	0.336 ***		0.305 ***	0.902 ***	0.302 ***	0.904 ***	-0.066 ***
Value_Ind	0.835 ***	0.946 ***	0.423 ***	0.926 ***	0.440 ***		0.250 ***	0.958 ***	0.259 ***	-0.020 ***
VRES_Ind	0.745 ***	0.318 ***	0.924 ***	0.357 ***	0.894 ***	0.293 ***		0.277 ***	0.957 ***	-0.069 ***
Value_D,Ind	0.845 ***	0.918 ***	0.462 ***	0.940 ***	0.445 ***	0.965 ***	0.364 ***		0.240 ***	-0.018 ***
VRES_D,Ind	0.721 ***	0.322 ***	0.875 ***	0.314 ***	0.902 ***	0.316 ***	0.936 ***	0.278 ***		-0.070 ***
AR	0.115 ***	0.133 ***	0.051 ***	0.139 ***	0.046 ***	0.127 ***	0.046 ***	0.133 ***	0.036 ***	

Panel B – Analyst Coverage Sample

	Price	Value	VRES	Value_D	VRES_D	Value_Ind	VRES_Ind	Value_D,Ind	VRES_D,Ind	AR
Price		0.735 ***	0.507 ***	0.749 ***	0.505 ***	0.787 ***	0.488 ***	0.807 ***	0.482 ***	-0.040 ***
Value	0.775 ***		0.245 ***	0.952 ***	0.267 ***	0.924 ***	0.244 ***	0.882 ***	0.250 ***	-0.036 ***
VRES	0.773 ***	0.249 ***		0.278 ***	0.967 ***	0.317 ***	0.912 ***	0.344 ***	0.866 ***	-0.073 ***
Value_D	0.792 ***	0.963 ***	0.315 ***		0.247 ***	0.896 ***	0.270 ***	0.918 ***	0.239 ***	-0.032 ***
VRES_D	0.768 ***	0.287 ***	0.956 ***	0.269 ***		0.327 ***	0.882 ***	0.327 ***	0.887 ***	-0.063 ***
Value_Ind	0.807 ***	0.929 ***	0.368 ***	0.906 ***	0.384 ***		0.227 ***	0.956 ***	0.240 ***	-0.035 ***
VRES_Ind	0.720 ***	0.246 ***	0.909 ***	0.296 ***	0.876 ***	0.223 ***		0.272 ***	0.938 ***	-0.072 ***
Value_D,Ind	0.823 ***	0.896 ***	0.415 ***	0.925 ***	0.392 ***	0.959 ***	0.300 ***		0.220 ***	-0.032 ***
VRES_D,Ind	0.691 ***	0.248 ***	0.853 ***	0.246 ***	0.884 ***	0.240 ***	0.927 ***	0.210 ***		-0.063 ***
AR	0.083 ***	0.095 ***	0.032 ***	0.104 ***	0.023 ***	0.089 ***	0.032 ***	0.096 ***	0.022 ***	

Table A (continued)

Panel C – No Analyst Coverage Sample

	Price	Value	VRES	Value_D	VRES_D	Value_Ind	VRES_Ind	Value_D,Ind	VRES_D,Ind	AR
Price		0.839 ***	0.323 ***	0.843 ***	0.322 ***	0.871 ***	0.307 ***	0.896 ***	0.301 ***	-0.014 *
Value	0.780 ***		0.163 ***	0.959 ***	0.192 ***	0.952 ***	0.163 ***	0.918 ***	0.180 ***	0.002
VRES	0.681 ***	0.120 ***		0.175 ***	0.968 ***	0.208 ***	0.860 ***	0.224 ***	0.820 ***	-0.069 ***
Value_D	0.779 ***	0.973 ***	0.158 ***		0.170 ***	0.925 ***	0.171 ***	0.932 ***	0.171 ***	0.003
VRES_D	0.706 ***	0.197 ***	0.955 ***	0.152 ***		0.226 ***	0.838 ***	0.227 ***	0.834 ***	-0.076 ***
Value_Ind	0.797 ***	0.915 ***	0.249 ***	0.896 ***	0.298 ***		0.139 ***	0.962 ***	0.172 ***	-0.002
VRES_Ind	0.610 ***	0.131 ***	0.861 ***	0.153 ***	0.831 ***	0.052 ***		0.177 ***	0.899 ***	-0.075 ***
Value_D,Ind	0.797 ***	0.890 ***	0.279 ***	0.896 ***	0.304 ***	0.940 ***	0.146 ***		0.145 ***	0.000
VRES_D,Ind	0.606 ***	0.155 ***	0.816 ***	0.147 ***	0.830 ***	0.139 ***	0.884 ***	0.048 ***		-0.077 ***
AR	0.105 ***	0.171 ***	-0.021 ***	0.173 ***	-0.016 **	0.159 ***	-0.030 ***	0.159 ***	-0.030 ***	

[a] The number of observations for each correlation reflect the numbers reported in Table 1.

[b] See Table 1 for variable definitions.