Predicting Stock Price based on the Residual Income Model, Regression with Time Series Error, and Quarterly Earnings.

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Abstract

Over the past decade of accounting research, the Residual Income Model (RIM) has been widely accepted as a theoretical framework for equity valuation (Peasnell 1982, Ohlson 1995, Penman and Sougiannis 1998, Frankel and Lee 1998, DeChow et al. 1999, Myers 1999, Francis et al. 2000, Sougiannis and Yaekura 2001, Baginsky and Wahlen 2003, Choi et al. 2006). The RIM models the stock price of a single firm as a function of book value, a series of abnormal earnings, and other information. In this paper, I present three distinctive features in applying the theoretical RIM. First, I discuss a method to employ quarterly information. Prior research has not used quarterly data out of concern for seasonality, but I show that seasonality can be removed by including four consecutive quarterly terms of abnormal earnings in each price equation. Second, I present a method to adapt the theoretical RIM to regressions that are more efficient for the task of forecasting stock price. Specifically, valuation is equated to the capitalization of book value, a finite stream of abnormal earnings, and other information not captured in earnings. This is different from prior studies that model other information as impacting stock price only via the earnings channel, thus creating an intermediate step in forecasting stock price, because future earnings must be estimated first. Third, I use out-of-sample forecasting, which is more appropriate than in-sample forecasting used in prior research. The results are price forecasts that are more accurate and less biased than currently reported in the literature.

Predicting Stock Price based on the Residual Income Model, Time Series Regressions, and Quarterly Earnings.

1. Introduction

The Residual Income Model (RIM) is a widely used theoretical framework for equity valuation based on accounting data (Peasnell 1982, Ohlson 1995, Penman and Sougiannis 1998, Frankel and Lee 1998, DeChow et al. 1999, Myers 1999, Francis et al. 2000, Sougiannis and Yaekura 2001, Baginsky and Wahlen 2003, Choi et al. 2006). In the RIM, the stock price of a single firm is a function of book value, a series of abnormal earnings, and other information captured via v_t. Prior research has applied the RIM using annual earnings, but not quarterly earnings, presumably to avoid seasonality in quarterly data. But of course, 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 very useful.

In this paper, I apply the RIM using quarterly earnings to benefit from quarterly information. 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. 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 forecasts as essential signals of firm valuation (Frankel and Lee 1998, Francis et al. 2000, Sougiannis and Yaekura 2001).

Besides using new data, this paper also discusses a new view of the theoretical RIM, specifically the role of other information captured in v_t. In prior research, v_t is modeled as impacting future abnormal earnings, but this creates an intermediate step in forecasting stock price because future earnings must be estimated first to estimate stock price. On the contrary, I model v_t as the error from truncating an infinite series of excess earnings to estimate valuation over a finite period. In this view, v_t impacts value directly, not via the earnings channel. In essence, this view recognizes that a near-zero portion of valuation stems from factors not to be captured in financial statements. This view results in more parsimonious RIM regressions, and therefore should help improve forecast accuracy. But for this view to be validated, v_t must have a zero-mean normal distribution, and for RIM regressions to work, v_t must meet the statistical regression assumptions. I show empirical diagnostics to validate this view and to capture the statistical properties of v_t. To begin, I focus on the violations of the naïve RIM regression, which assumes that v_t is white noise. As expected from including four consecutive quarters, the data diagnostics do not reveal a seasonal pattern in v_t. The diagnostics show that v_t is stationary and has nearly normal distribution, indicating that the RIM regression is structurally adequate to capture valuation, and therefore validating the theoretical RIM. However, the diagnostics show strong autocorrelation in v_t, which I address by using regressions with time series errors. The diagnostics also show volatility and variances in v_t, which I address with GARCH modeling and transformations. My procedure to identify the time series properties of v_t is as recommended by Tsay (2002) and Shumway and Stoffer (2005). After identifying the properties of v_t, I jointly estimate the RIM regression and the time series models of v_t. My prediction errors are very low compared with the current literature.

A third and distinctive feature of this paper is out-of-sample forecasting. Prior studies use in-sample forecasting, in other words, they do not separate the estimation period from the forecast period, resulting in artificially lower forecast error than true because hindsight information is incorporated in forecast values. However, hindsight information is not possible in a practical forecast context. 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. My forecast results are better than prior studies although I use out-of-sample forecasts while most prior studies do not.

For a brief review of prior forecast results, prior valuation studies based on the RIM have obtained very large forecast errors, although the RIM is found to produce more accurate forecasts than alternatives such as the dividend discount model and the free cash flow model (Penman and Sougiannis 1998, Francis et al. 2000). Forecast errors are disturbingly large, and valuations tend to understate stock price (Choi et al. 2006, Sougiannis and Yaekura 2001, Frankel and Lee 1998, DeChow et al. 1999, Myers 1999). Myers (1999), summarizing studies using in-sample forecasts, state that value estimates understate stock price by 10 to 40 percent on average. The errors are larger with out-of-sample forecasts. Barth et al. (2004), who use out-of-sample forecasts, report mean absolute prediction error above 160%. The large errors could be due to incorrect implementations of the valuation models, for example by assuming inappropriate terminal values, discount rates, and growth rate (Lundholm and O'Keefe 2001, Sougiannis and Yaekura 2001), or due to survival bias in the estimation data (Myers 1999). Despite the large errors, attempts to enrich the RIM with conditioning variables only yield worse results than the basic model (Myers

1999). Empirically, large forecast errors cast doubt on the RIM and the concept of accounting-based valuation. Table 1 summarizes the forecast results published in four top accounting journals since 1995, and one working paper by Barth et al. (2004), who use out-of-sample forecasts. As seen from Table 1, all papers yield very large forecast errors, except Courteau et al. (2001), however these authors incorporate Value Line analysts' price forecast in their own price forecasts, leaving less to say about the valuation roles of accounting variables in their models.

<Table 1 about here>

This paper is important for four reasons. First, this paper contributes to the theoretical discussion of the RIM by focusing on the role of other information captured via v_t. In this paper, v_t arises from truncating the theoretical RIM for empirical regression analysis, should be near zero if truncation is correct, and impacts value not via the earnings channel. In prior research, v_t impacts future abnormal earnings, requiring RIM regressions to estimate future earnings first before estimating stock price. While the prior approach is more favorable for the task of forecasting earnings, this paper's approach is more efficient for the task of forecasting stock price. Second, this paper validates the RIM by showing that the model can produce reasonable forecast accuracy for firms meeting stringent data requirements. It is notable that this paper obtains low forecast errors despite separating the estimation and forecast samples (out-of-sample forecasting). This method is more appropriate but produces higher error than when the forecast sample is included in estimation. Third, to my knowledge, this paper is the first to employ quarterly data in the RIM (except for a working paper by Higgins and Lu (2007)). Many investment professionals' activities and performance evaluations are tied to quarterly forecasts, however prior research has not provided applications for quarterly data. Fourth, this paper highlights the necessity to use statistical tools in adapting the theoretical RIM for empirical analyses. It demonstrates a method to implement the RIM by identifying the statistical properties of v_t to perform a joint estimation of the RIM and the time series model of v_t. Time series identification is based on sample data, rather than theoretically imposed. This paper also discusses the use transformations to adjust v_t for RIM regressions.

The paper proceeds as follows. Section 2 reviews the theoretical RIM, discusses its adaptations for empirical analyses, and contrasts the role of v_t in this paper from prior studies. 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 replicates the presented approach with different data. Section 6 summarizes and concludes the paper.

2. The RIM

2.1. Review of 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.

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

where

P_t is stock price at time t.

r_t is the discount rate during time period t.

d_t is dividend at time t.

$E_t[.]$ is the expectation operator.

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 the relation between book value of equity bv_t, earnings x_t and dividends d_t as the Clean Surplus Relation.

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

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

Assuming book value grows at the discount rate:

$$bv_t = (1 + r_t) * bv_{t-1} \qquad (4)$$

After substituting Equations (3) and (4) to Equation (1) to eliminate dividends, it can be shown that stock price is a function of only accounting variables:

$$P_t = \mathrm{E}_t\left[\sum_{k=0}^{\infty}(1 + r_t)^{-k}(x_{t+k} - r_t bv_{t+k-1})\right] \qquad (5)$$

In Equation 5, the theoretical value of the firm is equal to the present value of all its residual incomes (or abnormal earnings, or excess earning). Equation 5 is the theoretical RIM (Residual Income Model).

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

In practice, it is impossible to work with an infinite stream of residual incomes as in Equation 5, and approximations over finite horizons are necessary. If one assumes that firm value can be well approximated with accounting variables as in Equation 5 over a finite horizon, Equation (5) can be modified as:

$$P_t = bv_{t-1} + \sum_{k=0}^{n} (1+r_t)^{-k} (x_{t+k} - r_t bv_{t+k-1}) + v_t \qquad (6)$$

In Equation 6, firm value is the sum of previous book value, the capitalization of a finite stream of abnormal earnings, and v_t the capitalization of "other information".

Previous book value bv_{t-1} is added to reflect that, over a short horizon, it contributes to valuation of firms with zero or negative abnormal earnings. For example, book value serves as a value-relevant proxy of loss firms (Collins et al. 1999), and it reflects a firm's liquidation or abandonment value (Berger et al. 1996). The term v_t arises from truncating an infinite series to capture excess earnings over a finite horizon of n periods. If the finite horizon is adequate, the term v_t can be interpreted as the capitalization of "other information", in other words, information other than abnormal earnings that affects stock price. To ascertain that value can be well approximated by accounting variables in Equation 7, v_t must be near-zero. Then, Equation 6 is equivalent to the well-recognized valuation model expressed by Penman and Sougiannis (1998, Equation 3), who cite Preinreich (1938), Edwards and Bell (1961), and Peasnell (1982). 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. Note that beginning book value bv_{t-1} is used, because using an ending value would cause abnormal earnings x_t^a to be double-counted on the right hand side of the equation.

Re-expressing Equation 6 as a cross-sectional and time-series regression equation:

$$y_{it} = \beta_{i0} + \beta_{i1} bv_{it-1} + \sum_{k=0}^{n} \beta_{i,1+k} E_t[x_{i,t+k} - r_t bv_{i,t+k-1}] + v_{it} \tag{7}$$

where y is value, i denotes a firm, n the finite number of periods in the horizon over which the value of a firm can be well approximated based on accounting values, t is the number of intervals where price data are observed, and v_t is the regression error term.

For Equation 7 to be used in regression analysis, v_t must have the statistical properties that conform to regression assumptions. The manner in which v_t is addressed may well determine the empirical success of the RIM. Much empirical research motivated by Ohlson (1995) has set v_t to zero. Because v_t is unspecified, setting it to zero is of pragmatic interest, however, this would mean that only financial accounting data matter in equity valuation, a patently naïve view. More recent research has sought to address v_t, for example by assuming time series (Dechow et al. 1999, Callen and Morel 2001), and by assuming relations between v_t and other conditioning observables (Myers 1999). Alternatively, many studies assume a terminal value to succinctly capture the tail of the infinite series after the finite horizon (Courteau et al. 2001, Frankel and Lee 1998).

Gathering the term $E_t[x_{i,t+\tau} - r_t bv_{i,t+\tau-1}]$ as abnormal earnings $x_{i,t+k-1}^a$, Equation 7 can be rewritten as:

$$y_{it} = \beta_{i0} + \beta_{i1} bv_{it-1} + \sum_{k=0}^{n} \beta_{i,k+1} x^{a}_{i,t+k-1} + v_t = \underset{\sim t}{x}' \underset{\sim}{\beta} + v_t \qquad (8)$$
$$k = 0,\ 1,\ 2,\ ...,n;\quad t = 1,\cdots,T.$$

Equation 8 is the generic RIM regression. Different forms of this generic model result from different choices of n.

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^a_t 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, $\underset{\sim t}{x}' = (1, bv_t, x^a_{t+1}, x^a_{t+2}, x^a_{t+3}, x^a_{t+4}, ...)'$ 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. Differently from prior research, 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:

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

$$x^a_t = x_t - r_t bv_{t-1}$$

$$bv_t = bv_{t-1} * (1 + r_t)$$

The predictors in Equation (9) parallel analysts' information in their forecasting task: in the middle of quarter t, analysts' knowledge consists of book value at the beginning of the quarter (bv_{t-1}), quarterly earnings forecasts of the current quarter (x_t), quarterly earnings forecasts of 1, 2, and 3 quarters ahead ($x_{t+1}, x_{t+2}, x_{t+3}$), and the current quarterly Treasury bill rate (r_t).

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.

2.4. Contrasting Different Views of v_t

In essence, my formulation of the RIM may be viewed as the classic theoretical RIM (Equation 5) and the assumption that, over a finite horizon, price includes a portion v_t which is the capitalization of "other information". In this view, "other information" is value-relevant but not reflected in transaction-based accounting earnings. The best empirical models should capture the statistical properties of v_t. This way, although I cannot specifically define this "other information", I still can forecast stock price by modeling the statistical properties of v_t appropriately.

This approach is different from Ohlson (1995) and other studies that add the following information dynamics to the RIM regression:

$$x^a_{i,t+1} = \omega x^a_{i,t} + v_{it} + \varepsilon_{it+1}$$
$$v_{it} = \rho v_{i,t+1} + \varepsilon_{it}$$

where ω is the coefficient representing the persistence of abnormal earnings, and v_t follows an AR(1) autoregressive structure. This information dynamics links other information in the current period to future excess earnings, not to current stock price. It focuses on abnormal earnings and the issue of earnings persistence, which is favorable for the task of forecasting earnings, and is a fruitful way to study the properties of future earnings. But this focus creates an intermediate step for the task of forecasting stock price, because RIM regressions must estimate future abnormal earnings first before estimating stock price.

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). [1] The selection criteria are:

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.

[1] 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.

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. Therefore, for validity, Section 5 will discuss the robustness of this paper's methods to a different data type and a different sampling method.

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. Book value and price data are retrieved from Worldscope. Treasury bill rates are from Datastream, and earnings forecasts from I/B/E/S.

Table 2 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 2 about here>

Table 3 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 3 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 4. Figures 1 and 2 in Table 4 summarizes the distribution of v_t, which shows near normality with a zero mean. Figure 3 is a time plot of v_t, with relative stationarity, 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. A Phillips-Peron test finds non-stationarity at that time point, but a Dickey-Fuller test shows stationarity over the whole estimation period. The time plot does not reveal a seasonality pattern. Overall, v_t seems satisfactory in terms of normality, stationarity, and non-seasonality.

<Table 4 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 4 shows other statistics for testing the adequacy of the naïve model. Durbin-Waston D is small, indicating strong positive correlation in the v_t series. Portmanteau Q is very large, indicating that v_t is not white noise. Lagrange-Multiplier LM is very large, 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.

It should be noted that, in Equation 9 as in all RIM regression models in previous studies, the variables on the right-hand side correlate with each other strongly. For example, in my estimation sample, book value per share and the four consecutive quarterly terms of excess earnings are significantly correlated with each other at p-value < 0.0001. This is not surprising, given that book values and earnings are related accounting variables. Correlation among the right-hand-side variables is often termed multi-collinearity, a situation which does not invalidate the models' t and F tests, and tends not to affect predictions of new observations (Neter et al. 1990). In other words, multi-collinearity does not pose a problem for the forecasting task. However, multi-collinearity increases the variances of parameter estimates, therefore the simple interpretation of the regression coefficients as measuring marginal effects is unwarranted (Neter et al. 1990).

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. I also consider the following augmented models. To address volatility, I consider a basic GARCH model. Due to spikes of large value resulting in higher variances, I consider using various transformations (log, square root, and cubic root) to mitigate the impact of high variances. It is interesting to consider the transformed models because their structural forms do not originate from the theoretical development of the RIM, but they emerge as a statistical tool in the process of adapting the theoretical RIM for regression analyses. In fact, transformed models have the best statistical adequacy and, as will be discussed, also produce some of the best forecasts. For comparison, I also consider the naïve model and AR(1) model. Table 5 describes all the regression models employed.

<Table 5 about here>

4. Results

4.1. Estimation

The estimated parameters of the fitted models are reported in Table 6. 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, 5) the AR(1, 4) model with log transformation, 6) the AR(1, 4) model with square root transformation, 7) the AR(1, 4) model with cubic root transformation, respectively. The rows show the estimated parameters and the tests of model adequacy.

<Table 6 about here>

For model adequacy, I use the Dickey-Fuller (DF) test of stationarity, 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. All models meet the stationarity test, having significant DF statistics over the whole estimation period. This is not surprising, given that v_t from the naïve model itself is relatively stationary. Lagrange-Multiplier is very large in the naïve model (LM=2756.81), is substantially reduced in the untransformed models 2-4 (LM=33.92, 43.59 and 18.78, respectively), and is very small in the transformed models 3-7 (LM=0.23, 15.61, and 7.41 respectively). Small LM statistics are consistent with white noise, so the transformed models are the most adequate in this regard. Durbin-Watson, which I use as an indicator of serial correlation, is very small in the naïve model (DW=0.37 as previously reported), is substantially larger in model 2 (D=1.75), and is above 1.9 for all remaining models. Because a DW statistic close to 2 means no serial correlation, models 3-7 are adequate in this regard. 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 about 17% in the untransformed models 2-3, and about 21% in the transformed models 4-7. In the naïve model, which does not specify autocorrelation structure, the total R-square equals the regress R-square, which is 26.71%. With respect to explanatory power, the transformed models are the most adequate. Overall, the transformed models surface from the estimation process as the most adequate.

From the estimated parameters, book value per share is significantly positive in all models, except in the naïve model and model 5 where it is insignificant. 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 far more important than book value in creating share value. However, due to multi-collinearity as discussed in the diagnostics section, one should not interpret an estimated parameter as conveying any inherent effect, but only a partial effect given the other independent variables. For example, from Model 4, the estimated parameter for book value is 0.39, however the usual interpretation that "$1 of book value is associated with $0.39 in stock price" is unwarranted.

4.2. Forecast results

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 7 shows the forecast results for Q1 2005 (one-step-ahead forecasts). As presented, all models have significantly positive MEs, indicating that model valuations are higher than actual price. Understandably, the naïve model has the largest ME (mean = 36.46%, median = 14.21%). The AR(1) model has a mean ME of 14.82%, slightly better than the AR(1, 4) model, which has a mean ME of 16.08%. The log model has the smallest ME (mean = 8.06%, median = 2.08%). The basic GARCH model has the next to lowest ME (mean = 9.00%, median = 3.32%).

<Table 7 about here>

As to the results of MAPE, the GARCH model has the smallest MAPE (mean = 20.89% and median = 10.96%). The transformed models have comparably low MAPEs, with means ranging from 21.40%-22.57%. The mean MAPE of the AR(1) model is 24.53%, while that of the AR(1, 4) model is 25.18%. Similarly to the MAPE results, the MSPE results show that the GARCH model performs the best, followed closely by the transformed models, the AR(1) model, and the AR(1, 4) model. The naïve model produces the largest MAPE (mean = 47.84%, median = 23.01%).

Table 8 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. It can be seen that the transformed models are the best performers, followed by the GARCH model, the AR(1) model, and the AR(1,4) model. The transformed models produce the smallest MEs for most quarters. The log model, for example, has MEs equal to 0.64%, 1.66%, and 0.96% for Q2-Q4 2005, respectively, and has MAPEs equal to 9.10%, 10.53%, and 10.58% for those respective quarters. Collectively, the transformed models have MEs ranging from -4.43% to 9.91%, and MAPEs ranging from 9.10% to 13.56%. The GARCH model, the next best performer after the transformed models, has MEs ranging from 5.91% to 9.03%, and MAPEs ranging from 20.45% to 28.44%. The naïve model is the worst, producing the largest MEs, which range from 24.09% to 35.73%. The naïve model also produces the largest MAPEs, ranging from 49.14% to 41.37%.

<Table 8 about here>

The following is a synthesis of Tables 7 and 8. First, it is clear that the naïve model performs the worst, undoubtedly because the serial correlation of v_t is not addressed. This explains the large forecast errors documented in prior studies that do not adjust for serial correlation. Second, except for the naïve model, forecast bias and error of all models are better than documented by prior research, perhaps partially due to the characteristics of this paper's sample firms, which tend to be larger and better-followed than the typical firm captured in prior studies. But this paper's better forecast results may also be ascribed to more efficient modeling of the RIM (by specifying v_t to directly impact stock price), and/or finer data (using quarterly versus annual data), and future research is necessary to shed light on these issues. Third, the transformed models, perform the best in multiple steps ahead. This is not surprising, given that these models are deemed the most adequate during the estimation process. Fourth, 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, which consistently shows lower valuations than actual price (Myers 1999), and it is possible that the 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 it requires additional data and its application is more complex.

5. Replication with Different Data

In previous sections, I have presented a method to adapt the theoretical RIM to regressions that I claim are more efficient for the task of forecasting stock price. However, the previous discussions are based on a sample with perfectly complete quarterly data. In this section, I aim to shed more light on the presented method by assessing its empirical validity with annual and incomplete data. Specifically, I focus on all industrial firms in the total sample of SP500 firms to retrieve their data of stock price per share, book value per share, and I/B/E/S FY1 earnings forecast per share from 1976-2005. I focus on SP500 firms to attain the bulk of I/B/E/S forecast data while mitigating the scale problem. My goal of this exercise is to use estimation results from 1976-2003 to predict stock price at the end of 2004 and 2005. For each firm, the structure of the estimation model is expressed as:

$$y_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t = \underset{\sim}{x}_t^{'} \underset{\sim}{\beta} + v_t \qquad (10)$$
$$t = 1, \cdots, 28.$$

Equation 10 is identical to Equation 9, except that the periodic interval considered is year instead of quarter, the finite number of periods in the horizon over which the value per share is assumed to be well approximated is one year, and there are 28 years (1976-2003) in the estimation time series. All data must be complete for each price equation, and book values must be positive, but firms do not have to have a complete time series of 28 years to be included. The resulting estimation sample consists of 5536 firm-years.

Table 9 shows the diagnostics of the error term v_t from regression Equation 10 on the estimation sample. From the diagnostics, the RIM structure is satisfactory in terms of normality, and stationarity. There are two extreme outliers, due to two firms that have almost no data in the estimation period, so these 2 outliers and 6 other observations related to the 2 firms are purged from subsequent analyses. The diagnostics show AR(1) autocorrelation structure, and a SAS Proc Autoreg backstep procedure identifies significant autocorrelation at many lags, with AR(1) being the most significant. The diagnostics show ARCH disturbances and non-constant variances, which, as discussed for Table 4, can be addressed by estimating the RIM jointly with time series models of v_t .

<Table 9 about here>

Table 10 shows the RIM regression equations employed: 1) The naïve model, 2) the AR(1) model, 3) the AR(2) model, 4) the basic GARCH model, 5) the AR(1) model combined with log transformation, 6) the AR(1) model combined with square root transformation, 7) the AR(1) model combined with cubic root transformation, respectively.

<Table 10 about here>

Table 11 shows the estimated parameters and tests of model adequacy. As with quarterly data, the relative magnitudes of the parameters within each model highlight the stronger importance of abnormal earnings than book value. To assess the models' adequacy, the Durbin-Watson (DW), LaGrange Multiplier (LM), and Dickey-Fuller (DF) statistics to measure serial correlation, white noise, and stationarity, respectively. All models meet the stationarity test. The naïve model is the most inadequate, having strong positive serial correlation as indicated by low DW, and serious non-white noise as indicated by large LM. All other models have less serial correlation, as can be seen from DWs close to 2, due to adjustments to capture the time series properties of v_t. All other models are also substantially improved with regards to white noise, as can be seen from low LMs. The basic GARCH model is the most adequate as it has DW the closest to 2 and the smallest LM. The AR(2) model is the next best, followed by the AR(1) model, and the transformation models.

<Table 11 about here>

Table 12 shows the forecast results based on the seven models employed. Panel A presents the forecast results are for 2004 (one-year-ahead forecasts), and Panel B for 2005 (two-years-ahead forecasts). As shown, the forecast errors are very low. In one-year-ahead forecasts, the GARCH model produces the smallest average MAPE (18.12%). Except for the naïve model, the remaining models produce MAPEs in the range of 18.23%-20.42%. The naïve model performs the worst, with MAPE equal 29.32%. In two-years-ahead forecasts, the GARCH model still produces the best accuracy, with MAPE equal 29.42%. The remaining models produce MAPEs in the range of 29.88%-33.76%, except for the naïve model which has MAPE equal 49.24%. Overall, the GARCH model surfaces as the best forecaster, which is not surprising given that it is deemed the most adequate during estimation. The forecasts results have very low errors relative to prior research, considering out-of-sample forecasts.

<Table 12 about here>

In sum, this section shows that the method presented in this paper is applicable to a different truncation scheme, and to data of different frequency and degree of completeness. Overall, in adapting the theoretical RIM for empirical analyses, approximation over a finite horizon is necessary, however it is still 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.

6. Summary and Conclusion

Although the Residual Income Model (RIM) provides a theoretical framework for equity valuation, it has not fared well in empirical testing. Particularly, prior implementations of the RIM have yielded very large stock price forecast errors. The large errors cast doubt on the empirical validity of the model. This paper demonstrates that, for a sample of large and well-followed firms, implementation of the RIM can yield reasonable forecast accuracy.

In this paper, I start with the formal development of the RIM to derive a naïve regression equation that assumes valuation is well approximated over 4 consecutive quarters by a function of book value, forecast earnings, and other value-relevant information not captured in accounting earnings. My data diagnostics show that this naïve model is satisfactory in terms of normality, stationarity, 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. Therefore, I augment the naïve model by incorporating time series errors, GARCH effects, and transformations. 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. 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.

This paper yields three interesting empirical findings that merit expanded investigations in future research. First, quarterly forecasts can be used in valuation models. 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. Second, jointly estimating the theoretical RIM with empirical models that capture the statistical properties of v_t can improve forecasts. As shown in this paper, adjusting for serial correlation, ARCH disturbances, and non-constant variances helps better forecast future stock prices. Third, transformed models, are found to be some of the most adequate estimation models and accurate forecasters. This finding is interesting because transformations are departure from the theoretical RIM model, and only arise in the process of adapting the theoretical RIM to regression models for empirical analyses. Transformed models perform well because they adjust the statistical properties of v_t (reduce variances) to better comply with regression assumptions.

As contributions to methodological and theoretical discussions, this paper equates valuation to the capitalization of book value, the capitalization of a finite stream of abnormal earnings, and the capitalization of other information not captured in earnings. Because this approach views that valuation may stem from factors not to be captured in current or future financial statements, it recognizes the shortcomings of transaction-based accounting. This approach is different from many papers that model other information as impacting future residual incomes, essentially recognizing the value-relevance of other information only from the earnings channel. While future research is necessary to assess the theoretical merit of this approach, it is clear that the ensuing RIM regressions are more efficient for forecasting stock price, because RIM regressions do not have to forecast abnormal earnings first to forecast stock price. This paper highlights that, in adapting the theoretical RIM for empirical analyses, approximation over a finite horizon is necessary, however 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.

Table 1 - Prior Forecast Results Based on the Residual Income Model (RIM)

Authors	Out-of sample	MAPE	ME	MSPE
Penman and Sougiannis (CAR 1998) Valuation errors are lower using the RIM than the Free Cash Flows model and the Dividend Discount model.	No		-17.5% (Table 1)	
Frankel and Lee (JAE 1998) The ratio of valuation estimate and actual price predicts long-term returns.	No		-9% (Table 3)	
Myers (AR 1999) More complex models provide noisier estimates of firm value than more parsimonious models.	No		-58.90% (Table 2)	
DeChow et al. (JAE 1999) The RIM provides only minor improvements over attempts to implement the DDM by capitalizing earnings forecasts.	No	40.2% (Table 5)	25.9% (Table 5)	23.2% (Table 5)
Francis et al. (JAR 2000) RIM estimates are better than estimates based on dividends or free cash flows.	No	30.3% (Table 1)	-12.7% (Table 1)	
Courteau et al. (CAR 2001) Valuation models that employ price forecasts as terminal values generate the lowest prediction errors.	No	19.54% (Table 2)	8.39% (Table 2)	
Ali et al. (AR 2002) Frankel and Lee's result is due to market mis-pricing.	No		14% (Table 1)	
Baginsky and Wahlen (AR 2003) The difference between actual price and price estimated based on the RIM explains the market pricing of risk.	No		85.15% (Table 1)	
Choi et al. (CAR 2006) Valuation estimates are less biased and just as inaccurate as in prior research when the valuation model adjusts for accounting conservatism.	No	48.4% (Table 5)	4.4% (Table 5)	
Barth et al. (2004 Stanford Working Paper) Mean prediction errors are smallest when disaggregating earnings into cash flow and major accruals	Yes	168% (Table 4)		3166% (Table 4)

The tabulated papers are published in the Accounting Review (AR), the Journal of Accounting Research (JAR), the Journal of Accounting and Economics (JAE), and Contemporary Accounting Research (CAR), except for Barth et al. (2004) which is a working paper. Out-of-sample shows whether a paper uses separate data for estimation versus for forecasting. MAPE is mean average percentage error, defined as the absolute difference between forecast price and actual price scaled by actual price; ME is the mean error, defined as the signed 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 2 – 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	151	36.23	12.84	0.52	0.53	0.57	0.55
Q3 2005	147	37.92	13.30	0.56	0.60	0.58	0.63
Q4 2005	151	38.75	13.89	0.60	0.59	0.64	0.65
Q1 2006	150	41.44	14.07	0.58	0.65	0.67	0.71
Q2 2006	140	40.19	14.72	0.66	0.69	0.73	0.70
Q3 2006	139	40.47	14.60	0.66	0.70	0.68	0.74
Summary	1030	38.57	13.72	0.58	0.61	0.63	0.65

Table 3: 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 (1030 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

Table 4: 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

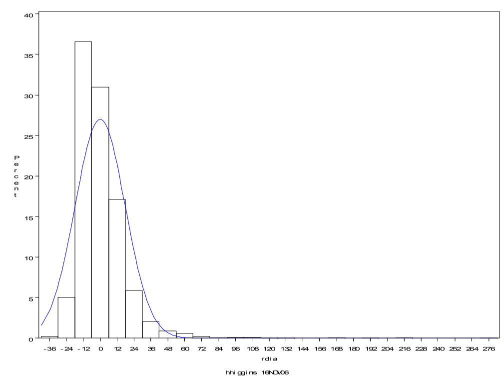

Figure 2
Histogram

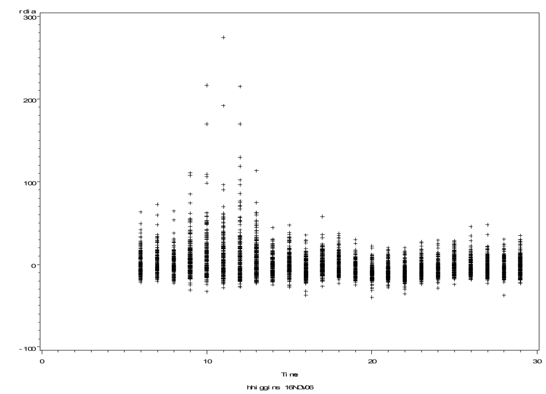

Figure 3
Time Plot

```
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

Table 5 – RIM Regressions

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

Table 6: Estimation Results

	Model 1	***Model 2***	***Model 3***	***Model 4***	***Model 5***	***Model 6***	***Model 7***
β_0	22.08 (<.0001)	21.86 (<.0001)	21.67 (<.0001)	14.59 (<.0001)	2.91 (<.0001)	4.52 (<.0001)	2.71 (<.0001)
β_1	-0.02 (.6926)	0.19 (.0012)	0.23 (.0001)	0.39 (<.0001)	0.0008 (<.5403)	0.02 (<.0001)	0.01 (<.0001)
β_2	5.78 (=.0004)	8.21 (<.0001)	8.29 (<.0001)	9.53 (<.0001)	0.18 (<.0001)	0.68 (<.0001)	0.25 (<.0001)
β_3	6.57 (.0004)	6.69 (<.0001)	6.59 (<.0001)	8.48 (<.0001)	0.26 (<.0001)	0.56 (<.0001)	0.21 (<.0001)
β_4	12.37 (<.0001)	10.80 (<.0001)	10.65 (<.0001)	11.76 (<.0001)	0.43 (<.0001)	0.88 (<.0001)	0.33 (<.0001)
β_5	13.62 (<.0001)	8.22 (<.0001)	8.02 (<.0001)	9.48 (<.0001)	0.47 (<.0001)	0.67 (<.0001)	0.24 (<.0001)
AR1		0.82 (<.0001)	0.85 (<.0001)	0.83 (<.0001)	0.87 (<.0001)	0.86 (<.0001)	0.87 (<.0001)
AR4			-0.07 (<.0001)		-0.03 (<0.0001)	-0.05 (<0.0001)	-0.04 (<0.0001)
ARCH0				17.37 (<.0001)			
ARCH1				0.38 (<.0001)			
GARCH1				0.45 (<.0001)			
N	4128	4128	4128	4128	4128	4128	4128
Total R-square	26.71%	75.88%	76.14%	75.35%	82.62%	80.59%	81.53%
Regress R-square	26.71%	17.09%	17.55%	17.09%	21.11%	21.81%	22.19%
Durbin-Watson	0.37	1.75	1.90	1.82	1.97	1.94	1.95
LaGrange Multiplier	2756.81	33.92	43.59	18.78	0.23	15.61	7.41
Dickey-Fuller Test	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary

The RIM regression models 1-7 are as defined in Table 5: 1) the naive model, 2) the AR(1) model, 3) the AR(1, 4) model, 4) the basic GARCH model with AR(1), 5) the AR(1,4) model with log transformation, 6) the AR(1, 4) model with square root transformation, and 7) the AR(1, 4) model with cubic root transformation.

Table 7: Forecast Results for One Step Ahead – Q1 2005 (N=152)

Mean [Median]	***Model 1***	***Model 2***	***Model 3***	***Model 4***	***Model 5***	***Model 6***	***Model 7***
ME	36.46% [14.21%]	14.82% [7.74%]	16.08% [9.23%]	9.00% [3.32%]	8.06% [2.08%]	11.85% [5.66%]	10.33% [5.16%]
MAPE	47.84% [23.1%]	24.53% [11.72%]	25.18% [12.43%]	20.89% [10.96%]	21.40% [11.33%]	22.57% [11.58%]	21.97% [11.2%]
MSPE	101.83% [5.33%]	16.33% [1.37%]	17.12%*** [1.55%]	11.75% [1.20%]	12.16% [1.28%]	13.73% [1.34%]	12.90% [1.25%]

MAPE is mean average percentage error, defined as the absolute difference between forecast price and actual price scaled by actual price.
ME is the mean error, defined as the signed 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.
The models 1-7 are as defined in Table 5: 1) the naive model, 2) the AR(1) model, 3) the AR(1, 4) model, 4) the basic GARCH model with AR(1), 5) the AR(1,4) model with log transformation, 6) the AR(1, 4) model with square root transformation, and 7) the AR(1, 4) model with cubic root transformation. The model equations are described in Table 5.

Table 8: Forecast Results for Multiple Steps Ahead

Mean Median	*Model 1*		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*		*Model 7*	
	ME	MAPE	ME	MAPE	ME	MAPE	ME	MAPE	ME	MAPE	ME	MAPE	ME	MAPE
2-Step Ahead Forecasts Q2 2005 N=151	35.29% 11.16%	46.08% 20.97%	17.77% 7.51%	25.75% 14.10%	20.36% 10.43%	27.66% 13.76%	9.03% 2.15%	20.80% 10.93%	0.64% -1.29%	9.10% 6.45%	2.77% -0.71%	9.68% 6.20%	1.86% -1.04%	9.34% 6.02%
3-Step Ahead Forecasts Q3 2005 N=147	31.09% 10.95%	42.25% 19.75%	16.92% 7.48%	25.96% 14.46%	20.88% 10.87%	29.33% 14.31%	5.91% 0.67%	20.45% 11.99%	1.66% -0.08%	10.53% 7.22%	2.42% 0.45%	10.35% 7.70%	1.92% -0.18%	10.21% 7.78%
4-Step Ahead Forecasts Q4 2005 N=151	31.01% 7.77%	45.06% 21.98%	19.09% 9.78%	30.31% 16.13%	23.91% 9.45%	34.58% 17.75%	5.97% -0.74%	22.60% 14.77%	0.96% -0.36%	10.58% 6.87%	2.44% 0.38%	11.18% 7.95%	1.74% 0.07%	10.82% 7.83%
5-Step Ahead Forecasts Q1 2006 N=150	24.09% 2.56%	41.37% 21.12%	14.67% 3.70%	30.18% 16.90%	19.03% 3.30%	34.29% 17.81%	0.68% -6.09%	24.05% 16.27%	-4.43% -4.84%	9.94% 7.25%	-2.60% -3.74%	10.00% 7.28%	-3.37% -4.16%	9.87% 7.20%
6-Step Ahead Forecasts Q2 2006 N=140	35.73% 8.75%	49.14% 21.95%	25.63% 7.00%	36.86% 19.01%	30.94% 8.77%	42.39% 19.05%	8.62% -2.55%	27.01% 15.73%	9.21% 5.01%	12.38% 8.21%	10.56% 5.71%	13.56% 7.67%	9.91% 5.00%	12.99% 7.88%
7-Step Ahead Forecasts Q3 2006 N=139	32.72% 5.52%	48.30% 23.70%	24.56% 5.27%	37.93% 18.41%	29.99% 6.71%	43.80% 21.09%	6.45% -5.69%	28.44% 18.16%	-0.99% -4.38%	11.05% 7.43%	1.25% -3.66	12.17% 8.48%	0.30% -3.78%	11.68% 8.51%

Each cell contains first the mean, and then the median. MAPE is mean average percentage error, defined as the absolute difference between forecast price and actual price scaled by actual price. ME is the mean error, defined as the signed 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. The models 1-7 are as defined in Table 5: 1) the naive model, 2) the AR(1) model, 3) the AR(1, 4) model, 4) the basic GARCH model with AR(1), 5) the AR(1,4) model with log transformation, 6) the AR(1, 4) model with square root transformation, and 7) the AR(1, 4) model with cubic root transformation. The model equations are described in Table 5.

Table 9: Diagnostics of the Naïve RIM using Annual Data

N= 5536
Mean = 0
Median = -3.76
Range = 688.53
Interquartile range = 12.617
Standard Deviation = 15.16
Skewness = 10.36
Kurtosis = 341.95

Figure 1
Distribution

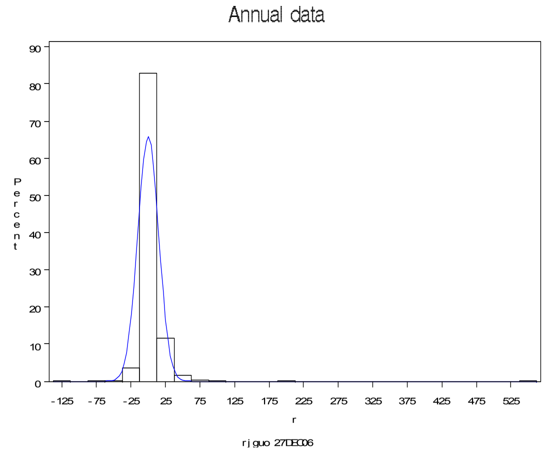

Figure 2
Histogram

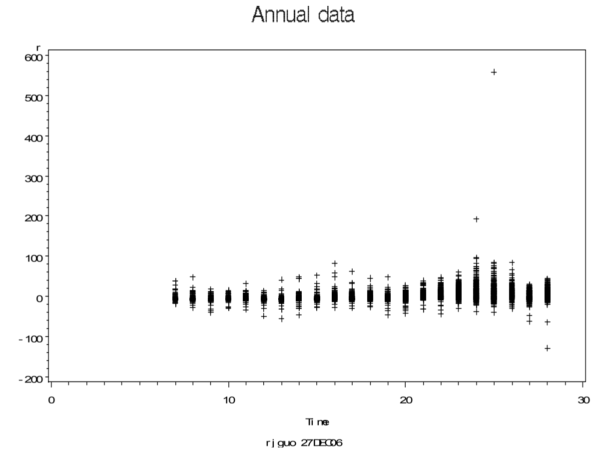

Figure 3
Time Plot

```
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 = 0.8453
Pr> D: <1.0000

Portmanteau Q= 3269.17
Pr>Q: < 0.0001

Lagrange Multiplier = 1875.35
Pr>LM: <0.0001

Figure 6
Autocorrelation and ARCH disturbances

Table 10: RIM Regressions for Annual Data

	Model	Equation
1	Naïve	$y_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
2	AR(1)	$y_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho v_{t-1} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
3	AR(2)	$y_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
4	AR(2) Basic GARCH	$y_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \varepsilon_t, \varepsilon_t = h_t e_t,$ $h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2, e_t \sim N(0,\sigma^2); \alpha_i > 0, i = 0,1; \beta_1 > 0; \alpha_1 + \beta_1 < 1$
5	Log, AR(1)	$\log(y_t) = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho v_{t-1} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
6	Square Root, AR(1)	$\sqrt{y_t} = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho v_{t-1} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
7	Cubic root, AR(1)	$\sqrt[3]{y_t} = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho v_{t-1} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$

Table 11: Estimation Results based on Annual Data

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
β_0	10.51 (<.0001)	14.96 (<.0001)	14.92 (<.0001)	28.81 (<.0001)	2.29 (<.0001)	3.56 (<.0001)	2.27 (<.0001)
β_1	0.34 (<.0001)	0.17 (<.0001)	0.17 (<.0001)	0.05 (<.0001)	0.01 (<.0001)	0.02 (<.0001)	0.01 (<.0001)
β_2	10.38 (<.0001)	5.54 (<.0001)	5.60 (<.0001)	3.20 (<.0001)	0.18 (<.0001)	0.54 (<.0001)	0.22 (<.0001)
AR1		0.75 (<.0001)	0.73 (<.0001)	0.77 (<.0001)	0.87 (<.0001)	0.82 (<.0001)	0.84 (<.0001)
AR2			-0.02 (.1771)	0.17 (<.0001)			
ARCH0				0.28 (<.0001)			
ARCH1				0.01 (<.0001)			
GARCH1				0.01 (<.0001)			
N	5528	5528	5528	5528	5528	5528	5528
Total R-square	40.45%	70.69%	70.67%	75.55%	81.49%	77.73%	79.44%
Regress R-square	40.45%	13.59%	13.89%	13.89%	12.72%	14.16%	14.06%
Durbin-Watson	0.74	2.15	2.12	2.09	2.21	2.18	2.18
LaGrange Multiplier	2182.74	31.15	21.58	11.70	59.90	43.18	47.87
Dickey-Fuller	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary	Stationary

The RIM regression models 1-7 are as defined in Table 10: 1) the naive model, 2) the AR(1) model, 3) the AR(2) model, 4) the basic GARCH model with AR(2), 5) the AR(1) model with log transformation, 6) the AR(1) model with square root transformation, and 7) the AR(1) model with cubic root transformation.

Table 12: Forecast Results Based on Annual Data

Panel A: 2004 (N=330)

Mean [Median]	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
ME	-8.91% [-16.60%]	-6.62% [-10.77%]	-6.88% [-10.72%]	-6.70% [-10.73%]	-5.94% [-10.75%]	-7.85% [-11.15%]	-7.80% [-11.61%]
MAPE	29.33% [24.59%]	19.47% [16.46%]	19.41% [15.58%]	18.12% [14.93%]	20.42% [15.72%]	18.83% [15.53%]	18.98% [15.49%]
MSPE	15.05% [6.05%]	7.12% [2.39%]	7.00% [2.43%]	5.27% [2.23%]	11.07% [2.47%]	5.94% [2.41%]	6.18% [2.40%]

Panel B: 2005 (N=326)

Mean [Median]	*Model 1*	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*
ME	-24.78% [-16.53%]	-11.58% [-14.94%]	-12.02% [-14.51%]	-0.06% [-10.92%]	-2.95% [-15.97%]	-6.91% [-15.78%]	-6.25% [-15.95%]
MAPE	49.24% [25.07%]	32.77% [21.42%]	32.95% [21.49%]	29.42% [20.19%]	33.76% [22.11%]	29.88% [22.11%]	30.62% [21.83%]
MSPE	883.78% [6.29%]	74.25% [4.59%]	83.42% [4.62%]	28.57% [4.08%]	88.27% [4.89%]	41.80% [4.89%]	58.31% [4.77%]

MAPE is mean average percentage error, defined as the absolute difference between forecast price and actual price scaled by actual price. ME is the mean error, defined as the signed difference between forecast price and actual price scaled by actual price. MSE is the mean squared error, defined as the squared difference between forecast price and actual price scaled by the squared actual price. The RIM regression models 1-7 are as defined in Table 10: 1) the naive model, 2) the AR(1) model, 3) the AR(2) model, 4) the basic GARCH model with AR(2), 5) the AR(1) model with log transformation, 6) the AR(1) model with square root transformation, and 7) the AR(1) model with cubic root transformation.

References:

Ali, Ashiq, Hwang, Lee-Seok and Trombley, Mark A.(2003). "Residual-Income-based Valuation Predicts Future Stock Returns: Evidence on Mispricing vs. Risk Explanations." *Accounting Review*, Vol 78, Issue 2 (April), 377.

Baginski, Stephen P. and Wahlen, James M.(2003). "Residual Income Risk, Intrinsic Values, and Share Prices." *Accounting Review*, Vol 78, Issue 1(January), 327.

Barth, Mary and Kallapur, S. 1996. "The Effects of Cross-Sectional Scale Differences on Regression Results in Empirical Accounting Research." *Contemporary Accounting Research* 13 *, 527-567.*

Barth, Mary, Beaver, William, Hand, John, and Landsman, Wayne. 2004. "Accruals, Accounting-Based Valuation Models, and the Prediction of Equity Values", Working paper, Stanford University and University of North Carolina at Chapel Hill.

Berger, P., E. Ofek, and I. Swary. 1996. "Investor Valuation of the Abandonment Option". *Journal of Financial Economics* 42: 257-287.

Bernard, Victor L (1995). "The Feltham-Ohlson Framework: Implications for Empiricists" *Contemporary Accounting Research,* Vol 11, Number 2 (Spring), 733-747.

Callen, Jeffrey L. and Morel, Mindy (2001). "Linear Accounting Valuation When Abnormal Earnings are AR(2)" *Review of Quantitative Finance & Accounting*, Vol 16, Issue 3 (May), 191-203.

Choi, Young-Soo, O'Hanlon, John E., Pope, Peter (2006). "Comparative Accounting and Linear Information Valuation Models" *Contemporary Accounting Research* 23, No. 1 (Spring), 73-101.

Collins, Daniel E., Pincus, Morton, and Xie, Hong. 1999. "Equity Valuation and Negative Earnings: The Role of Book Value of Equity" *The Accounting Review* 74, No. 1 (January): 29-61.

Tsay, Ruey S. (2002). "Analysis of Financial Time Series" (John Wiley & Sons).

Dechow, Patricia M. and Hutton, Amy P. (1999). "An Empirical Assessment of the Residual Income Valuation Model" *Journal of Accounting & Economics* (January), Vol 26, Issue 1-3, 1-34.

Edwards, E., and P. Bell. 1961. "The Theory and Measurement of Business Income" Berkeley, CA: University of California Press.

Shumway, Robert H., and Stoffer, David. (2006) "Time Series Analysis and Its Applications" (Springer).

Francis, Jennifer, Olsson, Per and Dennis, R.(2000). "Comparing the Accuracy and Explainability of dividend, Free Cash Flow, and Abnormal Earnings Equity Value Estimates" *Journal of Accounting Research*, Vol 38, Issue 1 (Spring), 45-70.

Frankel, Richard and Lee, Charles M.C(1998). "Accounting Valuation, Market Expectation, and Cross-sectional Stock Returns" *Journal of Accounting and Economics*, Vol25, Issue 3 (June), 283-319.

Hand, John (2001). "Discussion of Earnings, Book Values, and Dividends in Equity Valuation: An Empirical Perspective" *Contemporary Accounting Research*, Vol 18, No 1 (Spring), 212-130.

Lundholm, Russell and O'Keefe, Terry and Feltham, Gerald A.(2001). "Reconciling Value Estimate from the Discounted Cash Flow Model and the Residual Income Model" *Contemporary Accounting Research*, Vol 18 (Summer), Issue 2, 311-335.

Myers, James N. (1999). "Implementing Residual Income Valuation with Linear Information Dynamics" *Accounting Review*, Vol 74, Issue 1 (January), 1-28.

Neter, John, Wasserman, William, and Kutner, Michael. (1990). Applied Linear Statistical Models – Regression, Analysis of Variance, and Experimental Designs. Irwin.

Ohlson, James A. (1995). "Earnings, Book Values, and Dividends in Equity Valuation" *Contemporary Accounting Research*, Vol.11, Issue 2 (Spring), 661-687.

Peasnell, K. V. (1982). "Some Formal Connections Between Economic Values and Yields and Accounting Numbers", *Journal of Business Finance & Accounting,* Vol 9, Issue 3, 361-381.

Penman, Stephen H. and Sougiannis, Theodore(1998). "A Comparison of Dividend, Cash Flow, and Earnings Approaches to Equity Valuation", *Contemporary Accounting Research,* Vol15, Issue 3 (Autumn), 45-70.

Preinreich, G. 1938. "Annual Survey of Economic Theory: The Theory of Depreciation" *Econometrica (*July): 219-241.

Lo, Kin and Thomas Lys. "The Ohlson Model: Contribution to Valuation Theory, Limitations, and Empirical Applications", *Journal of Accounting, Auditing, and Finance* 15, Issue 3 (Summer), 337-367.

Lundholm, Russell J. and O'Keefe, Terrence B. (2001). "On Comparing Cash Flow and Accrual Accounting Models for the Use in Equity Valuation: A Response to Penman" *Contemporary Accounting Research*, Vol 18, Issue 4 (Winter), 681-696.

Rubinstein, Mark (1976). "The Valuation of Uncertain Income Streams and the Pricing of Options" *Bell Journal of Economics*, Vol 7, Issue 2 (Autumn), 407-408.

Sougiannis, Theodore, and Yaekura, Takashi. (2001). "The Accuracy and Bias of Equity Values Inferred from Analysts' Earnings Forecasts" *Journal of Accounting, Auditing, and Finance,* Vol. 16, Issue 4, 331-362.