Forecasting Stock Price with the Residual Income Model

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Abstract

This paper demonstrates a method to forecast stock price using analyst earnings forecasts as essential signals of firm valuation. The demonstrated method is based on the Residual Income Model (RIM), with adjustment for autocorrelation. Over the past decade, the RIM is widely accepted as a theoretical framework for equity valuation based on fundamental information from financial reports. This paper shows how to implement the RIM for forecasting, and how to address autocorrelation to improve forecast accuracy. Overall, this paper provides a method to forecast stock price that blends fundamental data with mechanical analyses of past time series.

Forecasting Stock Price with the Residual Income Model

Introduction

This paper demonstrates a method to forecast stock price using analyst earnings forecasts as essential signals of firm valuation. The demonstrated method is based on the Residual Income Model (RIM), a widely used theoretical framework for equity valuation based on accounting data. Despite its importance and wide acceptance, the RIM yields large errors when applied for forecasting. This paper discusses a statistical approach to improve stock price forecasts based on the RIM, specifically by showing that adjusting for serial correlation in the RIM's model (autocorrelation) yields more accurate price forecasts. The demonstrated approach complements other valuation techniques, as employing a basket of valid techniques builds confidence in pricing. Accurate price forecasts help build a profitable trading strategy, for example by investing in stocks with the largest difference between current price and forecast future price. In practice, although fundamentalists rely on true economic strengths of the firm for valuation, there is ample room for mechanical analyses of price trends. This paper serves investment professionals by providing a pricing method that blends fundamental information in analyst earnings forecasts with mechanical analyses of time series.

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 reported 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 and it is the purpose of this paper to exploit it to the best using statistical tools to predict stock price. To the extent that v_t contains serial correlation, as expected in firm data, modeling its time series properties should improve the forecasting performance of the RIM.

First, I demonstrate how to implement the RIM using one term of abnormal earnings. I review the theoretical framework, and model the RIM to parallel forecasters' task just before time t to forecast stock price at time t based on expected earnings for the period ending at t. The forecaster's information at the time of the task consists of book value at the beginning of the period (bv_{t-1}), expected earnings of the current period (x_t, for the period staring at t-1 and ending at t), and the normal capital charge rate for the period (r_t). Abnormal earning is defined as the difference between analyst earnings forecast (best knowledge of actual earnings) and the earnings number achieved under growth of book value at a normal discount rate. Underlying this definition is the idea that analyst earnings forecasts are essential signals of firm valuation (following Frankel and Lee 1998, Francis et al. 2000, and Sougiannis and Yaekura 2001).

Next, I demonstrate how to improve the implementation of the RIM. I describe the necessary procedures starting with a naïve regression. Then, I point out the violations of this naïve regression, and seek improvement by addressing these violations. Specifically, for RIM regressions to produce reliable results, v_t must have a normal zero-mean distribution and meet the statistical regression assumptions. However, the regression assumptions are often not met, due to strong serial correlation in v_t. Serial correlation arises when a variable is correlated with its own value from a different time lag, and is a notorious problem in financial and economic data. This problem can be addressed by using regressions with time series errors to model the properties of v_t. My diagnostics also show conditional heteroscedasticity in v_t, which can be addressed with GARCH modeling. My procedure to identify the time series properties of v_t is as recommended by Tsay (2002) and Shumway and Stoffer (2005). I show that, by jointly estimating the RIM regression and the time series models of v_t, forecast errors are substantially reduced.

My demonstration is based on SP500 firms, using 22 years of data spanning 1982 – 2003 to estimate the prediction models, which I then use to predict stock prices in a separate period spanning 2004 - 2005. The mean absolute percentage error obtained can be as low as 18.12% in one-year-ahead forecasts, and 29.42% in two-year-ahead forecasts. It is important to note that I use out-of-sample forecasts, whereas many prior studies use in-sample forecasting, in other words, they do not separate the estimation period from the forecast period. In-sample forecasts have artificially lower forecast error than out-of-sample because hindsight information is incorporated. However, to be of practical value, forecasts must be done beyond the estimation baseline.

For a brief review of prior results, prior valuation studies based on the RIM have focused more on determining value relevance, i.e., the contemporaneous association between stock price and accounting variables, not to forecast future prices. As will be noted in this paper, the harmful effect of autocorrelation is not apparent in estimation or tests of association, therefore value-relevance studies may not have to address this issue. However, when the RIM results are applied for forecasting, it yields large 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 (See discussions of large forecast errors in Choi et al. 2006, Sougiannis and Yaekura 2001, Frankel and Lee 1998, DeChow et al. 1999, Myers 1999). The errors are larger with out-of-sample forecasts, because the new observations to be forecasted are farther from the center of the estimation sample. The large errors could be due to many factors, including inappropriate terminal values, discount rates, and growth rate (Lundholm and O'Keefe 2001, Sougiannis and Yaekura 2001), and autocorrelation as argued in this paper. This paper discusses how to address the autocorrelation factor to improve RIM-based stock price forecasts.

The paper proceeds as follows. To demonstrate how to implement the RIM, Section 2 reviews the theoretical RIM, discusses its adaptations for empirical analyses, and describes its implementation with one term of abnormal earnings. To demonstrate how to improve the implementation of the RIM, Section 3 discusses the empirical data and diagnostics methods of v_t to identify its proper structures. Section 4 describes the results of estimating jointly the RIM regressions and the time series structures of v_t, and discusses the forecast results. Section 5 presents extension analyses. Section 6 summarizes and concludes the paper.

2. The RIM

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]

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:

[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 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).

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

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:

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

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 practice, it is impossible to work with an infinite stream of residual incomes as in Equation (6), and approximations over finite ad-hoc horizons are necessary. Consider an adaptation that purports to capture value over a finite horizon:

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

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

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_t^a 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.

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

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

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, $\underset{\sim}{x}_t^{'} = (1, bv_t, x_t^a, x_{t+1}^a, ..., x_{t+n}^a)'$ 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…

The manner in which v_t is addressed may well determine the empirical success of the RIM. In an early study, Penman and Sougiannis (1998, Equation 3) treats v_t as pure white noise. A number of empirical studies motivated by Ohlson (1995) 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 simplistic 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).

This paper 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 near-zero and normally distributed ($v_t \sim N(0, \sigma^2)$).Two is whether v_t 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 One Term of Abnormal Earnings

To simplify, I demonstrate implementation with one term of abnormal earnings, and accordingly n in Equation (8) is set to 0. I use 22 years from 1982 through 2003 (the estimating sample) to estimate model parameters, which I subsequently apply to forecast stock prices in 2004 and 2005 (the forecast sample). When more terms are used (n>0), the implementation is similar, and more fundamental information can be captured via future analyst earnings forecasts, which should lead to more accurate price forecasts. On the other hand, forecasts of the far future periods tend to be inaccurate and unavailable, which should lead to less accurate price forecasts. Regardless, there is typically room to improve forecast accuracy by adjusting for autocorrelation due to the serial nature of financial data.

For each included firm, the basic structure of my RIM regression is expressed as:

$$P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t = \underset{\sim}{x}_t' \underset{\sim}{\beta} + v_t \qquad (9)$$
$$t = 1, \cdots, 22.$$

$$x_t^a = x_t - r_t bv_{t-1}$$

The predictors in Equation (9) parallel the forecaster's information in forecasting stock price at a certain point in year t (starting at t-1 and ending at t). Forecaster's information consists of book value at the beginning of the year (bv_{t-1}), earnings forecasts of the current year (x_t), and the normal capital charge rate (r_t).My implementation of the RIM is based on Equation (9). In the most basic implementation (naïve model), v_t is assumed to be white noise, and stock price at t+1 is:

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x_{t+1}^a = \underset{\sim}{x}_{t+1}' \underset{\sim}{\hat{\beta}} \qquad (10)$$
$$t = 22, 23.$$

The estimation of β, $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2)'$, and the forecast of P_{t+1} $(\hat{P}_{t+1})$ can be done with basic regression techniques, for example using SAS Proc Autoreg.

3. Data, Diagnostics and Identification of Autocorrelation Structures

3.1. Data

A-priori, it is not known whether Equation (9) makes an adequate structure to capture valuation, and whether its application meets the statistical assumptions for regression analyses.

Diagnostics based on actual data are necessary to assess the above.[3] I demonstrate my approach using a sample of firms from the SP500 index as of May 2005. The focus on large firms reduces variances in the data that lead to various econometric issues, particularly scale effects, known to be pervasive problems in accounting studies (Lo and Lys 2000, Barth and Kallapur 1996)[4]. The large-firm focus helps mitigate econometric issues to better isolate the serial correlation issue and show the treatment effectively. Although the results pertain to large firms, they are meaningful because these firms nearly capture the total capitalization of the U.S. market. The selection criteria aim to retrieve data for implementing Equation (9):

a) Price and book value data must be available in the period 1982-2005 (Source: Datastream and Worldscope)
b) Earnings forecasts for the current year (I/B/E/S FY1) must be available (Source: I/B/E/S, mean consensus forecasts).
c) Book values must be greater than zero (only a couple of observations are lost due to this criterion).
d) Only industrial firms are included.

Three firms are deleted because they do not have data for most years. The resulting sample consists of 5,531 firm-years for estimation, and 656 firm-years for forecasting. Book value is

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[3] Many studies often add the following information dynamics to the RIM regression:

$$x^a_{t+1} = \omega x^a_t + v_t + \varepsilon_{1,t+1}$$

$$v_t = \rho v_{t-1} + \varepsilon_{2,t}$$

where ω is the coefficient representing the persistence of abnormal earnings. 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. Statistically, this closed form serves to correct autocorrelation. 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.

[4] 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.

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 it its history. Book value, price, and share data are retrieved from Worldscope. Earnings per share forecasts are FYR1 forecasts from I/B/E/S. For this demonstration, I define the normal capital charge rate as the Treasury bill rates, which are market yields on U.S. Treasury securities at 1-year constant maturity, quoted on investment basis, as released by the Federal Reserve. The implementations are similar when other capital charge rates are used.

Table 1 shows the summary data in each included year. Year 1982 through Year 2003 constitute the estimation sample, which is the basis for identifying models and for forming estimation parameters. Years 2004 and 2005 constitute the forecast sample. 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 $15.06 and $4.08, respectively. The median FY1 forecast is $0.74, and the median Treasury bill rate is 5.63%. From Panel B for the forecast sample, the median values for price per share and book per share are $36.26 and $8.56, respectively. The median FY1 forecast is $1.69, and the median quarterly Treasury bill rate is 1.89%. Values in the forecast sample are generally larger than those in the estimation sample.

<Table 2 about here>

3.2. Diagnostics and Identification of Autocorrelation Models

To use Equation (9) in a regression analysis, the error term v_t must meet the regression assumptions. The first assumption is normality, which may matter severely if other assumptions are not met. Further, the normal condition is important to infer that the structural form of the RIM regression, which arises from ad-hoc truncation, is appropriate. I examine 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 and a zero mean. Besides normality, I also examine stationarity because lack of stationarity is a violation of constant variance, and stationarity is important for autocorrelation modeling. Figure 3 is a time plot of v_t, showing relative stationarity, albeit with some heteroscedasticity (which will be addressed in Figure 6). Overall, v_t seems satisfactory in terms of normality and stationarity, suggesting that Equation (9) has an adequate structural form.

<Table 4 about here>

Another important assumption is that v_t be independent and identically distributed random variables (white noise), however this assumption is naïve. Because the estimation period includes multiple years, I naturally expect strong serial correlation in all variables of Equation (9). Since the seminal paper by Cochrane and Orcutt (1949), it is accepted econometric doctrine that serial correlation in the regression error, or autocorrelation, leads to inefficient use of data, but much of this inefficiency can be regained by transforming the error term to random. Many texts (for example Greene 1990, Neter et al. 1990) describe the consequences of autocorrelation on estimation, namely autocorrelation inflates the explanatory power of the estimation model, underestimates the estimated parameters' variances, and invalidates the models' t and F tests. When the error term is not independent, they contain information that can be used to improve the prediction of future values. Theoretical guides to address autocorrelation are provided by Tsay (2002) and Shumway and Stoffer (2006), and practical tutorials are provided in SAS Forecasting (1996).

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. These factors can be produced by SAS Proc Arima. The ACF in Figure 4, which is cut off at lag 12 for simpler exhibition, displays a nice exponential decay, consistent with an autoregressive positive correlation. The PACF in Figure 5, which is also cut off at lag 12, shows a great spike after lag 1, strongly indicating an AR(1) structure. The true underlying form is no doubt more complex, as the PACF also shows smaller spikes at later lags, suggesting a higher order AR structure. Indeed, a backstep procedure identifies autocorrelation through lag 5. Because there is a trade-off between complexity and efficiency in modeling time series (Tsay 2002), I select the AR(1) and AR(2) structures. Both encompass autocorrelation at lag 1, which accounts for most autocorrelation in the data, while the AR(2) structure helps assess the merit of higher order AR structures.[5]

I also test for autocorrelation using generalized Durbin-Watson and Godfrey's general Lagrange Multiplier tests (Godfrey 1978a, 1978b). These tests can be produced with SAS Proc Autoreg. From Figure 6, 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-type volatility. These statistics are consistent with the findings in Figures 4-5, and further suggests volatility in the v_t series. Volatility over time, also termed conditional heteroscedasticity, is a special feature that Tsay (2002) addresses with GARCH modeling. Following Tsay (2002, page 93), I select the basic GARCH model to assess volatility in conjunction with the above-identified AR(2) structure. Table 4 describes all the regression models identified from my data diagnostics.

<Table 4 about here>

It should be noted that, in Equation (9), the variables on the right-hand side correlate with each other strongly. For example, in my estimation sample, book value per share and abnormal 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

[5] I eventually find that both work equally well, consistent with the wisdom that sophisticated time series models are not superior to the simple AR(1) model. In fact, the received empirical literature is overwhelmingly dominated by AR(1), as it is optimistic to expect to know precisely the correct form of autocorrelation in any situation (Greene 2000).

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).

4. Results

4.1. Estimation Results

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

<Table 5 about here>

To assess 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 are used in this assessment. Small LMs are consistent with white noise LM is very large in the naïve model (LM=2182.74), is substantially reduced in AR(1), AR(2), and basic GARCH models (LM=31.15, 21.58, and 11.70, respectively). For this sample size, the DW upper limit is just under 2, and DW larger than 2 means no serial correlation. DW is much smaller than 2 in the naïve model (DW=0.74), and is above 2 in the AR(1), AR(2) and basic GARCH models (DW=2.15, 2.12, and 2.09, respectively). The total R-squares of all models are high[6], but after removing the serial correlation effect, the explanatory power of the structural model is measured by the regress R-square value, which is 13.59% in the AR(1) model, 13.89% in the AR(2) model, and 13.89% in the GARCH model. In the naïve model, the R-square value is an overstatement of the true explanatory power. Overall, it can be seen that the adjusted models have more white noise, i.e. are more adequate than the naïve model. From the estimated parameters, ρ_1 is very high (0.73 to 0.77 at p-value=0.0001). Such pronounced autocorrelation should

[6] According to the seminal study by Cochrane and Orcutt (1949), high correlations between autocorrelated series may be obtained purely by chance, and when this happens what is largely explained is the variance due to the regular movements through time.

affect forecasts if not addressed. Book value per share and abnormal earnings are significantly positive in all models, consistent with the theoretical RIM.

4.2. Forecast results

The forecasts are the corresponding regressions' predicted outputs for one-year-ahead and two-years-ahead beyond the estimation baseline. They are computed based on estimation results from the estimation sample, which are applied to knowledge of beginning book values and FYR1 earnings forecasts for the forecast years, and incorporated with the equivalent AR and GARCH parameters of v_t. Forecast can be produced by SAS Proc Autoreg, and are measured as follows.

Model 1 - Naïve:

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x_{t+1}^a = \underset{\sim}{x}_{t+1}^{'} \underset{\sim}{\hat{\beta}}$$

$$t = 22, 23.$$

Model 2 - AR(1):

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x_{t+1}^a + \hat{\rho} v_t = \underset{\sim}{x}_{t+1}^{'} \underset{\sim}{\hat{\beta}} + \hat{\rho} v_t$$

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

$$t = 22, 23.$$

Model 3 - AR(2):

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x_{t+1}^a + \hat{\rho}_1 v_t + \hat{\rho}_2 v_{t-1} = \underset{\sim}{x}_{t+1}^{'} \underset{\sim}{\hat{\beta}} + \hat{\rho}_1 v_t + \hat{\rho}_2 v_{t-1}$$

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

$$v_{t-1} = P_{t-1} - \hat{P}_{t-1}$$

$$t = 22, 23.$$

Model 4 - AR(2) Basic GARCH:

$$\hat{P}_{t+1} = \hat{\beta}_0 + \hat{\beta}_1 bv_t + \hat{\beta}_2 x^a_{t+1} + \hat{\rho}_1 \nu_t + \hat{\rho}_2 \nu_{t-1} + \hat{\varepsilon}_{t+1} = \underset{\sim}{x}'_{t+1} \underset{\sim}{\hat{\beta}} + \hat{\rho}_1 \nu_t + \hat{\rho}_2 \nu_{t-1} + \hat{\varepsilon}_{t+1}$$
$$\nu_t = P_t - \hat{P}_t$$
$$\nu_{t-1} = P_{t-1} - \hat{P}_{t-1}$$
$$\varepsilon_{t+1} = h_{t+1} e_{t+1}$$
$$h^2_{t+1} = \alpha_0 + \alpha_1 \varepsilon^2_t + \gamma_1 h^2_t$$
$$e_{t+1} \sim N(0,1); \alpha_0 > 0, \alpha_1 \geq 0, \gamma_1 \geq 0; \alpha_1 + \gamma_1 < 1$$
$$t = 22, 23.$$

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. Steps-ahead forecasts are predictions from the respective regressions for new observations.

Panel A of Table 6 shows the forecast results for 2004 (one-year-ahead). As presented, all models have average negative MEs, indicating that model forecasts are smaller than actual price. Understandably, the naïve model performs the worst, having the most negative ME (mean = -8.91%, median = -16.60%. The AR(1) model has a mean ME of -6.62%, slightly better than the GARCH model (with mean ME = -6.70%) and the AR(2) model (with mean ME = -6.88%).

<Table 6 about here>

As to the results of MAPE, the naïve model stands out as the worst, having the largest MAPE (mean = 29.33%, median = 24.59%). The GARCH model has the smallest MAPE (mean = 18.12% and median = 14.93%). The AR(1) and AR(2) models have slightly larger MAPE (with mean = 19.47% and 19.41%, respectively). Similarly, from the results of MSPE, the naïve model performs the worst, having the largest MSPE (mean = 15.05%, median = 6.05%), whereas MSPE is 7.12%, 7.00%, and 5.27% in the AR(1), AR(2), and GARCH models, respectively.

Panel B of Table 6 presents the forecast results for 2005 (two-years-ahead). The naïve model yields the worst errors, with MAPE, MSPE and ME equal to 49.24%, 883.78%, and -24.78%. The GARCH model produces the best accuracy, producing the smallest MAPE (mean= 29.42%) and MSPE (mean=28.57%), and the smallest magnitude of ME (mean=-0.06%). The AR(1) model is the next best, with mean MAPE, MSPE and ME equal to 32.77%, 74.25%, and -11.58%, respectively. The AR(2) model is very comparable to the AR(1) model, with MAPE, MSPE and ME equal to 32.95%, 83.42%, and -12.02%, respectively.

It is appropriate to conclude from the results that, because all models in Tables 7 and 8 are implemented using the same data and estimation procedures except for the adjustment of autocorrelation, this adjustment reduces forecast errors.

To assess the ability of time series models of v_t, one can compare the AR(1) and AR(2) models. Theoretically the AR(2) model should be better because it accounts for autocorrelation more completely than the AR(1) model. However, the empirical results do not show marked advantage of one over the other. This underlines the trade-off between completeness and efficiency: while AR(2) is a more complete model, it requires more data and is more complex to apply than AR(1). On the other hand, the GARCH model, which addresses both auto correlation and volatility, performs better than the others. Overall, Section 4 shows that adjusting for autocorrelation leads to more adequate estimation models and more accurate prediction models. Better estimation models help better explain contemporaneous stock prices, while better prediction models improve forecasts of future stock prices.

5. Extension Analyses to Address Scale Effects

A concern is that scale differences may affect regression results. Scale differences arise because large (small) firms have large (small) values of many variables. Cross-sectionally, scale differences exist when large and small firms are sampled together (Barth and Kallapur 1996). Serially, scale differences arise when firms have inconsistent scale over time, for example due to stock splits and stock dividends (Brown et al. 1999). Barth and Kallapur (1996) discuss that scale differences result in heteroscedastic regression error variances, which lead to coefficient bias if the magnitude differences are unrelated to the research question. According to Brown et al. (1999), a scale-affected regression will have higher R-square than that from the same regression without scale effects. Many studies discuss the scale problem and seek to address it (for example, Lo and Lys 2000, Barth and Kallapur 1996, Kothari and Zimmerman 1995, and Sougiannis 1994). Some common accounting scale proxies are total assets, sales, book value of equity, net income, number of shares, and share price, and many authors deflate by a scale proxy to address scale differences (Barth and Kallapur 1996). For example, Kothari and Zimmerman (1995) scale by number of shares, and Sougiannis (1994) by total assets.

My reported results should not be affected severely by scale differences because I use large SP500 firms only, I deflate by number of shares, which is one common method to address cross-sectional scale differences, and I adjust shares for splits, stock dividends and other capital adjustments. However, because scale concern is pervasive, I replicate the analyses using two additional scaling schemes, namely scaling by beginning total assets, and using no scale. I adjust the three differently-scaled models for autocorrelation and produce price forecasts. In each of the three models, I aim to show that forecasts after adjusting for autocorrelation are more accurate than those formed naively (i.e., before adjusting for autocorrelation).

Panel A of Table 7 presents the diagnostics of the naïve model from Table 4, which is scaled by number of shares. Panels B and C present the diagnostics of the same model, but no deflation is used in Panel B, and all RIM variables are deflated by beginning total assets instead of number of shares in Panel C. To ensure a good comparison, all three models are based on precisely the same sample and procedures except for the deflation factor. From the data already collected, 5,353 observations that have beginning total assets are used in the scale analyses reported in Tables 8 and 9.

<Table 7 about here>

Table 7 shows the diagnostics of v_t in three differently-scaled models. The share-deflated distribution is the closest to normality compared to the other distributions which are highly skewed and highly peaked. All three models suffer from heteroscedasticity and autocorrelation. All three could benefit from techniques to address heteroscedasticity, however, the share-deflated model has the least amount of error variability. All three models have significant autocorrelation, however the asset-deflated model has the least autocorrelation relative to the others. In sum, all models have different types of violations to different extents.

Table 8 shows the estimation and forecast results from the three models. The naïve and AR(1) adjusted results are reported for each of the models. Because of different scales, R-square values cannot be used for comparison. All three adjusted models are deemed adequate judging from their levels of white noise (low LaGrange Multiplier and Durbin-Watson above 2). However, from the forecast results, the share-deflated model yields the lowest forecast errors, and the asset-deflated model yields the worst forecasts. Tables 8 and 9 yield insight consistent with Rawlings et al. (2001): for forecasting purpose, non-normality may affect forecasts severely, although its effect on estimation is not apparent.

<Table 8 about here>

The forecast results of Table 8 show lower adjusted MAPEs than naïve MAPEs for each of the three differently-scaled models. For example, in the un-deflated model, the median naïve MAPE is 51.27%, contrasted to the adjusted median of 18.67%, for a difference significant at p-value <.0001. In fact, for all three models, the difference between naïve and adjusted MAPEs is statistically different in both mean and median tests for 2004 forecasts. For 2005 forecasts, all tests of difference are significant except the mean test from the share-deflated model and the tests from the asset-deflated model. Overall, adjusted MAPEs are statistically lower than naïve MAPEs in all scaling schemes, supporting the conclusion that adjusting for autocorrelation improves price forecasts.

6. Summary and Conclusion

For the purpose of equity valuation, it is important to assess the true fundamental economic strengths of a firm. Over the past decade, the Residual Income Model (RIM) has become widely accepted as a theoretical framework for equity valuation based on fundamental information from accounting data. Successful applications of the RIM are desirable to contribute a fundamental perspective to pricing decisions.

Measuring abnormal earnings as the difference between analyst forecast and the cost of capital charge, this paper demonstrates a method to forecast stock price by applying the RIM, with adjustment for autocorrelation. A regression to adapt the theoretical RIM for cross-sectional empirical analyses models stock price as a function of book value at the beginning of the year, abnormal earnings of the current year defined as earnings forecasts of the current year minus a normal capital charge, and an unknown term v_t. After introducing the RIM, this paper shows how to implement the basic RIM with one term of abnormal earnings, and how to address autocorrelation in the RIM regression to improve forecast accuracy. The method to address autocorrelation is by diagnosing v_t to identify its proper structures, and then model the RIM regression jointly with the identified structures of v_t. Based on a concrete example of SP500 firms, the approach demonstrated in this paper results in a mean absolute percentage error as low as 18.12% in one-year-ahead forecasts and 29.42% in two-year-ahead forecasts.

Overall, this paper complements other valuation methods by blending fundamental accounting data and mechanical analyses of trends. It is noted that due to other econometric problems than autocorrelation in large and heterogeneous samples, the usefulness of adjusting for autocorrelation is best demonstrated with large firms.

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Table 1 – Total Sample

Time	N	Price per share	Beginning Book Value per share	***Earnings forecast of the current year (I/B/E/S FYR1)***
		Estimation Sample		
1982	176	\$5.89	\$3.70	\$0.44
1983	181	7.16	4.21	0.53
1984	188	6.85	4.28	0.71
1985	193	8.34	4.38	0.66
1986	197	9.06	4.35	0.57
1987	203	9.23	4.73	0.74
1988	210	9.66	4.71	0.88
1989	218	10.88	4.99	0.84
1990	226	9.63	5.25	0.72
1991	228	13.06	5.31	0.58
1992	237	14.27	5.56	0.71
1993	254	15.07	5.60	0.78
1994	266	14.44	5.41	0.91
1995	277	18.14	5.23	1.13
1996	285	21.20	5.59	1.11
1997	294	26.46	6.24	1.25
1998	303	29.67	6.79	1.25
1999	305	35.91	7.39	1.36
2000	312	34.98	7.80	1.58
2001	321	31.71	9.50	1.23
2002	327	25.73	11.17	1.28
2003	330	33.58	12.90	1.40
Summary	5531	17.77	6.14	0.94
		Forecast Sample		
2004	330	37.97	10.51	1.87
2005	326	44.29	10.65	2.20
Summary	656	41.13	10.58	2.04

Sample securities belong to industrial firms in the SP500 index as of May 2005. Summary figures are the total numbers of observations, and the averages of price per share, book value, and EPS forecasts by analysts.

Table 2: Descriptive Statistics

Panel A: Estimation Sample (5531 firm-years in 1982 – 2003)

	Min	5%	25%	Median	75%	95%	Max	Mean
Price per share (N=5531)	0.07	1.77	6.90	15.06	28.24	52.14	126.98	19.68
Beginning Book Value per Share (N=5531)	0.00	0.31	1.68	4.08	8.23	19.14	703.34	6.53
EPS forecast of the current year (N=5531)	-5.83	0.02	0.31	0.74	1.44	2.93	8.51	1.00
Annual treasury bill rate (N=22)	1.24	1.24	3.89	5.63	7.65	10.91	12.27	5.79

Panel B: Forecast Sample (656 firm-years in 2004 – 2005)

	Min	5%	25%	Median	75%	95%	Max	Mean
Price per share	0.29	10.18	24.46	36.26	51.26	74.40	107.96	38.69
Beginning Book Value per Share (N=656)	0.00	2.00	5.27	8.56	13.33	23.16	345.89	10.58
EPS forecast of the current year (N=656)	-4.11	0.14	1.02	1.69	2.69	5.12	10.81	2.04
Annual treasury bill rate (N=2)	1.89	1.89	1.89	1.89	3.62	3.62	3.62	2.75

All values are reported in US dollars, except Treasury bill rate which is in %. All firm data are adjusted for capital changes, including 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 of the current year is I/B/E/S FYR1 forecasts. Annual treasury bill rate is market yield on U.S. Treasury securities at 1-year constant maturity, quoted on investment basis, as released by the Federal Reserve.

Table 3: Diagnostics of v_t

N= 5531
Mean = 0
Median = -3.61
Range = 688.53
Interquartile range = 12.52
Standard Deviation = 12.85
Skewness = 1.53
Kurtosis = 7.84

Figure 1
Distribution

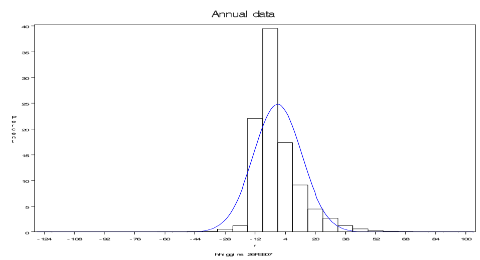


Figure 2
Histogram

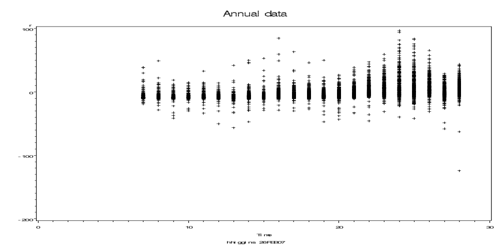


Figure 3
Time Plot

```
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 = 0.7353
Pr> D: <0.0001

Portmanteau Q= 3269.17
Pr>Q: < 0.0001

Lagrange Multiplier = 1875.35
Pr>LM: <0.0001

Figure 6
Autocorrelation and ARCH disturbances

The diagnostics of v_t are to assess the appropriateness of the naive RIM regression $P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t$,where v_t is the error term, P_t is stock price per share at time, bv_{t-1} is book value per share at the beginning of the current annual period which starts at t-1 and ending at t, x_t^a is abnormal earnings over the current period, defined as $x_t^a = x_t - r_t bv_{t-1}$, x_t is EPS forecast over the current period (I/B/E/S FYR1 earnings forecast), and r_t is the current Treasury bill rate. The distribution in Figure 1 and histogram in Figure 2 show near normality. The time plot in Figure 3 shows stationarity and some heteroscedasticity. Autocorrelation factors in Figures 4 and 5 show autoregressive pattern. Generalized Durbin-Watson tests and Godfrey's general Lagrange Multiplier test in Figure 6 show dependence, non-white noise, and ARCH disturbances.

Table 4: RIM Regressions

Model		Equation
1	Naïve	$P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
2	AR(1)	$P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho v_{t-1} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
3	AR(2)	$P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \varepsilon_t, \varepsilon_t \overset{iid}{\sim} N(0,\sigma^2)$
4	AR(2) Basic GARCH	$P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t, v_t = \rho_1 v_{t-1} + \rho_2 v_{t-2} + \varepsilon_t, \varepsilon_t = h_t e_t,$ $h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1}^2, e_t \sim N(0,1); \alpha_0 > 0, \alpha_1 \geq 0, \gamma_1 \geq 0; \alpha_1 + \gamma_1 < 1$

Table 4 shows the models identified from the diagnostics in Table 3. P_t is stock price per share at time t, bv_{t-1} is book value per share at the beginning of the current annual period which starts at t-1 and ending at t, x_t^a is abnormal earnings over the current period which I define as $x_t^a = x_t - r_t bv_{t-1}$, x_t is EPS forecast over the current period (I/B/E/S FYR1 earnings forecast), r_t is the current Treasury bill rate, v_t is the error term, ε_t is the disturbance term, β_{0-2} are RIM regression parameters, ρ_{1-2} are autocorrelation parameters, and α_{0-1} and γ_1 are GARCH parameters. The naïve model does not address autocorrelation. The AR(1) and AR(2) models assume v_t follows an AR(1) and an AR(2) structure, respectively. The AR(2) - GARCH model combines AR(2) assumption and GARCH modeling of v_t.

Table 5: Estimation Results of RIM Regressions

Estimated Coefficients (p-value) and Model Statistics		Naïve	AR(1)	AR(2)	AR(2) GARCH
β_0	Intercept	10.51 (<.0001)	14.96 (<.0001)	14.92 (<.0001)	28.81 (<.0001)
β_1	Book Value	0.34 (<.0001)	0.17 (<.0001)	0.17 (<.0001)	0.05 (<.0001)
β_2	Abnormal Earnings	10.38 (<.0001)	5.54 (<.0001)	5.60 (<.0001)	3.20 (<.0001)
ρ_1	AR Parameter		0.75 (<.0001)	0.73 (<.0001)	0.77 (<.0001)
ρ_2	AR parameter			-0.02 (=.1771)	0.17 (<.0001)
α_0	GARCH parameter				0.28 (<.0001)
α_1	GARCH parameter				0.01 (<.0001)
γ_1	GARCH parameter				0.01 (<.0001)
N		5531	5531	5531	5531
Total R-square		40.45%	70.69%	70.67%	75.55%
Regress R-square		n/a	13.59%	13.89%	13.89%
Durbin-Watson		0.74	2.15	2.12	2.09
LaGrange Multiplier		2182.74	31.15	21.58	11.70

The regression models have the same structural form but different treatments for autocorrelation. The structural form is $P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t$

where P_t is stock price per share at time, bv_{t-1} is book value per share at the beginning of the current annual period which starts at t-1 and ending at t, x_t^a is abnormal earnings over the current period which I define as $x_t^a = x_t - r_t bv_{t-1}$, x_t is EPS forecast over the current period (I/B/E/S FYR1 earnings forecast), r_t is the current Treasury bill rate, and v_t is the error term. β_{0-2} are RIM regression parameters, ρ_{1-2} are autocorrelation parameters, and α_{0-1} and γ_1 are GARCH parameters. The naïve model does not address autocorrelation. The AR(1) and AR(2) models assume v_t follows an AR(1) and an AR(2) structure, respectively. The AR(2) - GARCH model combines AR(2) assumption 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: Forecast Results

Panel A: 2004 (N=330) – One-Year-Ahead

Mean [Median]	Naïve	AR(1)	AR(2)	AR(2) GARCH
ME	-8.91% [-16.60%]	-6.62% [-10.77%]	-6.88% [-10.72%]	-6.70% [-10.73%]
MAPE	29.33% [24.59%]	19.47% [16.46%]	19.41% [15.58%]	18.12% [14.93%]
MSPE	15.05% [6.05%]	7.12% [2.39%]	7.00% [2.43%]	5.27% [2.23%]

Panel B: 2005 (N=326) – Two-Years-Ahead

Mean [Median]	Naïve	AR(1)	AR(2)	AR(2) GARCH
ME	-24.78% [-16.53%]	-11.58% [-14.94%]	-12.02% [-14.51%]	-0.06% [-10.92%]
MAPE	49.24% [25.07%]	32.77% [21.42%]	32.95% [21.49%]	29.42% [20.19%]
MSPE	883.78% [6.29%]	74.25% [4.59%]	83.42% [4.62%]	28.57% [4.08%]

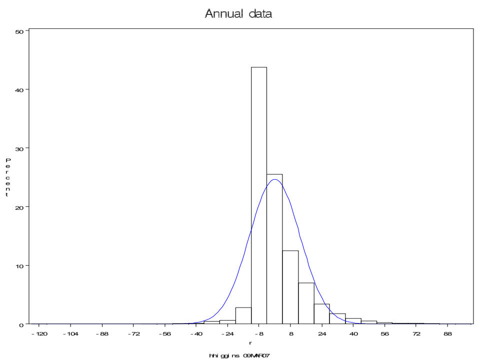
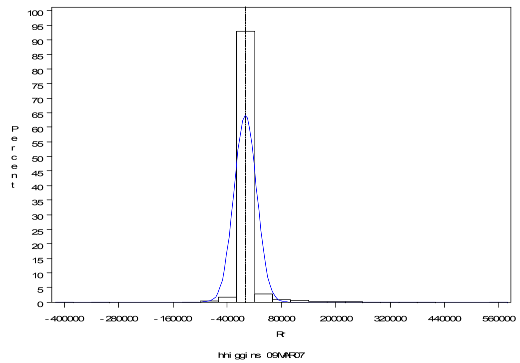
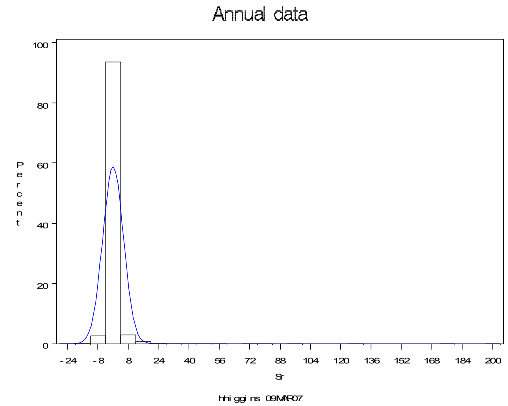
Stock price forecasts are predicted values from RIM regressions sharing the same structural form but differing in the treatments for autocorrelation. The structural form is $P_t = \beta_0 + \beta_1 bv_{t-1} + \beta_2 x_t^a + v_t$: where P_t is stock price per share at time, bv_{t-1} is book value per share at the beginning of the current annual period which starts at t-1 and ending at t, x_t^a is abnormal earnings over the current period defined as $x_t^a = x_t - r_t bv_{t-1}$, x_t is EPS forecast over the current period (I/B/E/S FYR1 earnings forecast), r_t is the current Treasury bill rate, and v_t is the error term.

The naïve model does not address auto correlation. The AR(1) and AR(2) models assume v_t follows an AR(1) and an AR(2) structure, respectively. The AR(2) - GARCH model combines AR(2) and GARCH modeling of v_t.

The forecasts are the corresponding regressions' predicted outputs for one-year-ahead and two-years-ahead beyond the estimation baseline. They are computed based on estimation results from the estimation sample, which are applied to knowledge of beginning book values and FYR1 earnings forecasts for the forecast years, and incorporated with the equivalent AR and GARCH parameters of v_t.

The forecast results are assessed based on three forecast error measures. 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.

Table 7: Diagnostics of the Error Term from Three Differently-Scaled RIM Regressions

Panel A: Deflation by Number of Shares	Panel B: No Deflation	Panel C: Deflation by Beginning Asset
		
N= 5353	N= 5353	N= 5353
Mean = 0	Mean = 0	Mean = 0
Median = -3.57	Median = -3,535.12	Median = -0.37
Range = 216.05	Range = 954,383	Range = 223.16
Interquartile range = 12.80	Interquartile range = 3,687	Interquartile range = 1.50
Standard Deviation = 12.94	Standard Deviation = 24,862	Standard Deviation = 5.44
Prob > White's Chi-square < 0.0001	Prob > White's Chi-square < 0.0001	Prob > White's Chi-square = 0.0087
Variability = -3.62	Variability = -7.03	Variability = -14.70
Skewness = 1.53	Skewness = 6.36	Skewness = 21.68
Kurtosis = 7.51	Kurtosis = 120.16	Kurtosis = 662.12
Durbin-Watson D = 0.75	Durbin-Watson D = 0.66	Durbin-Watson D = 1.40
(Pr < D: <0.0001 Positive correlation)	(Pr<D: <0.0001 Positive correlation)	(Pr<D: <0.0001 Positive correlation)

This Table shows replications using different scaling schemes for the RIM regression of equity value on beginning book value of equity and abnormal earnings. In Panel A, all regression variables are at firm-level divided by number of common shares outstanding adjusted for capital adjustments including stock splits and dividends. In Panel B, all variables are at firm level un-deflated. In Panel C, all variables are at firm-level divided by total assets. The diagnostics assess the distribution and autocorrelation properties of the error terms.

Table 8: Estimation and Forecast Results from Three Differently-Scaled RIM Regressions

	Panel A: Deflation by Number of Shares		Panel B: No Deflation		Panel C: Deflation by Beginning Asset	
	Naïve	**AR(1) Adjusted**	**Naïve**	**AR(1) Adjusted**	**Naive**	**AR(1) Adjusted**
Estimation Results						
β_0	10.76	13.50	3703	9198	-0.57	-0.57
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_1	0.33	0.21	2.91	1.00	1.50	1.46
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
β_2	10.36	7.59	0.28	0.09	34.96	35.19
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
ρ_1		0.67		0.82		0.31
		(<.0001)		(<.0001)		(<.0001)
N	5353	5353	5353	5353	5353	5353
Total R-square	39.96%	65.03%	37.30%	74.38%	38.92%	44.47%
Regress R-square	na	23.37%	na	10.03%	na	31.57%
Durbin-Watson	0.75	2.11	0.66	2.11	1.40	2.02
LaGrange Multiplier	2135.77	33.92	2592.06	25.79	486.50	6.82
Forecast Results						
Mean MAPE 2004	29.76%	19.44%	83.47%	24.73%	77.93%	59.93%
Test of difference	P-value <0.0001		P-value <0.0001		P-value = 0.0089	
Median MAPE 2004	24.49%	15.37%	51.27%	18.67%	57.15%	40.55%
Test of difference	P-value <0.0001		P-value <0.0001		P-value <0.0001	
Mean MAPE 2005	48.76%	32.58%	97.07%	53.73%	210.76%	203.24%
Test of difference	P-value = 0.3293		P-value = 0.0219		P-value = 0.9608	
Median MAPE 2005	24.72%	21.23%	50.77%	27.07%	58.52%	52.67%
Test of difference	P-value = 0.0307		P-value <0.0001		P-value = 0.2730	

This Table shows replications using different scaling schemes for the RIM regression of equity value on beginning book value of equity and abnormal earnings. In Panel A, all RIM regression variables are at firm-level divided by number of common shares outstanding adjusted for capital changes such as splits and stock dividends. In Panel B, all variables are at firm level un-deflated. In Panel C, all variables are at firm-level divided by total assets. MAPE is mean average percentage error, defined as the absolute difference between forecast price and actual price scaled by actual price, where forecast price equals the regression's predicted output multiplied by the corresponding scale. The Table purports to show that AR(1) forecasts are better than naïve forecasts regardless of scaling schemes.