Using Quarterly Earnings to Predict Stock Price

By

Huong N. Higgins
Worcester Polytechnic Institute
Department of Management
100 Institute Road
Worcester, MA 01609
Tel: (508) 831-5626
Fax: (508) 831-5720
Email: hhiggins@wpi.edu

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Abstract

This paper develops a stock price prediction model based on quarterly earnings forecasts. The prediction model is based on the residual income model by Ohlson (1995), and adjustment for auto-correlation by Higgins (2009). Prior research has not used quarterly data out of concern for seasonality, however seasonality can be removed by including four consecutive quarterly terms of abnormal earnings in each price equation. The prediction results suggest that quarterly earnings forecasts can be useful inputs to models of price forecasts.

Using Quarterly Earnings to Predicting Stock Price

1. Introduction

The Residual Income Model (RIM) by Ohlson (1995) is a widely used theoretical framework for equity valuation based on accounting data (see for example Tsay et al. 2008 and Higgins 2009). In the RIM, the stock price of a single firm is a function of book value, a series of abnormal earnings, and other information. Much prior research has applied the RIM using annual earnings, but has rarely used quarterly earnings, presumably to avoid seasonality in quarterly data. But financial analysts produce quarterly data more frequently, and therefore market participants are more sensitized to quarterly than annual data. Market participants also prefer price forecasts at quarterly rather than annual intervals for timely decision-making. For these reasons, valuation models based on quarterly data that can avoid the pitfalls of seasonality should be useful.

In this paper, I use the RIM to predict stock price using quarterly earnings data. To remove seasonality, I include a series of four quarterly earnings terms in the RIM, so that each price equation is based on a full year of information. This method of removing seasonality is as in Higgins and Lu (2009) and Higgins et al. (2005). I adjust for serial correlation to make forecasts based on time series data. Adjusting for serial correlation is necessary because it is a notorious problem in financial and economic data (Cochrane and Orcutt 1949, and Tsay 2002). Serial correlation is not apparently harmful in tests of association, but it leads to huge forecast errors. My method of adjusting for serial correlation is as Higgins (2009), who shows that one can reduce forecast errors substantially by jointly estimating the RIM regression and the time series models of the residual in the RIM.

To parallel the forecasting task of financial analysts, I aim to forecast without hindsight knowledge of actual earnings. Specifically, I define abnormal earnings as the difference between analyst forward earnings forecast (best knowledge of actual earnings) and the earnings number achieved under growth of book value at the normal discount rate. This approach recognizes analyst earnings forecasts as essential signals of firm valuation (following Frankel and Lee 1998, and Sougiannis and Yaekura 2001), that analyst information is fully and quickly reflected in stock price (see Yen and Lee 2008 for a thorough discussion of the efficient market hypothesis), and that time series information are useful (Dopuch et al. 2008).

Focusing on SP500 industrial firms, I use 24 quarters of data spanning Q1 1999 – Q4 2004, to estimate the prediction models, which I then use to predict stock prices in a separate period spanning Q1 2005 - Q3 2006. Diagnostics performed on these data show that seasonality is not serious, suggesting that seasonality concerns are addressed when four abnormal earnings terms are included. The magnitudes of errors in stock price forecasts are relatively small, suggesting that quarterly earnings are useful inputs to models of stock price prediction.

This paper continues a line of research that studies firm valuation based on quarterly earnings. One problem of using quarterly data is that the researcher has to address seasonality, which is a difficult task. As a result of this difficulty, many studies do not address seasonal effects (as discussed by Lambert 2004). Due to quarterly interim reports in the U.S., a large number of studies use quarterly earnings to assess analysts' information and performance. However, studies that use quarterly earnings specifically for valuation or stock price forecasts are relatively rare. One exception is Bagnoli et al. (1999), whose focus is on whisper forecasts. Other exceptions are Higgins and Lu (2009), Ying et al. (2005) and Higgins et al. (2005), whose focus is on introducing a Bayesian approach, or contrasting Bayesian versus classical maximum-likelihood approaches. This paper contributes to this line of research by assessing the possibility of using analysts' quarterly earnings forecasts for price forecasting by simply relying on classical maximum-likelihood approaches.

The paper proceeds as follows. Section 2 reviews the theoretical RIM, and discusses its adaptations for empirical analyses. Section 3 discusses the empirical data and the methods to identify the time series properties of v_t. Section 4 describes the results of estimating jointly the RIM regressions and the time series models of v_t, and discusses the forecast results. Section 5 summarizes and concludes the paper.

2. The RIM

The RIM is a theoretical model which links stock price to book value, earnings in excess of a normal capital charge (abnormal earnings), and other information (v_t). Other information v_t can be interpreted as capturing value-relevant information about the firm's intangibles, which are poorly measured by financial numbers. This interpretation recognizes that a portion of valuation stems from factors not to be captured in financial statements. Other information v_t can also be interpreted as capturing different sorts of errors and noises, including model mis-specification, measurement error, serial correlation, and white noise. Given the possible imperfections of any valuation model, the content of v_t is elusive. Higgins (2009) uses statistical tools to address v_t to predict stock price.

2.1. The Theoretical RIM

In economics and finance, the traditional approach to value a single firm is based on the Dividend Discount Model (DDM), as described by Rubinstein (1976). This model defines the value of a firm as the present value of its expected future dividends.

$$P_t = \sum_{k=0}^{\infty}(1+r_t)^{-k}\left[d_{t+k}\right] \qquad (1)$$

where P_t is stock price, r_t is the discount rate, and d_t is dividend at time t. Equation (1) relates cum-dividend price at time t to an infinite series of discounted dividends where the series starts at time t.[1]

[1] Many prior RIM papers use ex-dividend price equations, the results of which carry through to relate price at time t to equity book value at time t and discounted abnormal earnings starting at

The idea of DDM implies that one should forecast dividends in order to estimate stock price. The DDM has disadvantages because dividends are arbitrarily determined, and many firms do not pay dividends. Moreover, market participants tend to focus on accounting information, especially earnings.

Starting from the DDM, Peasnell (1982) links dividends to fundamental accounting measurements such as book value of equity, and earnings:

$$bv_t = bv_{t-1} + x_t - d_t \qquad (2)$$

where bv_t is book value at time t. Ohlson (1995) refers to Equation (2) as the Clean Surplus Relation.

From Equation (2), dividends can be formulated in terms of book values and earnings:

$$d_t = x_t - (bv_t - bv_{t-1}) \qquad (3)$$

Define $x_t^a = x_t - r_t bv_{t-1}$, termed "abnormal earnings', to denote earnings minus a charge for the use of capital. (4)

From (3) and (4):

$$d_t = x_t^a - bv_t + (1 + r_t) * bv_{t-1} \qquad (5)$$

Rewriting Equation (1):

$$P_t = [d_t] + \frac{1}{1+r_t}[d_{t+1}] + \frac{1}{(1+r_t)^2}[d_{t+2}] + \frac{1}{(1+r_t)^3}[d_{t+3}] + ...$$

Using (5) to replace d_t, d_{t+1}, d_{t+2} … , in Equation (1) yields:

time t+1. This paper's Equation (1) uses cum-dividend price and carries through to relate price at time t to equity book value at time t-1 and discounted abnormal earnings at time t. This approach helps define abnormal earnings based on expected earnings of the contemporaneous period and therefore can aid the actual price forecast task. In other words, in linking price and contemporaneous abnormal earnings, this model parallels the forecaster's decision in forecasting stock price at a certain point in period t (starting at t-1 and ending at t), when her information consists of book value at the beginning of the year (bv_{t-1}), and earnings forecasts of the current year (x_t).

$$P_t = bv_{t-1} + \sum_{k=0}^{\infty}(1+r_t)^{-k}[x^a_{t+k}] \qquad (6),$$

provided that $\frac{bv_{t+n}}{(1+r_t)^n} \to 0$. As in Ohlson (1995), this provision is assumed satisfied.

I refer to Equation 6 as the theoretical RIM, which equates firm value to the previous book value and the present value of firm current and future abnormal earnings.[2]

2.2. Adapting the Theoretical RIM for Empirical Analyses – RIM Regression

In adapting the theoretical RIM for empirical analyses, approximation over a finite horizon is necessary, as it is impossible to incorporate an infinite stream of residual incomes. Higgins (2009) argues that it is possible to make decent price forecasts if the researcher captures the statistical properties of the truncated information and makes adjustments so that the RIM regressions conform to the regressions' assumptions. Specifically, she assumes Equation (6) over a finite horizon:

$$P_t = bv_{t-1} + \sum_{k=0}^{n}(1+r_t)^{-k}[x^a_{t+k}] + v_t \qquad (7)$$

and then applies statistical methods to address the regression error v_t. In Equation (7), stock price equals the sum of previous book value, the capitalization of a finite stream of abnormal earnings, and v_t, the capitalization of other information. In using beginning book value bv_{t-1}, abnormal earnings x^a_t is not double-counted on the right-hand-side.

The role of abnormal earnings is consistent with the intuition that a firm's stock price is driven by its generation of new wealth minus a charge for the use of capital. Abnormal earnings are new wealth above the normal growth from previous wealth, are not affected by dividend policy, and are defined at any levels of actual earnings depending on what the market perceives as the normal earnings levels if capital grows at a certain expected rate.

[2] This development of the theoretical RIM follows the steps described by Ohlson (1995), except that Ohlson (1995) uses ex-dividend price.

Re-expressing Equation (7) as a cross-sectional and time-series regression equation:

$$P_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{n} \beta_{k+2} x_{t+k}^a + v_t = \underset{\sim t}{x}' \underset{\sim}{\beta} + v_t \qquad (8)$$
$$k = 0,\ 1,\ 2,\ ...,n;\quad t = 1,\cdots,T.$$

where n is the finite number of periods in the horizon over which price can be well approximated based on accounting values, t is the number of intervals where price data are observed, P_t is stock price per share at time t, bv_{t-1} the beginning book value per share for the period beginning at t-1 and ending at t, x_t^a the abnormal earning per share of the period ending at time t, $\underset{\sim}{\beta} = (\beta_0, \cdots \beta_{n+2})'$ the vector of intercept and slope coefficients of the predictors, $\underset{\sim t}{x}' = (1, bv_t, x_t^a, x_{t+1}^a, ..., x_{t+n}^a)'$ the vector of intercept and predictors, and the regression error v_t. The intercept (β_0) is added to account for any systematic effects of omitted variables. Equation (8) describes the structure for empirical analyses, which I refer to as the RIM regression.

The term v_t should be thought of as capturing all non-accounting information used for valuation. It highlights the limitations of transaction-based accounting in determining share prices, because while prices can adjust immediately to new information about the firm's current and/or future profitability, generally accepted accounting principles primarily capture the value-relevance of new information through transactions. The term v_t can also be thought of as capturing different sorts of noises and errors, including pure white noise, and possibly model mis-specification, omitted variables, truncation error, serial dependence, ARCH disturbance, etc…

Higgins (2009) uses two criteria to assess v_t. One is whether v_t contributes to an adequate structure to capture valuation. Specifically, to ascertain that value can be well approximated by accounting variables in Equation (8), v_t must be normally distributed with zero mean and variance ($v_t \sim N(0, \sigma^2)$).Two is whether v_t has the statistical assumptions for regression analysis. Specifically, for Equation (8) to be used in regression analysis, v_t or its models must have the statistical properties that conform to regression assumptions of independent and identical distribution.

2.3. Implementing the RIM Regression with Quarterly Data

I start from Equation 8, using y_t as denoting the stock price per share at time t, bv_{t-1} the beginning book value per share at time t, x_t^a the abnormal earning per share of the period ending at time t, $\underset{\sim}{\beta} = (\beta_0, \cdots \beta_n)'$ the vector of intercept and slope coefficients of the predictors, $\underset{\sim t}{x}' = (1, bv_t, x_{t+1}^a, x_{t+2}^a, x_{t+3}^a, x_{t+4}^a, ...)'$ the vector of intercept and predictors, and the residual term v_t.

In implementing Equation 8 with quarterly data, I set n=3, to include four consecutive quarterly earnings terms. The purpose is to neutralize seasonality effects from individual quarterly items by adding them together to form a full year of earnings information in each equation. I use two distinct samples for estimating and for forecasting to better parallel the practical forecasting task. I use 24 quarters from Q1 1999 through Q4 2004 (the estimating sample) to estimate model parameters, which I subsequently apply to forecast stock prices in Q1 2005 through Q3 of 2006 (the forecast sample). For each included firm, the basic structure of my RIM regression is expressed as:

$$y_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{3} \beta_{k+2} x_{t+k}^a + v_t = \underset{\sim t}{x}' \underset{\sim}{\beta} + v_t \qquad (9)$$
$$k = 0, 1, 2, 3; \; t = 1, \cdots, 24.$$

where bv_{t-1} is book value at the beginning of the quarter, x_t is analyst quarterly earnings forecasts of the current quarter (I/B/E/S QTR1 forecasts), $x_{t+1}, x_{t+2}, x_{t+3}$ are quarterly earnings forecasts of 1, 2, and 3 quarters ahead (I/B/E/S QTR2, QTR3, and QTR4 forecasts), r_t is the normal rate of capital charge defined as the current quarterly Treasury bill rate, x_t^a is abnormal earnings in the current quarter defined as forecast earnings beyond a charge for the use of capital (or $x_t^a = x_t - r_t bv_{t-1}$), and $x_{t+1}^a, x_{t+2}^a, x_{t+3}^a$ are abnormal earnings in 1, 2, and 3, quarters ahead. In the quarters ahead, I define the normal level of book value to grow from the previous normal level, or $bv_t = bv_{t-1} * (1 + r_t)$. Therefore,

$$x_{t+1}^a = x_{t+1} - r_{t+1} bv_{t-1} * (1 + r_t),$$

$$x_{t+2}^a = x_{t+2} - r_{t+2} bv_{t-1} * (1 + r_t)^2,$$

$$x_{t+3}^a = x_{t+3} - r_{t+3} bv_{t-1} * (1 + r_t)^3.$$

It is not known a-priori whether a series of four quarterly abnormal earnings terms make an adequate structure to capture valuation, or whether Equation 9 meet the statistical assumptions for regression analyses. Therefore, diagnostics based on the actual data are necessary to ascertain the validity and applicability of Equation 9.

3. Data, Diagnostics and Identification of Time Series Patterns

3.1. Data

Sample firms are from the SP500 index as of May 2005. The choice of SP500 is to focus on the most established firms and to mitigate econometric problems due to scale differences (See Lo and Lys 2000, Barth and Kallapur 1996 for a discussion of scale differences and the consequences on regression results. Higgins (2009) examines three common scales and concludes that serial correlation exists in analyses using all three scales. [3] The selection criteria are:

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[3] Scale differences arise when large (small) firms have large (small) values of many variables. If the magnitudes of the differences are unrelated to the research question, they result in biased regression coefficients. Lo and Lys (2000) show that scale differences are severe enough to lead to opposite coefficient signs in RIM models. Barth and Kallapur (1996) argue that scale differences are problematic regardless of whether the variables are deflated or expressed in per-share form. Higgins (2009) argues that adjusting for serial correlation can reduce forecast error whether scale problems exist or not.

a) Price and book value data must be available continuously for 24 quarters, from Q1 1999 through Q4 2004 (Source: Worldscope and Datastream/Thomson Financial)

b) Quarterly earnings forecasts must be available for the current, and one, two, and three quarters ahead for all quarters (Source: I/B/E/S/Thomson Financial).

c) Book values must be greater than zero in all quarters.

d) Only industrial firms are included.

This selection process yields 172 firms for the estimation sample. Of those, 151 firms are includable in the forecast sample (2 firms have negative book value and 19 firms are de-listed in 2005). The most restrictive requirement is that firms must have quarterly earnings forecasts continuously for four quarters during the sample period, which slants the sample towards large, closely-followed firms. The date of each earnings forecast is the third Thursday of the last month in I/B/E/S QTR1 quarter.

Book value is computed as (total assets - total liabilities - preferred stock)/number of common shares. The number of common shares is adjusted for stock splits and dividends. Following this adjustment, for a firm that has stock split in any given year, its number of shares is reported assuming the split happens in all years in its history. Book value and price data are retrieved from Worldscope. Treasury bill rates are from Datastream, and earnings forecasts from I/B/E/S.

Table 1 shows the summary data in each included quarterly period. Q1 1999 through Q4 2004 constitute the estimation sample, which is the basis for identifying models and for forming estimation parameters. Q1 2005 through Q3 2006 is the forecast sample, the basis for assessing forecast performance by plugging results from the estimation sample to forecast sample's data. It can be seen that the estimation and forecast samples are distinct from each other, and there is an increasing trend over time in all tabulated values.

<Table 1 about here>

Table 2 shows summary descriptive statistics for the estimation sample in Panel A, and the forecast sample in Panel B. From Panel A for the estimation sample, the median values for price per share and book per share are \$31.85 and \$7.35, respectively. The median quarterly forecasts of the current quarter, and one, two, and three quarters ahead are \$0.30, \$0.32, \$0.34, and \$0.36, respectively. The median quarterly Treasury bill rate is 0.49%. From Panel B for the forecast sample, the median values for price per share and book per share are \$36.62 and \$11.39, respectively. The median quarterly forecasts of the current quarter, and one, two, and three quarters ahead are \$0.48, \$0.52, \$0.54, and \$0.56, respectively. The median quarterly Treasury bill rate is 0.96%. All values in the forecast sample are relatively larger than those in the estimation sample.

<Table 2 about here>

3.2. Diagnostics

To use Equation 9 in a regression analysis, the residual term v_t must be white noise, however this assumption is naïve. To determine more appropriate models than the naïve model, I assess the violations of this naïve model by examining the statistical properties of v_t and report the results in Table 3. Figures 1 and 2 in Table 3 summarizes the distribution of v_t, which shows near normality with a zero mean. Figure 3 is a time plot of v_t, with relatively constant variance, except for some very large residual terms occurring about Quarter 4 of 2001. Because a large v_t means higher actual prices than valued by the naïve model, the spikes in the time plot are consistent with serious overpricing of many stocks by Quarter 4 of 2001. The time plot does not reveal a seasonality pattern. Overall, v_t seems satisfactory in terms of normality, variance, and non-seasonality.

<Table 3 about here>

Because the estimation period includes multiple years, I expect strong serial correlation in all variables of Equation 9. Particularly, serial correlation in v_t would inflate the explanatory power of the estimation model, underestimate the estimated parameters' variances and invalidate the models' t and F tests (Neter et al. 1990). Therefore, serial correlation should result in inaccurate forecasts. Following Tsay (2002) and Shumway and Stoffer (2006), I use the autocorelation factors (ACF) and the partial autocorrelation factors (PACF) to assess the time series properties of v_t. The ACF in Figure 4, which is cut off at lag 12 for simpler exhibition, displays a nice exponential decay, indeed consistent with an autoregressive positive correlation. The PACF in Figure 5, which is also cut off at lag 12 for simplicity, shows a spike after lag 1 and lag 4, suggesting an AR (1, 4) structure. A SAS Proc Autoreg backstep procedure also identifies the structure AR(1, 4).

Figure 6 of Table 3 shows other statistics for testing the adequacy of the naïve model. Durbin-Watson D is small (0.3672), indicating strong positive correlation in the v_t series. Portmanteau Q is very large (1861.85), indicating that v_t is not white noise. Lagrange-Multiplier LM is very large (1859.87), indicating non-white noise and ARCH disturbances. These statistics are consistent with the findings in Figures 4 and 5, and further suggests volatility in the v_t series.

3.3 Identification of Time Series Models

From the diagnostics as discussed above, I consider the AR(1, 4) structure as the most appropriate time series model given my data. Substantively, it makes sense to think of the residual v_t to correlate with itself from the last quarter and from the same quarter the year before. To address volatility, I consider a basic GARCH model coupled with AR(1) following Tsay (2002) and Iqbal et al. (2007). For comparison, I also consider the naïve model and AR(1) model. Table 4 describes all the regression models employed: the naïve model, Model 2 which is AR(1), Model 3 which is AR(1 4), and Model 4 which is GARCH.

<Table 4 about here>

4. Results

4.1. Estimation

The estimated parameters of the fitted models are reported in Table 5. The columns contain the results for seven models: 1) the naïve model, 2) the AR(1) model, 3) the AR(1, 4) model, 4) the basic GARCH model coupled with AR(1). The rows show the estimated parameters and the tests of model adequacy.

<Table 5 about here>

For model adequacy, I use the Lagrange-Multipier (LM) test of white noise, and the Durbin-Watson (DW) test of serial correlation. It is difficult to attain white noise and non-serial correlation statistically, so LM and DW magnitudes should be used in this assessment. Small LM statistics are consistent with white noise. LM is very large in the naïve model (LM=2756.81), but is substantially reduced in Models 2-4 (LM=33.92, 43.59 and 18.78, respectively). DW close to 2 means no serial correlation. DW is very small in the naïve model (DW=0.37 as previously reported), but is substantially larger in Models 2-4 (D=1.75, 1.90, and 1.82, respectively). The total R-square value of all models are high, but after removing the serial correlation effect, the explanatory power of the structural model is measured by the regress R-square value, which is 17.09%, 17.55%, and 17.09%, in Models 2-4, respectively. Overall, the diagnostics show that Models 2-4 are adequate.

From the estimated parameters, book value per share is significantly positive in all models, except in the naïve model. The significance of book value underlines its role in valuation. However, the magnitude of book value is quite small compared to the parameter estimates for abnormal earnings in the same models. All four abnormal earnings terms are positive and highly significant in all models. Overall, the estimated results are consistent with the theoretical RIM, and consistent with the economic intuition that abnormal earnings are more important than book value in creating share value.

4.2. Forecast results

The forecasts are the corresponding regressions' predicted outputs for one quarter and multiple quarters beyond the estimation baseline (termed one-step-ahead forecasts and multiple-steps-ahead forecasts, respectively). They are computed based on estimation results from the estimation sample, which are applied to knowledge of beginning book values and quarterly earnings forecasts for the forecast years, and incorporated with the equivalent AR and GARCH parameters of v_t. Forecasts are measured as follows.

Model 1 - Naïve:

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x^a_{t+1} + \hat{\beta}_3 x^a_{t+2} + \hat{\beta}_4 x^a_{t+3} + \hat{\beta}_5 x^a_{t+4} = \underset{\sim}{x}'_{t+1} \underset{\sim}{\hat{\beta}}$$

$t = 24,...,30.$

Model 2 - AR(1):

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x^a_{t+1} + \hat{\beta}_3 x^a_{t+2} + \hat{\beta}_4 x^a_{t+3} + \hat{\beta}_5 x^a_{t+4} + \hat{\rho} v_t = \underset{\sim}{x}'_{t+1} \underset{\sim}{\hat{\beta}} + \hat{\rho} v_t$$

$$v_t = P_t - \hat{P}_t$$

$t = 24,...,30.$

Model 3 - AR(1,4):

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x^a_{t+1} + \hat{\beta}_3 x^a_{t+2} + \hat{\beta}_4 x^a_{t+3} + \hat{\beta}_5 x^a_{t+4} + \hat{\rho}_1 v_t + \hat{\rho}_2 v_{t-4} = \underset{\sim}{x}'_{t+1} \underset{\sim}{\hat{\beta}} + \hat{\rho}_1 v_t + \hat{\rho}_2 v_{t-4}$$

$$v_t = P_t - \hat{P}_t$$

$$v_{t-4} = P_{t-4} - \hat{P}_{t-4}$$

$t = 24,...,30.$

Model 4 - GARCH:

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x^a_{t+1} + \hat{\beta}_3 x^a_{t+2} + \hat{\beta}_4 x^a_{t+3} + \hat{\beta}_5 x^a_{t+4} + \hat{\rho}_1 \nu_t + \hat{\varepsilon}_{t+1} = \underset{\sim}{x}'_{t+1} \underset{\sim}{\hat{\beta}} + \hat{\rho}_1 \nu_t + \hat{\varepsilon}_{t+1}$$
$$\nu_t = P_t - \hat{P}_t$$
$$\varepsilon_{t+1} = h_{t+1} e_{t+1}$$
$$h^2_{t+1} = \alpha_0 + \alpha_1 \varepsilon^2_t + \gamma_1 h^2_t$$
$$e_{t+1} \sim N(0,1); \alpha_0 > 0, \alpha_1 \geq 0, \gamma_1 \geq 0; \alpha_1 + \gamma_1 < 1$$
$$t = 24,\ldots,30.$$

Empirically, it remains to be seen if the adjusted models are indeed better at predicting future stock prices. In the following, the forecast performance of each model is assessed based on three measurements, mean error (ME), mean absolute percentage error (MAPE), and mean squared percentage error (MSPE). ME, the difference between forecast and actual prices scaled by actual price, is a measure of forecast bias as it indicates whether forecast values are systematically lower or higher than actual values. MAPE, the absolute difference between forecast and actual prices scaled by actual price, is a measure of forecast accuracy. MSPE, the square of ME, is a measure of forecast accuracy that can accentuate large errors.

Table 6 shows the forecast results for Q1 2005 (one-step-ahead forecasts). All models have significantly positive MEs, indicating that model valuations are higher than actual price. Understandably, the naïve model has the largest ME (mean = 35.86%, median = 13.12%). The AR(1) model has a mean ME of 13.96%, slightly better than the AR(1, 4) model, which has a mean ME of 15.28%. The GARCH model has the lowest ME (mean = 10.01%, median = 4.21%).

<Table 6 about here>

As to the results of MAPE, the GARCH model has the smallest MAPE (mean = 17.85% and median = 9.61%). The mean MAPE of the AR(1) model is 20.42%, while that of the AR(1, 4) model is 21.37%. Similarly to the ME results, the MAPE results show that the GARCH model performs the best, followed by the AR(1) model, and the AR(1, 4) model. The naïve model produces the largest MAPE (mean = 46.08%, median = 23.09%).

The MSPE results also show the GARCH model to perform the best (mean = 8.34% and median 0.92%), followed by the AR(1) model (mean=11.46% and median=1.2%), and the AR(1,4) model (mean=12.90% and median=1.24%). The naïve model performs the worst (mean=96% and median=5.34%).

Table 7 shows the forecast results for multiple-steps ahead, Q2 2005 through Q3 2006. In the interest of space, only ME and MAPE results are shown. The GARCH model, which is the best performer, has MEs ranging from 0.68% to 8.81%, and MAPEs ranging from 18.58% to 27.22%. The naïve model is the worst, producing the largest MEs, which range from 22.16% to 33.67%. The naïve model also produces the largest MAPEs, ranging from 39.84% to 46.95%.

<Table 7 about here>

The following is a synthesis of Tables 6 and 7. First, it is clear that the naïve model performs the worst, most probably because the serial correlation of v_t is not addressed. This helps explain the large forecast errors documented in prior studies that do not adjust for serial correlation (Higgins 2009). Second, all models' forecasts tend to have positive MEs, indicating that valuation numbers are larger than actual prices, therefore applications of these results may be more suitable to sell decisions rather than buy decisions. The ME result is different from prior research that shows consistently lower valuations than actual price (Choi et al. 2006, DeChow et al. 1999, Myers 1999), and it is possible that the available time series of quarterly data spans a small number of years, mitigating the delisting bias that yields low valuations in prior research (Myers 1999). Fifth, the forecast performance does not decay fast as the forecast horizon lengthens, which is good for practical purposes because forecasters can make use of estimation results for many quarters. Finally, although the AR(1, 4) model is deemed more appropriate than the AR(1) model during the identification process, the AR(1, 4) performance is lower, perhaps because the importance of lag 4 is low yet its application is more complex. The GARCH results are the best, promising successful applications for the GARCH model in the future research.

6. Summary and Conclusion

Although the theoretical RIM is true for any interval, prior research has not employed quarterly forecasts, perhaps due to concerns for seasonality. This paper shows that seasonality is not a problem if four consecutive quarters are included in each price equation. The paper adapts the theoretical RIM by Ohlson (1995), which assumes an infinite stream of abnormal earnings, to a RIM regression with a finite number of abnormal earnings terms, specifically a stream of four quarterly terms of abnormal earnings, and then use statistical methods proposed by Higgins (2009) to address the truncated information.

Focusing on SP500 industrial firms, I use 24 quarters of data starting in Q1 1999 to estimate the prediction models, which I then use to predict stock prices in a separate period spanning Q1 2005 through Q3 2006. The data diagnostics show that a naïve RIM regression is satisfactory in terms of normality and seasonality, in other words, it is structurally adequate to capture values based on four terms of quarterly abnormal earnings; however, the diagnostics show strong auto-correlation, ARCH disturbances, and non-constant variances, which should lead to huge forecast errors. Therefore, using methods proposed by Higgins (2009), I augment the naïve model by incorporating time series errors and GARCH effects. My best one-quarter-ahead out-of-sample forecasts have absolute percentage errors in the range of 20%, and I also document low prediction errors for multiple quarters ahead. Overall, the paper shows that quarterly earnings forecasts can be useful inputs to stock price forecast models.

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Table 1 – Total Sample

Time	*N*	*Price per share*	*Book Value per share*	*Earnings forecast of the current quarter (EPS1)*	*Earnings forecast of one quarter ahead (EPS2)*	*Earnings forecast of two quarters ahead (EPS3)*	*Earnings forecast of three quarters ahead (EPS4)*
Estimation Sample							
Q1 1999	172	31.62	6.85	0.24	0.29	0.30	0.36
Q2 1999	172	34.60	6.91	0.28	0.30	0.36	0.32
Q3 1999	172	32.64	7.30	0.29	0.35	0.32	0.35
Q4 1999	172	39.59	7.39	0.35	0.31	0.35	0.36
Q1 2000	172	45.00	7.66	0.32	0.36	0.37	0.43
Q2 2000	172	44.50	7.84	0.38	0.39	0.45	0.41
Q3 2000	172	45.41	8.23	0.39	0.45	0.42	0.46
Q4 2000	172	39.90	8.69	0.44	0.40	0.44	0.45
Q1 2001	172	33.62	9.13	0.37	0.41	0.42	0.48
Q2 2001	172	35.68	9.63	0.38	0.38	0.45	0.42
Q3 2001	172	28.24	9.80	0.32	0.39	0.36	0.40
Q4 2001	172	33.43	10.11	0.31	0.30	0.34	0.35
Q1 2002	172	35.06	9.87	0.27	0.33	0.35	0.42
Q2 2002	172	30.41	9.78	0.32	0.34	0.42	0.37
Q3 2002	172	25.02	9.84	0.31	0.39	0.36	0.41
Q4 2002	172	26.65	10.02	0.37	0.33	0.38	0.37
Q1 2003	172	25.90	9.57	0.33	0.36	0.36	0.42
Q2 2003	172	29.96	9.76	0.35	0.35	0.42	0.37
Q3 2003	172	30.91	10.10	0.35	0.42	0.37	0.42
Q4 2003	172	35.10	10.28	0.41	0.36	0.41	0.41
Q1 2004	172	35.89	10.66	0.39	0.42	0.43	0.49
Q2 2004	172	36.96	10.97	0.47	0.45	0.52	0.48
Q3 2004	172	35.83	11.30	0.47	0.54	0.49	0.52
Q4 2004	172	39.42	11.57	0.54	0.50	0.53	0.53
Summary	4128	34.64	9.30	0.36	0.38	0.40	0.42
Forecast Sample							
Q1 2005	152	35.26	12.65	0.48	0.51	0.52	0.57
Q2 2005	154	36.23	12.84	0.52	0.53	0.57	0.55
Q3 2005	150	37.92	13.30	0.56	0.60	0.58	0.63
Q4 2005	153	38.75	13.89	0.60	0.59	0.64	0.65
Q1 2006	153	41.44	14.07	0.58	0.65	0.67	0.71
Q2 2006	144	40.19	14.72	0.66	0.69	0.73	0.70
Q3 2006	144	40.47	14.60	0.66	0.70	0.68	0.74
Summary	1050	38.57	13.72	0.58	0.61	0.63	0.65

This Table summarizes the sample of quarterly data used for extension analyses. Sample securities belong to industrial firms in the SP500 as of May 2005. Price and book value must be available continuously for 24 quarters, from Q1 1999 through Q4 2004 (from Worldscope and Datastream). Quarterly earnings forecasts must be available for the current, and one, two, and three quarters ahead for all quarters (EPS QTR1-QTR4 forecasts from I/B/E/S). Book values must be greater than zero in all quarters.

Table 2: Descriptive Statistics
Panel A: Estimation Sample (4128 firm-quarters in Q1 1999 – Q4 2004)

	Min	5%	25%	Median	75%	95%	Max	Mean
Price per share	1.6	8.08	20.55	31.85	45.15	69.19	293.56	34.64
Book Value per Share (BPS Beginning)	0.09	1.66	4.18	7.35	12.08	23.87	59.24	9.30
Quarterly earnings forecast of the current quarter (EPS0)	-0.49	-0.02	0.15	0.3	0.48	0.97	3.15	0.36
Quarterly earnings forecast of one quarter ahead (EPS1)	-0.42	0.0	0.16	0.32	0.515	0.98	2.63	0.38
Quarterly earnings forecast of two quarters ahead (EPS2)	-0.33	0.02	0.18	0.34	0.54	1.01	2.60	0.40
Quarterly earnings forecast of three quarters ahead (EPS3)	-0.46	0.03	0.19	0.36	0.55	1.04	2.56	0.42
Quarterly treasury bill rate	0.23	0.23	0.31	0.49	1.18	1.51	1.51	0.74

Panel B: Forecast Sample (1050 firm-quarters in Q1 2005 – Q3 2006)

	Min	5%	25%	Median	75%	95%	Max	Mean
Price per share	1.89	10.58	24.65	36.62	49.90	71.74	130.62	38.57
Book Value per Share (BPS Beginning)	0.23	3.17	6.68	11.39	18.38	32.06	54.06	13.72
Quarterly earnings forecast of the current quarter (EPS0)	-0.36	0.03	0.25	0.48	0.77	1.47	3.05	0.58
Quarterly earnings forecast of one quarter ahead (EPS1)	-0.32	0.05	0.29	0.52	0.79	1.50	2.56	0.61
Quarterly earnings forecast of two quarters ahead (EPS2)	-0.29	0.07	0.30	0.54	0.81	1.50	2.50	0.63
Quarterly earnings forecast of three quarters ahead (EPS3)	-0.27	0.08	0.31	0.56	0.84	1.58	2.90	0.65
Quarterly treasury bill rate	0.64	0.64	0.72	0.96	1.18	1.23	1.23	0.94

All values are reported in US dollars, except Treasury bill rate which is in %.
All firm data are adjusted for capital changes such as stock splits and stock dividends. Book value is computed as total assets minus total liabilities minus preferred stocks, divided by common shares outstanding. EPS forecasts are I/B/E/S QTR1-QTR4 forecasts. Quarterly treasury bill rate is market yield on U.S. Treasury securities at 1-year constant maturity and divided by four.

Table 3: Diagnostics of the Error Term in the Naïve RIM

N= 4128
Mean = 0
Median = -3.47
Range = 314.48
Interquartile range = 18.17
Standard Deviation = 17.71
Skewness = 3.89
Kurtosis = 36.10

Figure 1
Distribution

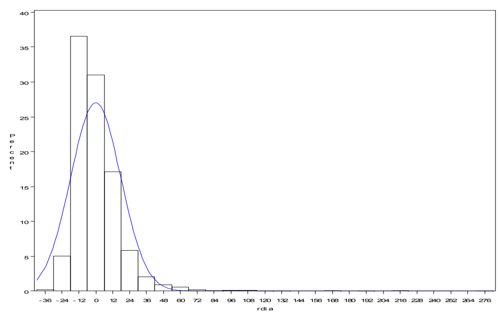

Figure 2
Histogram

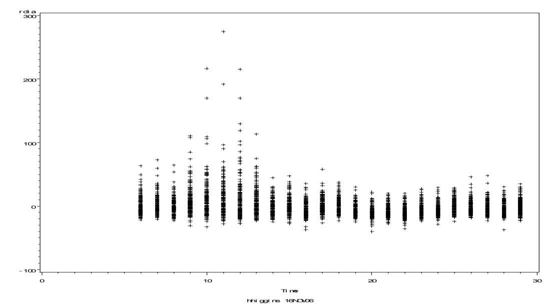

Figure 3
Time Plot

```
Lag  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1    |                    |********************|
2    |                   .|****************    |
3    |                   .|*************       |
4    |                   .|**********          |
5    |                   .|*******             |
6    |                   .|*****               |
7    |                   .|****                |
8    |                   .|***                 |
9    |                   .|**                  |
10   |                   .|*                   |
11   |                   .|.                   |
12   |                   .|.                   |
```

Figure 4
Autocorrelations (ACF)

```
Lag  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
1    |                   .|****************    |
2    |                  **|.                   |
3    |                   *|.                   |
4    |                   *|.                   |
5    |                   .|**                  |
6    |                   *|.                   |
7    |                   *|.                   |
8    |                   .|.                   |
9    |                   *|.                   |
10   |                   .|.                   |
11   |                   .|.                   |
12   |                   .|.                   |
```

Figure 5
Partial Autocorrelations (PACF)

Durbin-Watson D = 0.3672
Pr> D: <0.0001

Portmanteau Q=1861.85
Pr>Q: < 0.0001

Lagrange Multiplier = 1859.87
Pr>LM: <0.0001

Figure 6
Autocorrelation and ARCH disturbances

The diagnostics assess the appropriateness of the naïve RIM regression $y_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{3} \beta_{k+2} x^a_{t+k} + v_t$ where y_t is stock price per share at time t, bv_{t-1} is book value per share at the beginning of the current quarterly period which starts at t-1 and ends at t, and x^a_t is abnormal earnings and r_t is the Treasury bill rate of the quarterly period ending at t. Abnormal earnings are defined as follows: $x^a_t = x_t - r_t bv_{t-1}$, $x^a_{t+1} = x_{t+1} - r_{t+1} bv_{t-1} * (1+r_t)$, $x^a_{t+2} = x_{t+2} - r_{t+2} bv_{t-1} * (1+r_t)^2$, and $x^a_{t+3} = x_{t+3} - r_{t+3} bv_{t-1} * (1+r_t)^3$, where x_t, x_{t+1}, x_{t+2}, and x_{t+3} are EPS forecasts of the current quarter, and one-, two-, and three-quarters-ahead forecasts (I/B/E/S QTR1, QTR2, QTR3 and QTR4 forecasts, respectively). v_t is the regression error term.

Table 4 – RIM Regressions

	Model	Equation
1	Naïve	$y_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{3} \beta_{k+2} x_{t+k}^a + v_t, v_t = \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
2	AR(1)	$y_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{3} \beta_{k+2} x_{t+k}^a + v_t, v_t = \rho v_{t-1} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
3	AR(1, 4)	$y_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{3} \beta_{k+2} x_{t+k}^a + v_t, v_t = \rho_1 v_{t-1} + \rho_2 v_{t-4} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
4	GARCH	$y_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{3} \beta_{k+2} x_{t+k}^a + v_t, v_t = \rho_1 v_{t-1} + \varepsilon_t, \varepsilon_t = h_t e_t,$ $h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2, e_t \sim N(0,\sigma^2); \alpha_i > 0, i = 0,1; \beta_1 > 0; \alpha_1 + \beta_1 < 1$

This Table describes the RIM regressions identified from the diagnostics in Table 3. y_t is stock price per share at time t. bv_{t-1} is book value per share at the beginning of the current quarterly period which starts at t-1 and ends at t. x_t^a is abnormal earnings and r_t is the Treasury bill rate of the quarterly period ending at t. Abnormal earnings are defined as follows: $x_t^a = x_t - r_t bv_{t-1}$, $x_{t+1}^a = x_{t+1} - r_{t+1} bv_{t-1} * (1 + r_t)$, $x_{t+2}^a = x_{t+2} - r_{t+2} bv_{t-1} * (1 + r_t)^2$, and $x_{t+3}^a = x_{t+3} - r_{t+3} bv_{t-1} * (1 + r_t)^3$, where x_t, x_{t+1}, x_{t+2}, and x_{t+3} are EPS forecasts of the current quarter, and one-, two-, and three-quarters-ahead forecasts (I/B/E/S QTR1, QTR2, QTR3 and QTR4 forecasts, respectively). v_t is the regression error term, ε_t is the disturbance term. β_{0-5} are RIM regression parameters, ρ_{1-2} are AR parameters, and α_{0-1} and γ_1 are GARCH parameters. The naïve model does not adjust for autocorrelation. The AR(1) and AR(1,4) models assume v_t follows an AR(1) and and AR(1,4) structure, respectively. The GARCH model combines AR(1) and GARCH modeling of v_t.

Table 5: Estimation Results

Model Coefficients (P-value)		**Model 1 Naive**	**Model 2 AR(1)**	**Model 3 AR(1,4)**	**Model 4 GARCH**
β_0	Intercept	22.08 (<.0001)	21.86 (<.0001)	21.67 (<.0001)	14.59 (<.0001)
β_1	Book Value	-0.02 (.6926)	0.19 (.0012)	0.23 (.0001)	0.39 (<.0001)
β_2	QTR1 Abnormal Earnings	5.78 (=.0004)	8.21 (<.0001)	8.29 (<.0001)	9.53 (<.0001)
β_3	QTR2 Abnormal Earnings	6.57 (.0004)	6.69 (<.0001)	6.59 (<.0001)	8.48 (<.0001)
β_4	QTR2 Abnormal Earnings	12.37 (<.0001)	10.80 (<.0001)	10.65 (<.0001)	11.76 (<.0001)
β_5	QTR2 Abnormal Earnings	13.62 (<.0001)	8.22 (<.0001)	8.02 (<.0001)	9.48 (<.0001)
ρ_1	AR Parameter		0.82 (<.0001)	0.85 (<.0001)	0.83 (<.0001)
ρ_2	AR Parameter			-0.07 (<.0001)	
α_0	GARCH Parameter				17.37 (<.0001)
α_1	GARCH Parameter				0.38 (<.0001)
γ_1	GARCH Parameter				0.45 (<.0001)
N		4128	4128	4128	4128
Total R-square		26.71%	75.88%	76.14%	75.35%
Regress R-square		na	17.09%	17.55%	17.09%
Durbin-Watson		0.37	1.75	1.90	1.82
LaGrange Multiplier		2756.81	33.92	43.59	18.78

The regression models have the structural form $y_t = \beta_0 + \beta_1 bv_{t-1} + \sum_{k=0}^{3} \beta_{k+2} x_{t+k}^a + v_t$, where y_t is stock price per share at time t, bv_{t-1} is book value per share at the beginning of the current quarterly period which starts at t-1 and ends at t, x_t^a is abnormal earnings and r_t is the Treasury bill rate of the quarterly period ending at t. Abnormal earnings are defined as follows: $x_t^a = x_t - r_t bv_{t-1}$, $x_{t+1}^a = x_{t+1} - r_{t+1} bv_{t-1} * (1+r_t)$, , $x_{t+2}^a = x_{t+2} - r_{t+2} bv_{t-1} * (1+r_t)^2$ and $x_{t+3}^a = x_{t+3} - r_{t+3} bv_{t-1} * (1+r_t)^3$, where x_t , x_{t+1}, x_{t+2} , and x_{t+3} are EPS forecasts of the current quarter, and one-, two-, and three-quarters-ahead forecasts (I/B/E/S QTR1-QTR4 forecasts, respectively). v_t is the regression error term, β_{0-5} are RIM regression parameters, ρ_{1-2} are AR parameters, and α_{0-1} and γ_1 are GARCH parameters. The naïve model does not adjust for autocorrelation. The AR(1) and AR(1,4) models assume v_t follows an AR(1) and and AR(1,4) structure, respectively. The GARCH model combines AR(1) and GARCH modeling of v_t. Each model is assessed for explanatory power using regress R-square, autocorrelation using Durbin-Watson generalized test, and white noise using LaGrange Multiplier test.

Table 6: One-Step-Ahead Forecasts
Q1 2005 (N=152)

Mean Median	Model 1 Naïve	Model 2 AR(1)	Model 3 AR(1,4)	Model 4 GARCH
ME	35.86% 13.12%	13.96% 7.3%	15.28% 8.49%	10.1% 4.21%
MAPE	46.08% 23.09%	20.42% 10.98%	21.37% 11.12%	17.85% 9.61%
MSPE	96% 5.34%	11.46% 1.2%	12.9%*** 1.24%	8.34% 0.92%

Models 1-4 are as defined in Table 5: 1) the naive model, 2) the AR(1) model, 3) the AR(1, 4) model, and 4) the basic GARCH model with AR(1). The model equations are described in Table 4. The forecast results are assessed based on three forecast error measures. ME is the mean error, defined as the signed difference between forecast price and actual price scaled by actual price. MAPE is mean average percentage error, defined as the absolute difference between forecast price and actual price scaled by actual price. MSPE is the mean squared error, defined as the squared difference between forecast price and actual price scaled by the squared actual price.

Table 7: Multiple-Steps-Ahead Forecasts
Q2-2005 through Q3-2006

Mean **Median**	**Model 1** **Naïve**		**Model 2** **AR(1)**		**Model 3** **AR(1,4)**		**Model 4** **GARCH**	
	ME	MAPE	ME	MAPE	ME	MAPE	ME	MAPE
2-Step Ahead Forecasts Q2 2005 N=154	33.67% 10.37%	44.74% 21.37%	16.17% 6.96%	23.01% 12.84%	18.74% 8.72%	25.03% 12.6%	8.81% 2.8%	18.58% 9.61%
3-Step Ahead Forecasts Q3 2005 N=150	29.3% 9.54%	40.88% 19.42%	16.22% 7.51%	24.42% 13.63%	19.78% 10.08%	27.44% 13.2%	6.7% 1.03%	19.22% 10.67%
4-Step Ahead Forecasts Q4 2005 N=153	28.9% 5.93%	43.41% 21.51%	18.04% 8.04%	28.27% 15.22%	22.29% 8.85%	32.2% 16.26%	6.27% -0.68%	21.17% 12.41%
5-Step Ahead Forecasts Q1 2006 N=153	22.16% 1.8%	39.84% 20.72%	13.4% 1.77%	28.14% 15.79%	17.4% 2.87%	32% 17.07%	0.68% -5.73%	22.44% 15.09%
6-Step Ahead Forecasts Q2 2006 N=144	33% 7.12%	46.95% 21.09%	23.83% 6.2%	34.68% 18.47%	28.51% 8.33%	39.62% 18.21%	8.27% -1.81%	25.51% 15.15%
7-Step Ahead Forecasts Q3 2006 N=144	29.79% 3.55%	46.2% 23.03%	22.23% 2.87%	35.95% 18.26%	27.07% 5.05%	41% 19.92%	5.51% -6.58%	27.22% 18.04%

Models 1-4 are as defined in Table 5: 1) the naive model, 2) the AR(1) model, 3) the AR(1, 4) model, and 4) the basic GARCH model with AR(1). The model equations are described in Table 4. The forecast results are assessed based on two forecast error measures. ME is the mean error, defined as the signed difference between forecast price and actual price scaled by actual price. MAPE is mean average percentage error, defined as the absolute difference between forecast price and actual price scaled by actual price.