Decomposing the Market, Industry, and Firm Components of Profitability: Implications for Forecasting[†]

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Abstract: We decompose firms' quarterly profitability into market, industry, and idiosyncratic components and then investigate whether this process results in improved forecasts relative to a random walk, as well as other forecasting models. In the overall sample, we find modest improvements relative to a random-walk forecast. We document considerable variation in forecast improvements, based on firms' sensitivities to market- and industry-wide profitability. We also document that the greatest improvements are found for loss firms, with certain sub-samples exhibiting superior forecasts up to 65 percent of the time. Our results provide context to when analysing market and industry information is most relevant in forecasting profitability.

Keywords: Market; Industry; Profitability; Forecasting

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Abstract: We decompose firms' quarterly profitability into market, industry, and idiosyncratic components and then investigate whether this process results in improved forecasts relative to a random walk, as well as other forecasting models. In the overall sample, we find modest improvements relative to a random-walk forecast. We document considerable variation in forecast improvements, based on firms' sensitivities to market- and industry-wide profitability. We also document that the greatest improvements are found for loss firms, with certain sub-samples exhibiting superior forecasts up to 65 percent of the time. Our results provide context to when analysing market and industry information is most relevant in forecasting profitability.

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1 Introduction

Firm earnings are one of the most widely reported summary measures of firm performance, used to assess historical performance, as well as being a critical input into forecasting firms' expected values. A broad literature examines how available information about firm earnings can be utilized to facilitate the generation of more accurate forecasts. This study contributes to this literature by decomposing a firm's earnings into its three core components – a common market component, an industry-wide component, and a firm-idiosyncratic component – and then documenting how forecasts based on this decomposition results in superior forecasts of future profitability.[1] Yohn (2015) states that a central goal of financial statement analysis is to improve fundamental analysis in order to generate improved profitability forecasts. We advance this literature by separately quantifying the macroeconomic, industry, and firm-idiosyncratic components of profitability and demonstrating when doing so results in superior forecasts of firm profitability.

Our study extends prior studies (e.g., Schmalensee 1985; Rumelt 1991; and McGahan and Porter 1997) that separate a firm's accounting profitability into market, industry and firm-idiosyncratic components. In contrast with this prior work, however, our decomposition allows for cross-sectional variation in the market and industry components of profitability based on the historical sensitivities of firm-specific profitability with market and industry average profitability, similar to the earnings betas employed in Beaver, Kettler, and Scholes (1970) and Jackson, Rountree, and Sivaramakrishnan (2016).

Our decomposition of firm profitability into its components mirrors the approach advocated by many financial statement analysis texts to begin the forecasting process by first understanding the economy, the industry, and a firm's strategy (see, for example, Lundholm and Sloan 2013 and Wahlen, Baginski, and Bradshaw 2015). We follow this logic and, in the

[1] We use the terms earnings and profitability interchangeably.

spirit of Beaver et al. (1970) and Jackson et al. (2016), we estimate firm-specific "betas" that quantify the average association between a firm's profitability (measured as return on net operating assets (*RNOA*)) and market-level and industry-level *RNOAs*. Market-level *RNOA* is the sum of total earnings in the market divided by the sum of total net operating assets (*NOA*) in quarter *q* based on all *Compustat* firms with available data; industry *RNOA* is the total earnings divided by total *NOA* in quarter *q* for all *Compustat* firms with available data in industry *j*, where industry is defined as the six-digit GICS industry consistent with the findings in Bhoraj, Lee and Oler (2003).[2] We use these values to estimate market and industry-level *RNOA* betas, which allow us to isolate the firm-idiosyncratic component of a firm's *RNOA*.

We document modest improvements in forecasting, relative to a simple random-walk model, for the overall sample. However, these improvements are a function of the sensitivity of a firm's earnings to the market and industry. Thus, while there are some settings where decomposing the RNOA leads to little or no improvements, in some situations the component breakdown substantially improves forecast accuracy. In fact, we find the greatest improvement when forecasting earnings for loss firms. Our results help to calibrate when the techniques offered by many financial statement texts concerning understanding the market and industry will be most beneficial. Our methodology provides an initial step in this process that has the potential to greatly enhance financial statement analysis.

2 Prior research and research design

2.1 Prior research

Our study is related to two broad areas of accounting research: (1) studies that consider the role that market and industry factors play in explaining firm-level profitability and returns

[2] We confirm the Bhoraj et al. (2003) general findings related to the use of GICS using data extending through 2014.

and (2) studies that explore the impact of decomposing and disaggregating financial statement information on the accuracy of earnings forecasts.

A broad literature documents that accounting profitability and firms' returns can be separated into market, industry and firm-specific components (e.g., Ayers and Freeman 1997; Brown and Ball 1967; Foster 1981; Han, Wild, and Ramesh 1989; King 1966; Piotroski and Roulstone 2004). For example, Brown and Ball's (1967) results suggest that firms' annual earnings innovations can be decomposed into market and industry components as well as firm-specific components. Other studies document intra-industry information transfers when firms release earnings (e.g., Foster 1981) or when a manager issues an earnings forecast (Han et al. 1989), suggesting that the earnings and earnings forecasts include industry as well as firm-specific information. Consistent with these findings and the view that economic fundamentals are significant drivers of firm-specific returns, King (1966) documents the covariance between stock prices and market and industry returns. Furthermore, Ayers and Freeman (1997) suggest that stock prices reflect the industry component of earnings earlier than the firm-specific component, while Piotroski and Roulstone (2004) document systematic associations between the relative proportions of market-level, industry-level, and firm-specific information in stock prices and the activities of three types of informed market participants. In sum, this research highlights the links between firm-specific earnings and returns and the magnitudes of market-level and industry-level information.

Our study is also closely related to work that examines the association between decomposed/disaggregated measures of firm profitability and market participants' reactions to earnings and the ability to provide superior *RNOA* forecasts (e.g., Call, Hewitt, Shevlin, and Yohn 2015; Esplin, Hewitt, Plumlee, and Yohn 2014; Fairfield and Yohn 2001; Fairfield, Ramnath, and Yohn 2009; Fairfield, Sweeney, and Yohn 1996; Soliman 2008; Hui, Nelson, and Yeung 2015). For example, Fairfield and Yohn (2001) find that decomposing *RNOA* into asset turnover and profit margin can help predict future changes in *RNOA*, while Soliman (2008) provides evidence that this decomposition helps explain market responses to earnings. Esplin et al. (2014) document that disaggregating financial statements into operating and financing activities leads to superior profitability forecasts, but only when the component forecasting approach is used. Fairfield et al. (2009) examine whether and how industry-level analyses influences the superiority of firm-level profitability forecasts. They find that relying on industry-level analysis improves forecasts of growth but not of profitability. In general, this literature seeks to provide empirical evidence of how and whether disaggregating or decomposing firm profitability enhances the usefulness of that value or leads to superior forecasts of the same. We extend this work by exploiting the relationship between the market-level and industry-level *RNOA* components to guide the forecasting process.

2.2 Research design

Our goal is to provide empirical evidence of the relative importance of the market-level, industry-level, and firm-idiosyncratic components of firm-level profitability and to understand how these components might be used to improve forecasts of future firm-level profitability.[3] Consistent with prior studies, we measure firm profitability and the related market and industry components of firm profitability *RNOA* (Esplin et al. 2014; Fairfield and Yohn 2001; Soliman 2008). *RNOA* is defined as operating income before depreciation scaled by average net operating assets.[4]

We present three sets of analyses. First, we estimate within-sample industry-level and market-level betas that capture the *historical* relation between firm-level *RNOA* and industry

[3] Bernard (1995) highlights the importance of profitability predictions, stating that profitability prediction ''is tantamount to the ability to approximate current value'' (p. 736). This view is echoed in Nissim and Penman (2001) who state ''the analysis of current financial statements should be guided by the 'predictive ability' criterion: any enhancement that improves forecasts is an innovation'' (p. 124).

[4] Specifically, RNOA = Operating Income (Compustat item OIADPQ)/ average Net Operating Assets (Compustat items PPENTQ + ACTQ – LCTQ).

and market-level *RNOAs*. The firm-specific component of *RNOA* is the difference between total firm *RNOA* and the fitted values of the industry and market-level *RNOAs*. Second, we examine the relative magnitudes and signs of the three components of total firm *RNOA* and document cross-firm and -industry differences in the relative importance of industry and market-level profitability. We also document differences in the persistence of three components. Third, we employ the within-sample industry and market betas to form out-of-sample forecasts of total firm *RNOA* and provide evidence of the superiority of those forecasts.

3 Variable measurement and sample

3.1 Variable measurement

Following Soliman (2008), we define *RNOA* as operating income after depreciation (OIADPQ) scaled by average net operating assets, i.e., net property, plant, and equipment plus current assets less current liabilities (PPENTQ + ACTQ − LCTQ) using quarterly Compustat data. Thus, firm-specific *RNOA* ($RNOA_{i,j,q}$) is firm *i's RNOA* in industry *j* in quarter *q*. To calculate the industry-level *RNOA* ($RNOA_{j,q}^{I}$) for firm *i*, we divide the sum of the operating income after depreciation for all firms in industry *j* in quarter *q* by the average net operating assets for the same set of firms. We exclude the income and net operating assets of firm *i,* and define industry as the six-digit GICS classification (Bhojraj et al. 2003). Market-level *RNOA* ($RNOA_{q}^{M}$) is similarly estimated as the sum of operating income after depreciation by the sum of average net operating assets for all firms in quarter *q*, excluding firm *i*.

$$RNOA_{j,q}^{I} = \frac{OAIDPQ_{j,q} - OIADP_{i,j,q}}{NOA_{j,q} - NOA_{i,j,q}}$$

$$RNOA_q^M = \frac{OAIDPQ_q - OIADPQ_{i,j,q}}{NOA_q - NOA_{i,j,q}} \qquad (1)$$

Many firms operate across multiple business lines and within different industries. It is impractical in our setting to identify the component of earnings and net operating assets that are attributable to different industries within a firm. Our identification of $RNOA^I$ therefore is based upon the main industry of firm *i*. Schroder and Yim (2016) show that industry-specific forecasts are more accurate when applied to single-segment firms, but not for multiple-segment firms.

We employ these measures and estimate our industry and market betas using a two-step procedure. First, to obtain a measure of industry profitability that is orthogonal to market profitability, we regress $RNOA^M$ on $RNOA^I$ and take the residual, ε. In the second step we regress the market and the industry profitability net of the market effect on firm *RNOA*,[5] where the beta estimates capture the sensitivity to market and industry earnings:

$$RNOA_{j,q}^I = \beta_0 + \beta_1 RNOA_q^M + \epsilon$$

$$RNOA_{i,j,q} = \beta'_0 + \beta'_1 \epsilon_{j,q} + \beta'_2 RNOA_q^M + \epsilon' \qquad (2)$$

This model allows us to decompose firm-specific *RNOAs* into three components.

We calculate the historical sensitivities of firm-specific *RNOA*s with market and industry-level *RNOA* using up to 20 quarters of data (minimum 10 quarters), similar to the earnings betas employed in Beaver et al. (1970) and Jackson et al. (2016). The fitted values from the second step in equation (2) are used to calculate estimates of the market component of *RNOA* ($MktRNOA_{i,q}$), the industry component of *RNOA* ($IndRNOA_{i,q}$), and the firm-idiosyncratic component of *RNOA* ($IdiosRNOA_{i,q}$) as:

$$MktRNOA_{i,j,q} = \beta'_2 * RNOA_q^M, \qquad (3a)$$

$$IndRNOA_{i,j,q} = \beta'_1 * RNOA_{j,q}^I, \quad \text{and} \qquad (3b)$$

[5] By definition, the residual from the first stage is independent of $RNOA^M$.

$$IdiosRNOAi,j,q=RNOAi,j,q-MktRNOAi,j,q-IndRNOAi,j,q. \quad (3c)$$

Effectively, $IdiosRNOA_{i,q}$ is equal to the intercept plus the residual in the second step of equation (2), such that a larger $IdiosRNOA_{i,q}$ is a result of a lower $\beta'1$ and $\beta'2$. $IdiosRNOA_{i,q}$ is the component of profitability over which managers have the most discretion. Jackson et al. (2016) find that firms that are less sensitive to market/industry level affects (i.e., those with greater $IdiosRNOA_{i,q}$) are more likely to manipulate their profitability signals. Whether this influences the predictability of future earnings is an empirical question we address in this study.

Our model does not constrain the market or industry betas to be positive, which allows the market and industry *RNOAs* to be contrarian to one another and/or to the firm-idiosyncratic *RNOA*.[6] We provide evidence of cross-industry differences in the beta estimates and of the time-series persistence of these betas. Finally, we use these betas and information about the firm-idiosyncratic component of *RNOA* to generate forecasts of future firm-level *RNOA* and provide empirical evidence of the superiority of those forecasts relative to random-walk forecasts. Our estimation of the historical relation between firm-level *RNOA* and market-level and industry-level *RNOA* allows us to assess cross-firm differences in how the market and industry relate to firm-level profitability and then to exploit these relations in forecasting future firm-level *RNOA*.

3.2 Sample

We use Compustat quarterly data to construct firm-level *RNOA*s, which are also used to form industry and market-level *RNOAs*. Our sample includes all firm-quarter observations with

[6] Our approach to estimating the market, industry, and firm-specific profitability components differs from previous studies. Hui et al. (2015), for example, estimate an equal-weighted industry earnings, where the difference between total earnings and the industry earnings is the firm-specific component. This approach, however, does not allow for differential sensitivities to industry-level (nor market-level) earnings, which is less important in their study given the focus on cash flows versus accruals.

March, June, September, or December fiscal-quarter end dates from 1976 through 2014 and with the data necessary to calculate *RNOA*.[7] Prior to 1976, quarterly data to calculate net operating assets is sparse hence the start of the sample period. We require that firms report non-negative values of net operating assets to comprise our final sample but include all firms, irrespective of the sign of net operating assets in the calculation of $RNOA^M$ and $RNOA^I$. We winsorize *RNOA* at the firm level at the 1st and 99th percentiles by quarter to minimize the impact of outliers. As the beta estimates are noisy, we delete observations after winsorization with industry or market betas less than -3 or greater than 3. The noise inherent in betas outside of these ranges has a significant influence on the estimation of *MktRNOA* and *IndRNOA*, and hence *IdiosRNOA*. We limit the final sample to "functional-industry" quarters (i.e., observations with at least five observations per industry-quarter, (Bhoraj et al. 2003)), and firms with *NOA* greater or equal than \$100 million. Our final sample with sufficient data to estimate the components of *RNOA* – i.e., *MktRNOA*, *IndRNOA*, and *IdiosRNOA* – is 200,018 quarterly observations. We use this sample to provide our descriptive statistics and tests of persistence. Our final sample used in the forecasting tests is reduced because of the requirement of 20 quarters of data to estimate the parameters to apply to our final sample of 75,993 quarterly observations in out-of-sample tests. Table 1 provides the full breakdown of our sample selection procedure.

Table 2 Panel A provides summary statistics for firm-specific *RNOA* and the market-level, industry-level, and firm-idiosyncratic components of *RNOA*, based on equations 3(a), 3(b), and 3(c). Mean (median) *RNOA* is 0.0412 (0.0348) and is positive 89.8% of the time. When we decompose *RNOA* into its three components, we find that all components are positive more than half the time (*MktRNOA* 58.7 percent, *IndRNOA* 71.0 percent, and

[7] Restricting the sample to calendar quarters assures that we properly align firms in time to calculate market and industry-level information on a contemporaneous basis.

IdiosRNOA 57.2 percent). Mean (median) *MktRNOA* is 0.0128 (0.0091), *IndRNOA* is 0.0179 (0.0128), and *IdiosRNOA* is 0.0105 (0.0106). Industry profitability beta (*iRNOAbeta*) has a mean (median) of 0.2729 (0.1961), and market profitability beta (*mRNOAbeta*) has a mean (median) of 0.4234 (0.3369) meaning most firms' earnings move in coordination with industry/market level earnings, but the sensitivities are significantly lower than 1 unlike return betas.

Panel B presents Spearman (above the diagonal) and Pearson (below the diagonal) correlation coefficients. The correlations between firm *RNOA* and the three *RNOA* components (market-level, industry-level, and idiosyncratic *RNOA*) are all positive. *IdiosRNOA* has the strongest correlation with firm *RNOA* (ϱ = 0.464 and 0.373), while *MktRNOA* has the weakest (ϱ = 0.046 and 0.044). The correlations between *MktRNOA* and *IndRNOA* are also positive (ϱ = 0.046 and 0.039), although the values are economically smaller. In contrast, the correlations between *MktRNOA*/*IndRNOA* and idiosyncratic *RNOA* components are significantly negative. The strongest correlations are between *MktRNOA* and *IdiosRNOA* (ϱ = -0.664 and -0.690), which imply that almost half the variation in *MktRNOA* is offset by the variation in *IdiosRNOA*. This is a mechanical relationship, as *IdiosRNOA* is a function of *MktRNOA* and *IndRNOA*. Since it is not possible to estimate all three components of *RNOA* simultaneously, we estimate the market and industry components first where the remaining piece from the regression in equation (3) is the estimate of the firm-specific portion of *RNOA*.

Panel C of Table 2 reports the number of quarterly observations that fall into each of the eight possible combinations of positive/negative signs of *MktRNOA*, *IndRNOA*, and *IdiosRNOA*. We find that firm *RNOA* is most frequently a sum of positive *MktRNOA* and *IndRNOA* and negative *IdiosRNOA* (column (2)) – 31.7 percent of the time. About a quarter of the time (24.1 percent of the time) firm *RNOA* is a sum of negative *MktRNOA* and positive

IndRNOA and *IdiosRNOA* (column (5)). The fewest number of observations are found when total firm *RNOA* is made up of three negative components (0.3 percent of the sample) or when only *IndRNOA* is positive (5.0 percent of the sample).

In Panel D of Table 2 we report a measure of the relative proportion of the three *RNOA* components. Specifically, we calculate the proportion of total profitability that is attributable to *MktRNOA*, *IndRNOA*, and *IdiosRNOA* for each firm quarter, which we label as *news*. As noted earlier, at a firm level, *MktRNOA*, *IndRNOA*, and *IdiosRNOA* may be positive or negative; we use the absolute value of each component to calculate our news variables. Thus, these measures (defined below) capture the proportion of the sum of the absolute value of the three components that can be attributed to the market, the industry, or the idiosyncratic portion of *RNOA*. Specifically,

$$MktNews_{i,q}=|MktRNOA_{i,q}||MktRNOA_{i,q}+|IndRNOA_{i,q}+|IdiosRNOA_{i,q}| \quad (4a)$$

$$IndNews_{i,q}=|IndRNOA_{i,q}||MktRNOA_{i,q}+|IndRNOA_{i,q}+|IdiosRNOA_{i,q}| \quad (4b)$$

$$IdiosNews_{i,q}=|IdiosRNOA_{i,q}||MktRNOA_{i,q}+|IndRNOA_{i,q}+IdiosRNOA_{i,q}| \quad (4c)$$

As reported in Panel D of Table 2, on average, idiosyncratic *RNOA* provides the greatest proportion of the sum of the components (mean of 42.29 percent). Even so, both market and industry *RNOA* (means of 32.18 and 25.53 percent) generally contribute a large portion of news. This is also consistent with the correlations reported in Panel B, where *IdiosRNOA* had the strongest correlation with *RNOA*. All components have significant cross-sectional variation, however. The greatest variation is found in *IdiosNews* (standard deviation of 0.2125). In sum, these findings support the potential usefulness of considering each of the three components of profitability in understanding the persistence of *RNOA* and forming forecasts of future *RNOA*. In the next section we document the persistence of the three components of firm *RNOA* and examine the benefit of exploiting information contained in those components in the forecasting process.

4 Results

4.1 Persistence

Similar to prior studies that have decomposed *RNOA* into its financial components (e.g., profitability margin, asset turnover) and documented differential persistence of those components (e.g., Amir, Kama, and Livnat 2011; Fairfield and Yohn 2001; Soliman 2008), we examine the differential persistence of the market, industry, and firm-idiosyncratic components of *RNOAs*. The results of our analyses are presented in Table 3.

We consider two measures of persistence, one based on lagged values (prior quarter) and one based on seasonality in quarterly values (the relevant quarter from the prior year). We present the results of estimating the persistence across the *RNOA* components using two approaches. First, we separately estimate persistence using a lagged specification (equations (5a and 5b)) and a seasonal specification (equations (6a and 6b)). We expect that, if profitability is best described using a seasonal specification, we should observe a greater adjusted R^2 from equations (6a and b) compared to equations (5a and b), respectively.

$$RNOA_{i,q} = \alpha_0 + \alpha_1 RNOA_{i,q-1} + \varepsilon \tag{5a}$$

$$RNOA_{i,q} = \alpha_0 + \alpha_1 MktRNOA_{i,q-1} + \alpha_2 IndRNOA_{i,q-1} + \alpha_3 IdiosRNOA_{i,q-1} + \varepsilon \tag{5b}$$

$$RNOA_{i,q} = \alpha_0 + \alpha_1 RNOA_{i,q-4} + \varepsilon \tag{6a}$$

$$RNOA_{i,q} = \alpha_0 + \alpha_1 MktRNOA_{i,q-4} + \alpha_2 IndRNOA_{i,q-4} + \alpha_3 IdiosRNOA_{i,q-4} + \varepsilon \tag{6b}$$

Our second approach incorporates *both* a lagged and a seasonal aspect into the model (equations 7a and b). Again, if profitability is best described using a seasonal specification, we would expect to observe a significantly larger co-efficient on the seasonal earnings compared to prior quarter's earnings.

$$RNOA_{i,q} = \alpha_0 + \alpha_1 RNOA_{i,q-1} + \alpha_2 RNOA_{i,q-4} + \varepsilon \tag{7a}$$

$$\begin{aligned} RNOA_{i,q} = {} & \alpha_0 + \alpha_1 MktRNOA_{i,q-1} + \alpha_2 IndRNOA_{i,q-1} + \alpha_3 IdiosRNOA_{i,q-1} \\ & + \alpha_4 MktRNOA_{i,q-4} + \alpha_5 IndRNOA_{i,q-4} + \alpha_6 IdiosRNOA_{i,q-4} + \varepsilon \end{aligned} \tag{7b}$$

The results of estimating these models are presented in Table 3 Panel A: Columns (1) through (3) present the results of estimating equations (5a), (6a), and (7a), respectively and columns (4) through (6) present the results of estimating equations (5b), (6b), and (7b), respectively. The measured persistence of *RNOA* and the overall explanatory power of the lagged *RNOA* model (coefficient of 0.783 and adjusted R^2 of 0.571) are significantly greater than the seasonal model (coefficient of 0.726 and adjusted R^2 of 0.494). The lagged *RNOA* figures closely align with the *annual* estimates from Esplin et al. (2014), suggesting that quarterly data is similarly persistent. When both the lagged and seasonal variables are included in the model (column 3), the persistence of lagged earnings (0.535) is significantly greater than that of seasonal earnings (0.368). Including both in the model increases the explanatory power by over 12 percent relative to including lagged values only, suggesting while current *RNOA* is largely predicted by lagged *RNOA*, there is a seasonal aspect as well.

Columns (4) through (6) present the results of estimating the persistence of the three *RNOA* components (models (5b), (6b), and (7b). Again we find the adjusted R^2 using lagged data is greater than when seasonal data is used and that including both in the model is superior to relying on just one. More importantly, columns (4) through (6) reveal that the *RNOA* components are differentially persistent. In both Columns (4) and (5), *MktRNOA* has the highest persistence, followed by *IdiosRNOA* and *IndRNOA*. All differences between the components are statistically different, as are the differences between lagged and seasonal earnings components in column (6).

We do note that the adjusted R^2 across the total and decomposed earnings components in Panel A of Table 2 does not show any improvements. However, this does not mean that forecasting will not be improved through use of the decomposition of *RNOA* into the market, industry, and idiosyncratic components. This is an empirical question that we address in out-of-sample tests.

We present similar analyses in panel B of Table 3. In this panel, however, the dependent variable is one of the components (*MktRNOA*, *IndRNOA*, or *IdiosRNOA*) and the explanatory variables are the corresponding lagged (q-1) or seasonal (q-4) values. Consistent with our earlier analysis, lagged data provides significantly more explanatory power than seasonal data. When we combine lagged and seasonal data into the same model the importance of the seasonal variables pales relative to the lagged values; the inclusion of both has no economic impact on the adjusted R^2s. Furthermore, we document that the persistence of the *RNOA* components relative to the future *RNOA* components (e.g., $MktRNOA_{q-1}$ relative to $MktRNOA_q$) is significantly greater than the persistence of the *RNOA* components relative to future RNOA (e.g., $MktRNOA_{q-1}$ relative to $RNOA_q$). For example, the coefficient on $MktRNOA_{q-1}$ in Column 4 of Panel A (the $RNOA_q$ regression model) is 0.790, while the coefficient on $MktRNOA_{q-1}$ in the $MktRNOA_q$ regression model in Panel B is 0.912. While these values are not directly comparable, they do suggest that the *MktRNOA* is highly persistent. Whether this greater persistence results in superior forecasts of *RNOA* is an empirical question we address below.

In untabulated analysis we then assess the persistence across GICS industries (six-digit GICS code).[8] When partitioned into industry there is a large variation in persistence. For the most part, the lagged *RNOA* and their components are more persistent than seasonal profitability. However, in 30 percent of industries (20 out of 68) the seasonal profitability is more persistent. These industries where seasonality is more persistent are concentrated in the Consumer Discretionaries, Consumer Staples and Utilities sectors. Indeed, seasonality is more persistent in all of the five industries that make up the Utilities sector.

Across the different industries there is also significant differences in the variance of the persistence parameters of the components. The results show that for a number of industries

[8] For purposes of brevity we do not tabulate the results from the 68 different GICS industries with data. Results are available from the authors upon request.

there is little variation between the three lagged coefficients, and for the three seasonal coefficients, and as a result little difference from the coefficient estimate for the total *RNOA*. Where the coefficients significantly vary, we would expect that using the decomposition of profitability into the market, industry and firm idiosyncratic components would work better within these industries.

Also of interest is that there is not always consistency in the components of earnings being entirely more persistent in lagged or seasonal profitability. Industries 203030 (Marine) and 402020 (Consumer Finance) are more persistent in lagged market and idiosyncratic *RNOA*, but the industry component is more persistent with seasonal data. On the other hand, industries 203050 (Transportation Infrastructure) and 252010 (Household Durables) are more persistent in the lagged data with *MktRNOA* and *IdiosRNOA*, but more persistent in the lagged *IndRNOA*. Overall, this analysis shows that while the results in Table 3 may hold over the pooled sample, there are differences within industries, which highlights the potential usefulness of the decomposition.

In sum, our results indicate that, on average, the persistent of quarterly *RNOA* and the market, industry, and firm-level components of *RNOA* is better captured using a simple (one period) lagged value than a seasonally-lagged value. In addition, consistent with Esplin et al. (2014), our persistence findings suggest that using a component approach to forecasting might yield superior forecasts. These finding have important implications for researchers in designing their tests across a number of settings. It is important to note that much of what we believe about forecasting and the superiority of seasonal data stems from time-series applications, whereas our results presented here makes use of panel data models. Given the advances in panel data estimations over time, our findings reveal that while both lagged and seasonal values are often incrementally informative from a forecasting perspective, studies should include the lagged values as opposed to adhering to a strictly seasonal model.

4.2 Forecasting

Our primary analysis examines the benefits of decomposing historical firm-specific *RNOA* into its components (e.g., market, industry, and idiosyncratic) when preparing forecasts of future profitability. In constructing the forecast, we include (1) a single lag (*lagged*), (2) a four-quarter lag (*seasonally-lagged*), and (3) both *lagged* and *seasonally-lagged* data to gauge the influence of using different lags on forecast accuracy. Although the results from Table 3 suggest that the within sample forecasts are improved when both lagged and seasonally-lagged data are included, the extent of this improvement is unknown in an out-of-sample setting, as well as when we allow for variation across industries.

We consider three different forecasting approaches drawn from the prior literature (Call et al. 2014 and Esplin et al. 2014). The first forecasting approach uses 5 years (20 quarters) of reported *RNOA* to estimate the historical parameter estimates. These estimates are then applied to a holdout sample (to avoid a look-ahead bias) to forecast next quarter's *RNOA*.[9] For consistency, we estimate this model using a single lag (*TP1*), a four-quarter lag (*TP4*), and both (*TP14*) using pooled data. Thus, the coefficient estimates vary across time as opposed to across industries and/or firms (the '*T*' stands for 'total *RNOA*' and the '*P*' for 'pooled'). Following Call et al. (2015), we also estimate each regression on a firm-specific basis ('*F*') instead of using pooled data. We estimate lagged, seasonally-lagged, and combined models: lagged (*TF1*), seasonally-lagged (*TF4*), and the combined (*TF14*) estimates of total *RNOA*.

Our second forecasting approach is an aggregate approach, as employed in Esplin et al.

[9] Our results are qualitatively the same if we use 10 years (i.e., 40 quarters) or 3 years (i.e., 12 quarters) of prior observations in forecasting earnings. Using a shorter time series is akin to setting the weights in later years to 1, and the earlier years to 0. Early research in time-series forecasting implies that later years should be weighted more heavily, however the approach has not been applied to panel data. The robustness of our findings to alternative estimation periods indicates that weighting more recent observations does not materially alter the superiority of alternate forecasting models.

(2014). This approach generates forecasts of *RNOA* based on the lagged values of the components in a single time-series regression model. We generate forecasts using lagged (*AP1*), seasonally-lagged (*AP4*) and combined (*AP14*) models with pooled data, as well as the corresponding firm-specific data (*AF1*, *AF4*, *AF14*).

The third and final approach is the components approach employed in Esplin et al. (2014). This approach generates forecasts of *RNOA* by first generating separate forecasts of each of the three components – *MktRNOA*, *IndRNOA*, and *IdiosRNOA* – and then combining these forecasted components into the forecasted *RNOA*. Similar to the other two approaches, we generate estimates by pooling all observations using lagged, seasonally lagged, and the combined model (*CP1*, *CP4*, *CP14*). In the final estimation, we again follow Esplin et al. (2014) and use all observations to forecast *MktRNOA*, only industry data to forecast *IndRNOA*, and estimate *IdiosRNOA* on a firm-specific basis (*CR1*, *CR4*, *CR14*). This last approach allows for an explicit relaxation of the assumption that profitability and growth of all firms reverts to a common benchmark at the same rate (Fairfield et al. 2009), while still allowing for industry and firm-specific reversions.

We evaluate the forecast accuracy of the models in out-of-sample tests. The baseline comparison forecast for all models is a simple random walk where the forecast is equal to the previous quarter's *RNOA* (*RW1*).

The results are presented in Table 4. Statistics are presented using each of the three forecasting approaches, based on lagged, seasonally-lagged, and the combined model as discussed above. We include mean and median signed and absolute forecast errors; the final column (% Superior) presents the proportion of observations where the absolute forecast error is smaller than the baseline (*RW1*) forecast error. We bold when % Superior is greater than 50 percent to highlight when the forecasting model shows *improvement* over *RW1*.

Consistent with Bradshaw, Drake, Myers, and Myers (2012), we find that only a few models actually perform better than a random walk (*RW1*).[10] In particular, the smallest mean (median) absolute forecast error in our sample is generated from using *AP14* (0.010 (0.007)), followed closely by *TP14* (0.010 (0.007)) and then *RW4* (0.011) and *RW1* (0.012). These models also produce the largest proportion of superior forecasts (over 50 percent of the time they are better than *RW1*), along with *RW4*. Consistent with the persistence results in Panel A of Table 2, the forecasting models that are more accurate incorporate both lagged and seasonally-lagged data. Additionally, in all instances the pooled models perform better than estimating on a firm-specific basis, which is intuitively appealing since it implies we learn more about firm-specific earnings by benchmarking it relative to other firms.

Table 5 Panel A presents the proportion of observations where the absolute forecast error is less than that obtained by using prior quarter's earnings to predict current earnings (*RW1*) (% Superior) after splitting the observations into the eight possible subsamples based on the sign of *MktRNOA*, *IndRNOA*, and *IdiosRNOA*. No clear pattern exists across the eight partitions as to which method is superior, however. Forecasts based on *TP14* and *AP14* provide the most consistent improvements relative to *RW1*. The final two columns show that almost all models provide superior forecasting to *RW1* when only *IdiosRNOA* is positive, or when all components are negative. Excluding these final two columns, it is also interesting to note that improvements in forecasting using *AP14* and *TP14* reach economically significant levels of 65% (*AP14* and *TP14* in Column (5)) and many others ranging from 55-57%.

Table 5, Panel B limits the sample to the 4,026 observations from loss firms, which generally are viewed as more problematic in forecasting terms since losses can only persist so long before a company goes bankrupt. In this setting, the combined model no longer dominates. For instance, *AP1* provides superior forecasts to *AP14* in four of the seven

[10] Bradshaw et al. (2012) also find that analyst forecasts generally do not outperform random walk forecasts. This, along with analysts not forecasting *RNOA* and a convoluted method to try to back out an analyst *RNOA* forecast from the *I/B/E/S* files is the reason we do not benchmark our approach against analyst forecasts.

groupings. Even more important is the potential for greatly improved forecasting relative to RW1 with superiority reaching 75.3% for *AP1* in column (2). We find that forecasts that incorporate the sensitivity to market, industry, and firm-specific factors often provide a mechanism to improve forecast accuracy, especially when forecasting subsequent to losses.

We then explore under which situations the aggregate-pooled approach using lagged and seasonal earnings (*AP14*) is superior, as found in Esplin et al. (2014). Table 6 presents results after sorting the sample into deciles based on firm size (market value of equity), growth (market-to-book), riskiness (leverage), the relative importance of the three components of *RNOA* (*MktNews*, *IndNews*, *FirmNews*), and the sensitivity of *RNOA* to the market and industry components of *RNOA* (*mRNOAbeta*, *iRNOAbeta*). We also present results after partitioning the sample by NBER Business Cycle (contraction and expansion), and between profit and loss firms.

The first column in each panel provides the mean absolute forecast improvement relative to our benchmark (*RW1*), i.e.,the difference between the mean absolute forecast error for the aggregate pooled approach and the mean absolute error for *RW1*. The second column provides the proportion of observations that are superior to the benchmark (% Superior). The final three columns provide the mean proportion of market, industry and firm-idiosyncratic news.

Using the deciles in Table 6, we are effectively testing in which settings the *AP14* approach would yield the greatest improvements, and hence, when it would be most useful as a forecasting tool. In general, we find that the aggregate approach works best in smaller firms (Panel A), the lowest market-to-book deciles (Panel B) with the exception of the lowest decile, and more highly levered firms (Panel C) mainly concentrated in deciles 7 to 9.

We also find that % Superior increases as the proportion of market news (*MktNews*, Panel D) decreases and the proportion of industry news (*IndNews*, Panel E) increases. No clear pattern exists for the proportion of firm idiosyncratic news (*IdiosNews*, Panel F) even though the difference between the highest and lowest deciles is statistically significant. The relation from *MktNews* and *IndNews* is confirmed when ranking firms into deciles based on the market and industry profitability betas, *mRNOAbeta* (Panel G) and *iRNOAbeta* (Panel H), respectively.

The results in Panel I are consistent with the improvements in forecasting using the aggregate approach is greater during contraction periods (recession) relative to expansion periods. However, the improvement (% Superior) is positive (greater than 50%) in both periods. We also observe that the portion of *RNOA* attributed to the market and idiosyncratic (industry) components is lower (greater) during contraction quarters relative to expansion quarters. While there are statistical differences between expansion and contraction periods, the economic significance is not meaningful. For profit firms (Panel J), while the % Superior is 59.2%, it is economically and statistically lower than the 64.7% for loss firms. Also, the improvement for loss firms (0.0064) is almost three times as large as for profit firms (0.0023).

We also note that across every subsample in Table 6, the superiority of *AP14* relative to *RW1* is greater than the superiority of *TP14*. This would suggest that the decomposition of *RNOA* into the market, industry and idiosyncratic components provides useful information above simply using total *RNOA*.

Finally, we analyse the forecast improvements using *AP14* across 67 industries.[11] Overall, we find that in 48 of the 67 industries (71.6 percent) the aggregate forecasting method provides (on average) more accurate forecasts of *RNOA* than using the *RW1* approach. When expanded to sectors (GICS two-digit codes), all industries within the

[11] Industry 452040 (Office Electronics) drops out from the sample due to having insufficient data in the out-of-sample tests. Again, we do not tabulate the results for purposes of brevity, but they are available upon request from the authors.

Consumer Discretionaries (25), Consumer Staples (30) and Utilities (55) are all above superior to *RW1* over 50 percent of the time, and six of the seven industries within the Financials sector (40) are above 50 percent.

The results would also support the *AP14* approach to be the most effective within the Leisure Equipment and Products (252020), Real Estate (404010), Electric Utilities (551010), Gas Utilities (551020), Multi-Utilities (551030) and Water Utilities (551040) where the superiority over a random walk is greater than 75 percent. These industries are all characterised by having amongst the most variance in the coefficients on the market, industry and idiosyncratic components of *RNOA*, which we expected would be the industries who would benefit the most from the decomposition. Of the other industries with the greatest degree of variance in the coefficients, the *% Superior* of *AP14* in the industries is greater than 62 percent.

5 Conclusions

In this study we develop a method for decomposing profitability into three components: a market component, an industry component, and a firm-idiosyncratic component. We calculate the three components and document that they are differentially persistent in terms of explaining future RNOA. Finally, we use these components in a forecasting setting and demonstrate that doing so generally provides superior forecasting ability compared to either a random walk or seasonal random walk.

Our study also provides evidence on the seasonality in quarterly profitability. While much of the extant research assumes (explicitly or implicitly) a seasonal pattern in quarterly profitability, our results suggest otherwise. Specifically, we demonstrate that, while there is persistence in seasonal profitability, the level of persistence is far outweighed by lagged profitability in most instances. When the three components of profitability (i.e., market, industry, and firm-idiosyncratic) are considered, the seasonal aspects of profitability are economically small compared with the prior quarter's earnings. Whether seasonality exists in quarterly revenues and expenses, however, is unaddressed in our research design.

While we develop a measure of decomposing earnings we acknowledge the method is noisy and data intensive. Specifically, we require up to 20 quarters (and at least 10 quarters) of prior profitability to calculate our betas, and those betas may be estimated with error. Future research may develop improved ways of decomposing profitability into the three components. Despite the noise in the estimations, however, our method is valid in applying an approach advocated in many financial statement texts in analysing firm performance.

References

Amir, E., I. Kama, and J. Livnat. 2011. Conditional versus unconditional persistence of RNOA components: implications for valuation. *Review of Accounting Studies*. (16): 302-327.

Ayers, B. and R. N. Freeman. 1997. Market assessment of industry and firm earnings information. *Journal of Accounting and Economics* 24 (2): 205-218.

Beaver, W., P. Kettler, and M. Scholes. 1970. The association between market determined and accounting determined risk measures. *The Accounting Review* 45 (4): 654-682.

Bernard, V. L. 1995. The Feltham-Ohlson framework: Implications for empiricists. *Contemporary Accounting Research* 11 (2): 733–747.

Bhojraj, S., C.M.C. Lee, and D.K. Oler. 2003. What's my line? A comparison of industry classification schemes for capital market research. *Journal of Accounting Research* 41 (5): 745-774.

Bradshaw, M.T., M.S. Drake, J.N. Myers, and L.A. Myers. 2012. A re-examination of analysts' superiority over time-series forecasts of annual earnings. *Review of Accounting Studies* 17 (4): 944-968.

Brown, P., and R. Ball. 1967. Some preliminary findings on the association between the earnings of a firm, its industry, and the economy. *Journal of Accounting Research* 5: 55-77.

Call, A.C., M. Hewitt, T. Shevlin, and T.L. Yohn. 2015. Firm-specific estimates of differential persistence and their incremental usefulness for forecasting and valuation. *The Accounting Review* forthcoming.

Esplin, A., M. Hewitt, M. Plumlee, and T.L. Yohn. 2014. Disaggregating operating and financial activities: Implications for forecasts of profitability. *Review of Accounting Studies* 19 (1): 328-362.

Fairfield, P., R. Sweeney, and T. Yohn. 1996. Accounting classification and the predictive content of earnings. *The Accounting Review* (July): 337–355.

Fairfield, P. and T. Yohn. 2001. Using asset turnover and profit margin to forecast changes in profitability. *Review of Accounting Studies* (December): 371–385.

Fairfield, P., S. Ramnath, and T. Yohn. 2009. Do industry-level analyses improve forecasts of financial performance? *Journal of Accounting Research* 47 (1): 147-178.

Foster, G. 1981. Intra-industry information transfers associated with earnings releases. *Journal of Accounting and Economics* 3 (3): 201-232.

Han, J., J. Wild, and K. Ramesh. 1989. Managers' earnings forecasts and intra-industry information transfers. *Journal of Accounting and Economics* 11 (1): 3-33.

Hui, K.W., K.K. Nelson, and P. E. Yeung. 2015. On the persistence and pricing of industry-wide and firm-specific earnings, cash flows and accruals. *Journal of Accounting and Economics* forthcoming.

Jackson, A.B., B.R. Rountree, and S. Sivaramakrishnan. 2016. Earnings co-movements and earnings manipulation. Working paper, UNSW Australia and Rice University.

King, B. 1966. Market and industry factors in stock price behavior. *Journal of Business* 39 (January): 139-190.

Kothari, S.P., and J. Shanken. 2003. Time-series coefficient variation in value-relevance regressions: A discussion of Core, Guay, and Van Buskirk and new evidence. *Journal of Accounting and Economics* 34 (1-3): 69-87.

Lundholm, R., and R. Sloan. 2013. *Equity Valuation and Analysis with eVal*. 3rd edition. New York, NY: McGraw-Hill Irwin.

McGahan, A.M., and M.E. Porter. 1997. How much does industry matter, really? *Strategic Management Journal* 18: 15-30.

Nissim, D. and S. Penman. 2001. Ratio analysis and equity valuation: From research to practice. *Review of Accounting Studies* (6): 109–154.

Piotroski, J., and D. Roulstone. 2004. The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review* 79 (4): 1119-1151.

Rumelt, R.P. 1991. How much does industry matter? *Strategic Management Journal* 12 (3): 167-185.

Schmalensee, R. 1985. Do markets differ much? *American Economic Review* 75 (3): 341-351.

Schroder, D., and A. Yim. 2016. Industry effects in firm and segment profitability forecasting. Working paper, University of London.

Soliman, M.T. 2008. The use of DuPont analysis by market participants. *The Accounting Review* 83 (3): 823-853.

Wahlen, J., S. Baginski, and M. Bradshaw. 2015. Financial Reporting, Financial Statement Analysis, and Valuation – A Strategic Perspective, 8th Edition, *South-Western Cengage Learning*

Yohn, T.L. 2015. Research on the use of financial statement information for forecasting profitability. *Accounting & Finance* forthcoming.

Appendix 1
Forecasting Classifications

		Lagged	Seasonal	Lagged and Seasonal
Random Walk		*RW1*	*RW4*	
TOTAL	*Pooled*	*TP1*	*TP4*	*TP14*
	Firm	*TF1*	*TF4*	*TF14*
AGGREGATE	*Pooled*	*AP1*	*AP4*	*AP14*
	Firm	*AF1*	*AF4*	*AF14*
COMPONENT	*Pooled*	*CP1*	*CP4*	*CP14*
	Revert	*CR1*	*CR4*	*CR14*

This appendix describes the methods used to forecast earnings for quarter *q+1*. Random walk forecasts of profitability are based on a quarterly or seasonal random-walk expectation. Thus, *RW1 (RW4) RNOA* forecasts for *q+1* equal reported *RNOA* in quarter *q* (*q-3*).

For each of the three additional methods used to forecast *RNOA* (TOTAL, AGGREGATE, and COMPONENT), we also employ a lagged, seasonal, and combined (lagged and seasonal) approach. The lagged approach limits the in-sample estimation to quarter *q RNOA*, the seasonal approach limits the in-sample estimation to quarter *q-3 RNOA*. Specifically, forecasts labelled Lagged include quarterly data from the use of a *pooled* method (where regression models include pooled observations across all firms to obtain quarter-specific coefficients). The total method uses total earnings over the prior 40 quarters to estimate the persistence coefficient to apply out-of-sample in forecasting quarter *q+1* earnings. The lagged approach only utilises current earnings (equation (A1a)), the seasonal approach utilizes quarter *q-3* earnings (equation (A1b)), while the lagged and seasonal approach includes earnings from quarter *q* and quarter *q-3* (equation (A1c)):

$$RNOA_{i,q} = \lambda_0 + \lambda_1 RNOA_{i,q-1} + \varepsilon \,, \qquad \text{(A1a)}$$

$$RNOA_{i,q} = \lambda_0 + \lambda_1 RNOA_{i,q-4} + \varepsilon \,, \qquad \text{(A1b)}$$

$$RNOA_{i,q} = \lambda_0 + \lambda_1 RNOA_{i,q-1} + \lambda_2 RNOA_{i,q-4} + \varepsilon \,. \qquad \text{(A1c)}$$

Forecast of future profitability ($RNOA_{i,q+1}$) are based on in-sample coefficients applied out-of-sample, as in equation (A2):

$$RNOA_{i,q+1} = \hat{\lambda}_1 * RNOA_{i,q} \,, \qquad \text{(A2a)}$$

$$RNOA_{i,q+1} = \hat{\lambda}_1 * RNOA_{i,q-3} \,, \qquad \text{(A2b)}$$

$$RNOA_{i,q+1} = \hat{\lambda}_1 * RNOA_{i,q} + \hat{\lambda}_2 * RNOA_{i,q} \,. \qquad \text{(A2c)}$$

Under the pooled method, we estimate equations (A1) using all observations to obtain quarter specific estimates. Under the firm method we allow for different persistence coefficients for each firm by only using firm-specific data in the regressions to obtain firm-quarter specific estimates.

The aggregate method allows for differential persistence parameters across the three components of earnings. As with the total method, we include models using lagged quarter earnings (equation (A3a)), seasonal earnings (equation (A3b)) and both lagged and seasonal earnings (equation (A3c)). We also estimate the coefficient parameters based on the pooled sample and on a firm-specific basis.

$$RNOA_{i,q} = \gamma_0 + \gamma_1 MktRNOA_{i,q-1} + \gamma_2 IndRNOA_{i,q-1} + \gamma_3 FirmRNOA_{i,q-1} + \varepsilon \qquad \text{(A3a)}$$

$$RNOA_{i,q} = \gamma_0 + \gamma_1 MktRNOA_{i,q-4} + \gamma_2 IndRNOA_{i,q-4} + \gamma_3 FirmRNOA_{i,q-4} + \varepsilon \qquad \text{(A3b)}$$

$$\begin{aligned} RNOA_{i,q} = {} & \gamma_0 + \gamma_1 MktRNOA_{i,q-1} + \gamma_2 MktRNOA_{i,q-4} + \gamma_3 IndRNOA_{i,q-1} + \\ & \gamma_4 IndRNOA_{i,q-4} + \gamma_5 FirmRNOA_{i,q-1} + \gamma_6 FirmRNOA_{i,q-4} + \varepsilon \end{aligned} \qquad \text{(A3c)}$$

The final approach we take is a components approach. Under the components approach we separately forecast the three components of earnings (for ease of exposition, we only state equation (A4) using current *RNOA*, but estimate it using seasonal and a combination of current and seasonal earnings).

$$MktRNOA_{t,q} = \phi_0 + \phi_1 MktRNOA_{t,q-1} + \varepsilon \ , \tag{A4a}$$

$$IndRNOA_{t,q} = \varphi_0 + \varphi_1 IndRNOA_{t,q-1} + \varepsilon \ , \tag{A4b}$$

$$FirmRNOA_{t,q} = \delta_0 + \delta_1 FirmRNOA_{t,q-1} + \varepsilon \ . \tag{A4c}$$

After calculating the separate components of earnings, we take the forecasts and combine them to arrive at our forecast of earnings for quarter *q+1*, as in equation (A5).

$$\begin{aligned} RNOA_{i,q+1} &= MktRNOA_{t,q+1} + IndRNOA_{t,q+1} + FirmRNOA_{t,q+1}, \\ RNOA_{i,q+1} &= \hat{\phi}_1 * MktRNOA_{t,q} + \hat{\varphi}_1 * IndRNOA_{t,q} + \hat{\delta}_1 * FirmRNOA_{t,q} \end{aligned} . \tag{A5}$$

Under the pooled components method we estimate equation (A4) using pooled data to determine quarter-specific coefficient parameters. Under the revert approach we estimate equation (A4a) using all pooled data for a quarter-specific estimate; equation (A4b) using all pooled data in each industry for an industry-quarter-specific parameter; and equation (A4c) using firm-specific data to obtain firm-specific estimates.

TABLE 1
Sample Selection

Total Observations with *RNOA*	963,974
less non March, June, September, December quarter-ends	175,442
Non-function industries	19,724
Negative *NOA*	53,851
Insufficient data to obtain *iRNOAbeta* or *mRNOAbeta*	172,051
Observations with *iRNOAbeta* or *mRNOAbeta* less than -3 or greater than +3	200,845
Missing $RNOA_{q-1}$ or $RNOA_{q-4}$	43,505
NOA less than $100 million	98,538
Total Sample for Persistence Tests	**200,018**
less missing 20 quarters of historical data, or one-quarter ahead *RNOA*	124,085
Total Sample for Out-of-Sample Forecasting Tests	**75,933**

TABLE 2
Profitability Decompositions

Panel A: Descriptive Statistics – Total and component RNOA measures

	Mean	Std Dev.	p1	Q1	Median	Q3	p99	% Pos
RNOA	0.0412	0.0469	-0.0700	0.0178	0.0348	0.0598	0.1908	89.8%
MktRNOA	0.0128	0.0545	-0.1230	-0.0189	0.0091	0.0462	0.1453	58.7%
IndRNOA	0.0179	0.0465	-0.1145	-0.0022	0.0128	0.0370	0.1610	71.0%
IdiosRNOA	0.0105	0.0821	-0.1926	-0.0342	0.0106	0.0511	0.2465	57.2%
mRNOAbeta	0.4234	0.8239	-1.8173	-0.0442	0.3369	0.8939	2.5943	
iRNOAbeta	0.2729	1.1380	-2.5502	-0.4097	0.1961	1.0041	2.8126	

Panel B: Correlations

	RNOA	*MktRNOA*	*IndRNOA*	*IdiosRNOA*
RNOA	-	0.046	0.136	0.464
MktRNOA	0.044	-	0.046	-0.664
IndRNOA	0.099	0.039	-	-0.519
IdiosRNOA	0.373	-0.690	-0.462	-

Panel C: Frequency of positive and negative RNOA components.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MktRNOA	+	+	+	+	-	-	-	-
IndRNOA	+	+	-	-	+	+	-	-
IdiosRNOA	+	-	+	-	+	-	+	-
N	20,338	63,312	21,974	21,974	48,293	10,068	23,750	552
%	10.2	31.7	11.0	5.9	24.1	5.0	11.9	0.3

Panel D: Descriptive Statistics – News measures

	Mean	Std Dev.	p1	Q1	Median	Q3	p99
MktNews	0.3218	0.1927	0.0078	0.1741	0.3067	0.4402	0.8381
IndNews	0.2553	0.1993	0.0029	0.0945	0.2103	0.3721	0.8123
IdiosNews	0.4229	0.2125	0.0156	0.2698	0.4201	0.5709	0.9011

This table presents summary statistics of our measures for the full sample (N = 200,018) – with sufficient data to estimate *RNOA* and market (*MktRNOA*), industry (*IndRNOA*), and firm-idiosyncratic (*IdiosRNOA*) components of profitability (*RNOA*) over the period 1978 to 2014. There is 1 observation where *MktRNOA*, *IndRNOA,* and *IdiosRNOA* are zero, so we are unable to calculate *MktNews*, *IndNews,* and *FirmNews*. Panel A presents descriptive statistics for the calculated total *RNOA*, market-level, industry-level, and firm-specific RNOAs. Panel B presents correlations among these measures. Panel C presents the proportion of the sample that falls within each of the eight possible combinations of positive/negative *RNOAs*. Panel D presents the ratio of the absolute value of each component *MktRNOA*, *IndRNOA,* and *IdiosRNOA* divided by the summation of the absolute value of all three components.

TABLE 3
Persistence Parameters

Panel A: Persistence of RNOA and components of RNOA

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.009	0.010	0.003	0.009	0.011	0.003
$RNOA_{q-1}$	0.783		0.535			
$RNOA_{q-4}$		0.726	0.368			
$MktRNOA_{q-1}$				0.790		0.545
$MktRNOA_{q-4}$					0.732	0.363
$IndRNOA_{q-1}$				0.769		0.516
$IndRNOA_{q-4}$					0.719	0.385
$IdiosRNOA_{q-1}$				0.785		0.540
$IdiosRNOA_{q-4}$					0.726	0.364
Adj R^2	0.571	0.494	0.641	0.571	0.494	0.641

Panel B: Persistence of RNOA components

	Intercept	q-1	q-4	Adj R^2
	0.001	0.912		0.836
$MktRNOA_q$	0.005		0.630	0.411
	0.001	0.947	-0.047	0.837
	0.002	0.875		0.765
	0.006		0.677	0.472
$IndRNOA_q$	0.002	0.793	0.113	0.772
	0.001	0.884		0.767
	0.002		0.680	0.465
$IdiosRNOA_q$	0.000	0.820	0.086	0.771

This table presents the results from estimating the persistence parameters. Panel A presents the results of regressing future *RNOA* on lagged and seasonal *RNOA* and on the *RNOA* components (*MktRNOA*, *IndRNOA*, and *IdiosRNOA*). Panel B presents the results of regressing current *MktRNOA*, *IndRNOA*, and *IdiosRNOA* on the relevant lagged and seasonal RNOA components. N=247,263. All coefficients are significant at less than the 1% level.

TABLE 4
Forecast Errors

	Forecast Error		**Absolute Forecast Error**		
	Mean	**Median**	**Mean**	**Median**	**% Superior**
RW1	0.000	-0.001	0.012	0.009	
RW4	0.000	0.000	0.011	0.007	**53.5%**
TP1	-0.008	-0.008	0.014	0.011	37.4%
TP4	-0.007	-0.006	0.013	0.009	47.3%
TP14	-0.002	-0.002	0.010	0.007	**59.4%**
TF1	-0.026	-0.023	0.028	0.023	20.6%
TF4	-0.022	-0.017	0.024	0.018	31.0%
TF14	-0.013	-0.011	0.017	0.013	37.6%
AP1	-0.009	-0.008	0.014	0.011	36.8%
AP4	-0.007	-0.006	0.013	0.009	47.2%
AP14	-0.002	-0.002	0.010	0.007	**59.5%**
AF1	-0.030	-0.027	0.034	0.028	17.7%
AF4	-0.021	-0.017	0.026	0.019	30.2%
AF14	-0.016	-0.014	0.026	0.019	28.8%
CP1	-0.004	-0.004	0.012	0.009	45.0%
CP4	-0.010	-0.008	0.014	0.010	42.6%
CP14	-0.003	-0.003	0.012	0.009	**51.3%**
CR1	-0.007	-0.006	0.017	0.012	36.8%
CR4	-0.014	-0.011	0.024	0.018	30.9%
CR14	-0.005	-0.004	0.016	0.012	40.0%

This table presents the mean and median forecast error (the difference between the reported *RNOA* and forecasted *RNOA*) and absolute forecast errors and the % Superior (the proportion of observations where the absolute forecast error is less than that obtained by *RW1* to predict current earnings). The forecasting methods (e.g., *RW4*, *TP1*, *TP4*) are defined in Appendix 1. N = 75,933.

TABLE 5
Superiority of Forecasting Methods

Panel A: All Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MktRNOA	+	+	+	+	-	-	-	-
IndRNOA	+	+	-	-	+	+	-	-
IdiosRNOA	+	-	+	-	+	-	+	-
RW4	**53.2%**	48.9%	49.6%	44.9%	**60.3%**	**50.7%**	**65.6%**	46.5%
TP1	34.8%	34.1%	38.8%	42.2%	37.7%	35.7%	39.5%	**69.8%**
TP4	40.2%	41.2%	45.8%	44.8%	**53.6%**	43.7%	**64.5%**	**55.8%**
TP14	**55.9%**	**55.3%**	**56.8%**	**55.4%**	**65.4%**	**56.3%**	**71.4%**	**62.8%**
TF1	12.1%	16.2%	27.7%	34.6%	16.6%	17.2%	23.9%	**55.8%**
TF4	18.6%	21.3%	32.1%	36.7%	36.1%	26.0%	**55.9%**	46.5%
TF14	26.3%	30.1%	40.8%	44.6%	39.7%	32.6%	**56.3%**	46.5%
AP1	34.5%	35.8%	37.4%	44.4%	36.5%	37.3%	35.2%	**69.8%**
AP4	40.4%	42.1%	45.5%	44.8%	**53.0%**	44.2%	**63.3%**	**55.8%**
AP14	**56.9%**	**56.2%**	**56.7%**	**54.9%**	**65.0%**	**56.6%**	**70.3%**	**65.1%**
AF1	10.7%	14.5%	23.9%	28.2%	14.3%	15.0%	18.9%	48.8%
AF4	20.4%	21.2%	31.0%	31.7%	36.2%	23.7%	**50.4%**	41.9%
AF14	22.0%	23.7%	30.8%	30.8%	31.2%	23.9%	40.3%	39.5%
CP1	45.7%	47.7%	46.3%	**54.7%**	42.3%	44.0%	37.2%	**72.1%**
CP4	32.5%	34.7%	40.6%	42.6%	**50.2%**	40.2%	**63.3%**	**60.5%**
CP14	**50.0%**	48.8%	**51.6%**	**51.4%**	**52.8%**	47.5%	**58.3%**	**62.8%**
CR1	37.8%	33.7%	43.0%	48.2%	31.0%	25.0%	48.4%	**72.1%**
CR4	23.7%	20.2%	36.8%	35.4%	31.8%	19.4%	**53.0%**	44.2%
CR14	40.6%	34.9%	43.5%	43.0%	39.2%	27.3%	**56.2%**	**55.8%**

Panel B: Loss Firms								
	All	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MktRNOA		+	+	+	-	-	-	-
IndRNOA		+	-	-	+	+	-	-
IdiosRNOA		-	+	-	+	-	+	-
RW4	**53.3%**	**53.6%**	**52.1%**	45.2%	**65.4%**	**54.8%**	**59.0%**	46.5%
TP1	**72.9%**	**78.4%**	**72.3%**	**70.1%**	**74.0%**	**74.1%**	**77.4%**	**69.8%**
TP4	**56.4%**	**59.8%**	**55.1%**	48.5%	**66.8%**	**57.5%**	**62.7%**	**55.8%**
TP14	**64.8%**	**68.0%**	**64.1%**	**59.5%**	**72.0%**	**64.9%**	**69.2%**	**62.8%**
TF1	**68.6%**	**71.1%**	**68.9%**	**64.5%**	**72.6%**	**65.7%**	**72.9%**	**55.8%**
TF4	**59.9%**	**63.9%**	**60.3%**	**52.9%**	**67.4%**	**57.2%**	**65.4%**	46.5%
TF14	**64.6%**	**69.1%**	**64.4%**	**58.0%**	**70.1%**	**63.8%**	**72.4%**	46.5%
AP1	**65.3%**	**75.3%**	**63.7%**	**69.1%**	**62.1%**	**71.9%**	**60.0%**	**69.8%**
AP4	**56.2%**	**59.8%**	**55.1%**	47.3%	**67.2%**	**57.8%**	**62.4%**	**55.8%**
AP14	**64.7%**	**68.0%**	**64.0%**	**59.1%**	**72.6%**	**65.1%**	**68.1%**	**65.1%**
AF1	43.6%	38.1%	42.4%	45.3%	48.5%	41.1%	43.0%	48.8%
AF4	49.0%	50.5%	47.7%	43.2%	**60.6%**	47.4%	**53.8%**	41.9%
AF14	44.3%	42.3%	44.6%	40.5%	49.7%	40.9%	47.5%	39.5%
CP1	**58.9%**	**77.3%**	**63.8%**	**71.2%**	31.5%	**53.7%**	45.7%	**72.1%**
CP4	**56.6%**	**58.8%**	**56.2%**	**50.3%**	**66.4%**	**52.6%**	**61.5%**	**60.5%**
CP14	**59.5%**	**66.0%**	**62.7%**	**60.9%**	**56.5%**	49.6%	**53.4%**	**62.8%**
CR1	47.2%	35.1%	**51.4%**	**55.8%**	20.6%	28.1%	**60.2%**	**72.1%**
CR4	44.5%	43.3%	41.8%	38.0%	**59.2%**	42.0%	**53.2%**	44.2%
CR14	49.4%	40.2%	**50.7%**	**50.8%**	48.5%	32.7%	**58.4%**	**55.8%**

This table presents the % Superior across eight subsamples, based on the signs of the components (*MktRNOA*, *IndRNOA*, and *IdiosRNOA*). Panel A includes the full sample, sorted into the eight subsamples. Panel B is limited to firm-quarters that report a loss, sorted into the eight subsamples. The forecasting methods (e.g., *RW4*, *TP1*, *TP4*) are defined in Appendix 1. N = 75,933 (4,026) in Panel A (Panel B).

TABLE 6
Aggregate Pooled Approach

Panel A: Size Deciles

	Improvement	% Superior	MktNews	IndNews	IdiosNews
Low	0.0028	59.8%	0.334	0.246	0.421
2	0.0028	59.5%	0.339	0.251	0.410
3	0.0024	58.6%	0.326	0.271	0.403
4	0.0029	59.7%	0.325	0.273	0.402
5	0.0025	58.8%	0.324	0.269	0.407
6	0.0022	58.7%	0.320	0.266	0.414
7	0.0017	56.7%	0.318	0.262	0.420
8	0.0018	56.6%	0.314	0.260	0.426
9	0.0017	56.2%	0.317	0.262	0.421
High	0.0008	51.9%	0.320	0.258	0.421
High - Low	-0.0020***	-7.8%***	-0.0134***	0.0126***	0.0008

Panel B: MTB Deciles

	Improvement	%Superior	MktNews	IndNews	IdiosNews
Low	0.0017	55.0%	0.345	0.248	0.407
2	0.0025	60.1%	0.335	0.267	0.398
3	0.0031	63.0%	0.323	0.284	0.393
4	0.0032	63.5%	0.323	0.281	0.396
5	0.0032	62.8%	0.320	0.279	0.401
6	0.0026	59.4%	0.319	0.269	0.412
7	0.0023	57.1%	0.324	0.255	0.421
8	0.0013	53.7%	0.325	0.252	0.423
9	0.0011	52.2%	0.316	0.243	0.442
High	0.0010	50.4%	0.308	0.239	0.452
High - Low	-0.0007***	-4.7%***	-0.0367***	-0.0091***	0.0458***

Panel C: Leverage Deciles

	Improvement	% Superior	MktNews	IndNews	IdiosNews
Low	0.0006	51.2%	0.340	0.227	0.433
2	0.0010	52.6%	0.343	0.229	0.429
3	0.0012	53.5%	0.339	0.242	0.419
4	0.0014	53.8%	0.338	0.239	0.424
5	0.0023	58.4%	0.333	0.256	0.411
6	0.0027	58.8%	0.313	0.285	0.402
7	0.0033	62.6%	0.303	0.296	0.401
8	0.0034	64.0%	0.301	0.291	0.408
9	0.0034	63.7%	0.308	0.289	0.403
High	0.0024	57.8%	0.320	0.266	0.414
High - Low	0.0017***	6.6%***	-0.019***	0.038***	-0.019***

Panel D: MktNews Deciles					
	Improvement	**% Superior**	**MktNews**	**IndNews**	**IdiosNews**
Low	0.0027	59.2%	0.039	0.386	0.575
2	0.0031	60.5%	0.109	0.356	0.535
3	0.0027	58.8%	0.172	0.331	0.498
4	0.0025	59.3%	0.229	0.310	0.461
5	0.0027	59.5%	0.281	0.283	0.436
6	0.0023	59.0%	0.332	0.255	0.414
7	0.0019	57.9%	0.383	0.228	0.388
8	0.0016	55.7%	0.444	0.197	0.359
9	0.0013	53.9%	0.534	0.162	0.304
High	0.0009	52.6%	0.714	0.111	0.174
High - Low	-0.0017***	-6.6%***	0.676***	-0.275***	-0.401***
Panel E: IndNews Deciles					
	Improvement	**% Superior**	**MktNews**	**IndNews**	**IdiosNews**
Low	0.0014	54.3%	0.423	0.018	0.559
2	0.0015	54.3%	0.406	0.057	0.537
3	0.0017	54.4%	0.385	0.099	0.516
4	0.0017	56.1%	0.368	0.143	0.489
5	0.0018	57.3%	0.353	0.190	0.458
6	0.0018	56.4%	0.331	0.242	0.427
7	0.0021	58.1%	0.308	0.302	0.390
8	0.0023	59.0%	0.279	0.380	0.341
9	0.0030	61.0%	0.237	0.496	0.267
High	0.0044	65.6%	0.147	0.691	0.162
High - Low	0.0031***	11.3%***	-0.276***	0.673***	-0.397***
Panel F: IdiosNews Deciles					
	Improvement	**% Superior**	**MktNews**	**IndNews**	**IdiosNews**
Low	0.0028	59.6%	0.472	0.463	0.064
2	0.0029	60.1%	0.420	0.409	0.171
3	0.0027	58.6%	0.393	0.352	0.254
4	0.0020	58.1%	0.375	0.304	0.321
5	0.0017	56.4%	0.357	0.265	0.378
6	0.0012	55.1%	0.338	0.231	0.430
7	0.0019	56.7%	0.309	0.202	0.489
8	0.0025	59.1%	0.265	0.167	0.567
9	0.0022	57.4%	0.200	0.138	0.662
High	0.0019	55.4%	0.107	0.086	0.807
High - Low	-0.0009***	-4.1%***	-0.365***	-0.377***	0.742***

Panel G: mRNOAbeta Deciles					
	Improvement	**% Superior**	**MktNews**	**IndNews**	**IdiosNews**
Low	0.0042	63.6%	0.362	0.191	0.447
2	0.0037	64.1%	0.301	0.258	0.441
3	0.0030	63.8%	0.226	0.307	0.467
4	0.0027	62.9%	0.118	0.349	0.533
5	0.0024	61.1%	0.082	0.387	0.531
6	0.0022	59.9%	0.258	0.332	0.411
7	0.0018	56.4%	0.372	0.281	0.347
8	0.0019	55.5%	0.448	0.234	0.318
9	0.0017	54.6%	0.494	0.191	0.315
High	0.0014	52.6%	0.501	0.150	0.349
High - Low	-0.0028**	-11.1%***	0.138***	-0.040***	-0.098***

Panel H: iRNOAbeta Deciles					
	Improvement	**% Superior**	**MktNews**	**IndNews**	**IdiosNews**
Low	0.0024	57.6%	0.272	0.230	0.498
2	0.0015	55.7%	0.338	0.112	0.550
3	0.0010	54.2%	0.391	0.036	0.573
4	0.0013	54.9%	0.374	0.133	0.493
5	0.0014	56.8%	0.349	0.222	0.429
6	0.0017	58.9%	0.334	0.290	0.376
7	0.0019	58.9%	0.312	0.349	0.339
8	0.0025	60.3%	0.287	0.399	0.314
9	0.0043	66.2%	0.268	0.435	0.297
High	0.0070	71.3%	0.238	0.475	0.287
High - Low	0.0046***	13.6%***	-0.034***	0.245***	-0.211***

Panel I: NBER Business Cycle					
	Improvement	**% Superior**	**MktNews**	**IndNews**	**IdiosNews**
Contraction	0.0022	57.8%	0.323	0.264	0.413
Expansion	0.0018	56.5%	0.328	0.244	0.429
Difference	0.0004***	1.3%***	-0.004***	0.020***	-0.016***

Panel J: Profit/Loss Firms					
	Improvement	**% Superior**	**MktNews**	**IndNews**	**IdiosNews**
Gain	0.0023	59.2%	0.314	0.272	0.414
Loss	0.0064	64.7%	0.348	0.201	0.451
Difference	0.0041***	5.6%***	0.034***	-0.071***	0.037***

This table presents the mean improvement in forecast accuracy relative to a random walk using prior quarter's earnings (*Improvement*), the percentage of forecasts more accurate than *RW1* (*% Surperior*), and the proportions of the total profitability that are explained by the market, industry, or firm-idiosyncratic components. N = 75,933.