THE UNIVERSITY of EDINBURGH

This thesis has been submitted in fulfilment of the requirements for a postgraduate degree (e.g. PhD, MPhil, DClinPsychol) at the University of Edinburgh. Please note the following terms and conditions of use:

- This work is protected by copyright and other intellectual property rights, which are retained by the thesis author, unless otherwise stated.
- A copy can be downloaded for personal non-commercial research or study, without prior permission or charge.
- This thesis cannot be reproduced or quoted extensively from without first obtaining permission in writing from the author.
- The content must not be changed in any way or sold commercially in any format or medium without the formal permission of the author.
- When referring to this work, full bibliographic details including the author, title, awarding institution and date of the thesis must be given.

Improving Practices of Price and Earnings Estimations

Ja Ryong Kim

Thesis presented for the degree of Doctor of Philosophy

University of Edinburgh

2015

Declaration

This thesis has been written and composed by the author. The work has not been submitted for any other degree, in whole or in part. This thesis is the original work of the author, except where specific reference is made to other sources.

Ja Ryong Kim

Acknowledgement

I would like to thank my supervisor, Professor William Rees, for his support and guidance. I also thank Maria Michou and Igor Goncharov for their helpful suggestions. I am also grateful to the University of Edinburgh for financial support for this research. Great thanks to my parents, Chi Hwan Kim and Young Gil Kim, and my brother, Ju Ha Kim. Special thanks to Fenfang Lin and Maggie Xu for their mental support over the past few years. Thanks also to Sasithorn Supatanakornkij, Tomas O'Briain and Vathunyoo Sila for reading this thesis and giving me suggestions.

I appreciate Professor Thomas McInish for guiding my research at the FMA European Doctoral Colloquium 2013. I thank conference participants at the FMA European Annual Conference 2013, the EFMA Annual Conference 2013, the EAA Annual Conference 2013, the BAFA Annual Conference 2013 and 2014, the BAFA Doctoral Colloquium 2011 and 2012, and the Scottish Doctoral Colloquium 2012 and 2013 for helpful comments and suggestions.

Table of Contents

List of Tables

CHAPTER 5

List of Figures

Abstract

Despite extensive research on price and earnings estimations, there are still puzzling results that have not been resolved. One of the puzzles in price estimation is that multiples using earnings forecasts outperform multiples using the residual income model (Liu, Nissim and Thomas, 2002). This puzzle undermines the validity of theory-based valuation models, which are originated from valuation theory and have been developed over the century. The first two projects of this thesis address this puzzle and explain mathematically how the pricing error of a multiple is determined by the correlation coefficient between price and a value driver. The projects then demonstrate that the puzzle in Liu, Nissim and Thomas (2002) is caused by the bad selection of residual income models and, in fact, the majority of residual income models (i.e. well-chosen residual income models) actually outperform multiples using earnings forecasts in pricing error. When models are examined in terms of future return generation, residual income models again outperform multiples using earnings forecasts, providing evidence that theory-based valuation models are superior to rule-of-thumb based multiples in price and intrinsic value estimations.

The third project addresses an issue in earnings estimation by cross-sectional models. Recently, Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014) introduce cross-sectional models in earnings estimation and argue that their cross-sectional models produce better earnings forecasts than analyst forecasts. However, their models suffer from one fundamental problem of cross-sectional models: the loss of firm-specific information in earnings estimation (Kothari, 2001). In other words, cross-sectional models apply the same coefficients (i.e. the same earnings persistence and future prospects) to all firms to estimate their earnings forecasts. The third project of this thesis addresses this issue by proposing a new model, a conditional cross-sectional model, which allows the coefficient on earnings to vary across firms. By allowing firms to use different earnings coefficients (i.e. different earnings persistence and future prospects), the project shows that a conditional cross-sectional model improves a cross-sectional model in all dimensions: a) bias, accuracy and earnings response coefficient; b) unscaled and scaled earnings estimations; and c) across all forecast horizons.

The thesis contributes to the price and earnings estimations literature. First, the thesis addresses the decade-old puzzle in price estimation and rectifies the previous misunderstanding of valuation model performance. By demonstrating the superiority of theory-based valuation models over rule-of-thumb based multiples, the thesis encourages further development of theory-based valuation models. Second, in earnings estimation, the thesis provides future researchers a new model, which overcomes the fundamental problem of cross-sectional models in earnings estimation while keeping their advantages. In sum, the thesis improves the knowledge and practices of price and earnings estimations.

1. Introduction

The purpose of equity valuation is to identify mispriced securities in investment (Kothari, 2001). Therefore, equity valuation basically assumes an inefficient market. By identifying mispriced securities, investors gain abnormal profits, and this leads to a more efficient capital market. Even in an efficient market, equity valuation still plays an important role. Kothari (2001) explains that equity valuation helps to identify the determinants of stock price, which are especially valuable for non-publicly traded firms. In all this process, valuation models play a central role in identifying the intrinsic value of firms.

The performance of valuation models is widely studied in the late 1990s and early 2000s. Three general findings on this literature are: 1) earnings forecasts contain more value relevant information on stock price or stock return than current earnings (Beaver, Lambert and Morse, 1980; Kim and Ritter, 1999; Yee, 2004); 2) among accounting-based valuation models, the residual income model performs better than the dividend discount model or discount cash flow model (Penman and Sougiannis, 1998; Francis, Olsson and Oswald, 2000; Frankel and Lee, 1998; Lee, Myers and Swaminathan, 1999); and 3) multiples using earnings forecasts outperform multiples using the residual income model (Liu, Nissim and Thomas, 2002).

The first finding is consistent with the definition of stock price (i.e. stock price is the discounted present value of expected future cash flows), and earnings forecasts reflect future cash flows better than current earnings. The second finding is disputed by Lundholm and O'Keefe (2001) that the outperformance of the residual income model over the dividend discount model or discount cash flow model is due to the use of inconsistent information in target price estimation. Lundholm and O'Keefe (2001) prove that, if consistent information based on the identical pro forma financial statements is used, three accounting-based valuation models are identical both theoretically and empirically. On the other hand, the reason for the third finding is not uncovered yet (Cooper and Lambertides, 2014). Liu, Nissim and Thomas (2002) comment on their puzzling result as "we investigate these results further and feel that these results indicate the trade-off that exists between signal and noise when more complex but theoretically correct structures are imposed". The first two projects of this thesis investigate this third finding more and explain how the puzzling result happens.

In addition, this thesis addresses another issue in earnings estimation. For decades, analyst forecasts are perceived as a superior proxy for the market expectation of earnings to time-series earnings forecasts (Brown, 1993; Kothari, 2001; Bradshaw et al., 2012). However, recently, Hou, van Dijk and Zhang (2012) argue that earnings forecasts from their cross-sectional model (HVZ model) are superior to analyst forecasts in terms of coverage, forecast bias and earnings response coefficient (ERC). Only in accuracy, analyst forecasts perform better than their cross-sectional model. Since then, the HVZ model is further used in valuation and implied cost of capital literature (Lee, So and Wang, 2014; Patatoukas, 2011; Chang, Landsman and Monahan, 2012; Jones and Tuzel, 2013). Li and Mohanram (2014) propose another cross-sectional model based on the finding that the HVZ model does not perform better than a random walk model (Gerakos and Gramacy, 2013). Based on valuation theory and the residual income model, Li and Mohanram (2014) develop the RI model that uses earnings, book value and accruals as estimators of future earnings. Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014) argue that cross-sectional models have wider coverage, more statistical power and suffer less from survivorship bias than time-series models. Despite these advantages, cross-sectional models suffer one fundamental problem: the loss of firm-specific information (Kothari, 2001). This is due to the use of the same coefficients of a cross-sectional model across all firms to estimate their earnings forecasts. In other words, all firms use the same (i.e. average) coefficients and apply the average future prospects of a cross section to their earnings forecasts. The third project of this thesis addresses this issue and proposes a new model, a conditional cross-sectional model, which allows the coefficient on earnings to vary across firms.

Therefore, the thesis consists of three projects. The first project investigates whether the puzzle, the outperformance of multiples using earnings forecasts over multiples using the residual income model, is a common result in price estimation. The project replicates and extends the methods of Liu, Nissim and Thomas (2002) in four dimensions: a) time; b) countries; c) calculation methods; and d) performance criteria. The project finds that the puzzling result is observed consistently across the four dimensions and hence is not a sample-specific result. Therefore, an investigation into how the puzzling result happens advances our understanding in price estimation.

The second project investigates into the puzzle and explains mathematically how the pricing error of a multiple is determined by the correlation coefficient between price and a value driver. The project then shows that the reason why Liu, Nissim and Thomas (2002) find the puzzling result is that they accidentally choose residual income models that perform worst among residual income models and compare their performance with the best-performing multiples. The project shows that the majority of residual income models (i.e. when residual income models are well chosen) actually perform better than earnings forecasts in multiples. In addition, when model performance is measured in terms of intrinsic value estimation by future return generation, the majority of residual income models again outperform multiples using earnings forecasts. The results provide evidence that theory-based valuation models are superior to rule-of-thumb based multiples in both price and intrinsic value estimations.

The third project addresses the problem of a cross-sectional model in earnings estimation by allowing the coefficient on earnings to vary across firms. A conditional cross-sectional model allows firms to use different earnings persistence and future prospects in their earnings forecasts. The results show that a conditional cross-sectional model improves the performance of a cross-sectional model in all dimensions: a) bias, accuracy and ERC; b) for unscaled and scaled earnings estimations; and c) across all forecast horizons up to five years. The results indicate that, by improving model specification, a conditional cross-sectional model uses the same amount of information as a cross-sectional model does but overcomes the main weakness of a cross-sectional model and improves its performance. The results of robustness tests demonstrate that the improvement is consistent across different subsamples and hence genuine.

The thesis contributes to the price and earnings estimations literature. First, by addressing the decade-old puzzle in price estimation, the thesis demonstrates that theory-based valuation models are in fact superior to rule-of-thumb based multiples in price and intrinsic value estimations. The finding provides support to the validity of theory-based valuation models and encourages future researchers to develop theory-based valuation models further. Second, by proposing a conditional cross-sectional model, the thesis provides future researchers an improved earnings estimation model, which keeps the advantages of a cross-sectional model while overcoming its main weakness and improving its performance.

2. Literature Review

2.1. Introduction

In 1930, Wiese (1930, Page 5) defines the value of securities as “the proper price of any security, whether a stock or bond, is the sum of all future income payments discounted at the current rate of interest in order to arrive at the present value”. Although Wiese’s definition of security value has to be changed from “future income payments” and “the current rate of interest” to “expected future income payments” and “the risk-adjusted future rate of interest”, respectively, he correctly identifies the two main factors in security value: expected future cash flows and discount rates. Since then, stock price is defined as the discounted present value of expected future cash flows. Based on this definition, equity valuation models have been developed to estimate the intrinsic value of firms.

The remainder of this literature review is structured as follows. Section 2 explains the development of valuation models including accounting-based valuation models and multiples. Section 3 explains the practices of the estimation of expected future cash flows, and Section 4 explains the practices of the estimation of discount rates. Section 5 explains the performance of valuation models in practice.

2.2. Model Developments

2.2.1. Dividend Discount Model

Based on the definition of security value, Williams (1938, Page 56) designs the first theory-based valuation model, the dividend discount model. Because dividends are future payments to investors for owning a stock of a firm, Williams (1938) develops the dividend discount model as:

$$P_0 = \sum_{t=1}^{t=\infty} \frac{DIV_t}{(1+r)^t} = \frac{DIV_1}{(1+r)^1} + \frac{DIV_2}{(1+r)^2} + \frac{DIV_3}{(1+r)^3} + \cdots \quad (1)$$

where P_0 is the stock price at start, DIV_t is the dividend at time *t*, and *r* is the cost of equity.

The dividend discount model is equivalent to a model that is derived from the definition of stock return. Miller and Modigliani (1961) explain this by expressing stock return as:

$$r_t = \frac{DIV_t + P_{t+1} - P_t}{P_t} \quad (2)$$

where r_t is the stock return at time *t*, DIV_t is the dividend, and P_t is the stock price.

Rearranging Equation (2) for P_t generates:

$$P_t = \frac{1}{1 + r_t}[DIV_t + P_{t+1}]$$

$$P_t = \frac{1}{1+r_t}\left[DIV_t + \frac{1}{1+r_{t+1}}(DIV_{t+1} + P_{t+2})\right] \quad (3)$$

When a constant discount rate and $\lim_{t\to\infty} P_t = 0$ are assumed, Equation (3) becomes identical to the dividend discount model in Equation (1).

The dividend discount model estimates stock price by using the ultimate cash flows to investors, dividends. Therefore, the dividend discount model is considered a model that reflects the definition of stock price most. Several studies find that dividends indicate the future performance of firms (Bhattacharya, 1979; John and Williams, 1985; Miller and Rock, 1985), justifying the use of dividends as a proxy for expected future cash flows.

However, the dividend discount model suffers from several issues. First, dividends are an indicator of value distribution, not value creation. According to the dividend displacement property (Miller and Modigliani, 1961), the distribution of dividends at present decreases the current book value and future earnings dollar-for-dollar. Therefore, an increase in dividends does not affect the total wealth of investors at present while decreases future earnings power. However, in the dividend discount model, an increase in dividends is often perceived as an increase in firm value.

Second, a lot of firms do not pay dividends and, therefore, the dividend discount model cannot be used for those firms. Lundholm and O'Keefe (2001) argue that unpaid dividends are accumulated in book value and therefore the book value that includes unpaid dividends should be used as a terminal value for the dividend discount model. They argue that the future book value, which includes unpaid dividends, should be calculated based on pro forma financial statements. However, given the fact that forecasting pro forma financial statements is more difficult than forecasting dividends alone, their argument still has a limitation in application and hence the dividend discount model is not widely used for firms that do not pay dividends.

Third, dividends are often determined by firm's dividend policy and hence do not change over time (Brav et al., 2005). Therefore, dividends have a limitation on reflecting firm's performance in a timely manner.

Despite the criticisms, the dividend discount model still remains as one of the most widely used and studied valuation models. Because of its characteristic that the model reflects the definition of stock price most, the dividend discount model is often used as the foundation for developing other theory-based valuation models.

2.2.2. Discount Cash Flow Model

The discount cash flow model aims to overcome the drawback of the dividend discount model by using a value creation indicator, cash flows, instead of a value distribution indicator, dividends. The discount cash flow model estimates firm value by using free cash flows after expenses and investments (Koller, Goedhart and Wessels, 2005, Page 61).

$$FV_0 = \frac{FCF_1}{(1+r_{WACC})} + \frac{FCF_2}{(1+r_{WACC})^2} + \frac{FCF_3}{(1+r_{WACC})^3} + \cdots \tag{4}$$

where FV_0 is the firm value at start, FCF_t is the free cash flow at time *t*, and r_{WACC} is the weighted average cost of capital.

Although free cash flows are not the same as dividends *per se*, they are a strong proxy for dividends. In addition, free cash flows are the result of firm's value creating activities. Therefore, an increase in free cash flows reflects an increase in firm's earnings power.

However, the discount cash flow model is not immune from criticisms. First, free cash flows of firms are often negative. Liu, Nissim and Thomas (2002) find that approximately 30% of their sample has negative free cash flows. Considering the fact that their sample is biased toward large firms, the figure would increase even more if smaller firms were included. In addition, although zero dividend payments can be interpreted as an accumulation of capital and an increase in future book value, interpreting negative free cash flows in the same way is problematic.

Second, Penman and Sougiannis (1998) explain that cash flow accounting does not reflect firms' performance in a timely manner than accrual accounting. Therefore, although cash flows represent 'real' profits from operations, it does not follow the matching principle of accounting.[1]

Third, forecasting free cash flows is unusually difficult. Free cash flows are calculated as net income plus depreciation, minus a change in working capital, minus capital expenditure. Therefore, forecasting free cash flows requires the forecasts of at least four variables and they inevitably incur large forecast errors.

Despite these issues, the discount cash flow model is also widely used in practice mainly due to its use of free cash flows as a value indicator and the customers' familiarity with the model (Demirakos, Strong and Walker, 2004).

2.2.3. Residual Income Model

The development of the residual income model is widely accredited to Ohlson (1995) and Feltham and Ohlson (1995), although the concept of the residual income model

[1] The matching principle of accounting explains that expenses should be recorded when they are incurred, instead of when cash is transferred.

exists before them (Kothari, 2001). Under the clean surplus relation, the residual income model becomes identical to the dividend discount model.[2] The residual income model estimates stock price as:

$$P_0 = B_0 + \frac{E_1 - rB_0}{(1+r)} + \frac{E_2 - rB_1}{(1+r)^2} + \frac{E_3 - rB_2}{(1+r)^3} + \cdots \tag{5}$$

where P_0 is the stock price at start, E_t is the earnings at time *t*, and B_t is the book value, and r is the cost of equity.

By using book value and earnings, the residual income model shifts focus from a value distribution indicator (i.e. dividends) to value creation indicators (i.e. book value and earnings). In addition, book value and earnings are the two bottom line values in balance sheets and income statements, respectively. Therefore, the residual income model uses the two most important accounting values to estimate stock price. In the residual income model, book value represents normal earnings (i.e. the value when the return on equity is equal to the cost of equity) and the discounted residual incomes represent abnormal earnings (i.e. the value when the return on equity is above or below the cost of equity). Due to the use of the two most important accounting values in the model and its identity with the dividend discount model, the residual income model has attracted huge popularity from academics (Kothari, 2001). However, Demirakos, Strong and Walker (2004) find that the residual income model is not widely used in practice (only in 1.9% of analyst reports), possibly due to analysts' and customers' unfamiliarity with the model.

[2] The clean surplus relation assumes that all changes in equity are reflected in the income statement in the period, except transactions between owners.

The residual income model also has attracted criticisms, especially of the assumption about the clean surplus relation. Dechow, Hutton and Sloan (1999) argue that extraordinary items should be included in earnings to satisfy the clean surplus relation. However, in practice, earnings without extraordinary items are often used. Ohlson (2005) claims that the clean surplus relation is often violated when there is a change in the number of shares outstanding. In that case, a change in book value per share is not equal to earnings per share minus dividend per share. In addition, the residual income model requires the estimations of future expected residual incomes and discount rates. These estimations require a considerable amount of data and hence reduce coverage of firms (Liu, Nissim and Thomas, 2002). On the other hand, valuation text books explain that these estimations of future expected residual incomes and discount rates in fact improve the accuracy of the residual income model by using a larger amount of firm-specific information (Penman, 1998b; Barker, 2001, Page 18; Penman, 2013, Page 129; Palepu, Healy and Peek, 2013, Page 287). Despite these criticisms, the residual income model remains as one of the most widely studied theory-based valuation models in academia due to the use of book value and earnings in the model and its equivalence to the dividend discount model.

2.2.4. Abnormal Earnings Growth Model

Ohlson (2005) and Ohlson and Juettner-Nauroth (2005) develop the abnormal earnings growth model to overcome the problem of the residual income model caused by the clean surplus relation assumption. By estimating stock price without relying on book value, Ohlson (2005) and Ohlson and Juettner-Nauroth (2005) argues that the abnormal earnings growth model avoids the violation of the clean surplus relation. The abnormal earnings growth model estimates stock price as:

$$P_0 = \frac{E_1}{r} + \frac{1}{r}\left[\sum_{t=1}^{\infty} \frac{\Delta E_{t+1} - r(E_t - DIV_t)}{(1+r)^t}\right] \quad (6)$$

where P_0 is the stock price at start, E_t is the earnings at time t, DIV_t is the dividend, and r is the cost of equity.

Capitalised one-year ahead earnings, $\frac{E_1}{r}$, represent normal earnings and the remaining terms (i.e. the change in earnings over the required growth of earnings) represent abnormal earnings. Ohlson (2005) argues that the abnormal earnings growth model is superior to the residual income model because 1) the former is not restricted to the clean surplus relation assumption by avoiding using book value in the model, and 2) it shifts the estimation focus from book value to earnings, which are the most widely studied and forecasted accounting variable.

However, the abnormal earnings growth model also suffers from criticisms. By shifting the estimation focus from book value to earnings, the model does not utilise information in balance sheets. The impact of the loss of balance sheet information can be indirectly estimated by the role of book value in the residual income model. According to Francis, Olsson and Oswald (2000), book value accounts for 72% of intrinsic value estimates in the residual income model. On the other hand, Penman (2005) argues that the abnormal earnings growth model lacks a theoretical foundation. He claims that the use of capitalised one-year ahead earnings as an anchoring value is arbitrary and, in fact, any capitalised accounting value can be an anchoring value such as cash flows, depreciation, sales or five-year ahead earnings.

Despite the claims by Ohlson (2005) and Ohlson and Juettner-Nauroth (2005) that the abnormal earnings growth model is superior to the residual income model, the abnormal earnings growth model is not widely used and studied in academia and practice, possibly due to its late development.

2.2.5. Multiples

The dividend discount model, discount cash flow model, residual income model and abnormal earnings growth model are absolute, theory-based valuation models. Absolute valuation models estimate equity value based on the expected future cash flows of a target firm, regardless of what other firms are valued at the time. On the other hand, multiples are relative valuation models. Instead of using information on the target firm, multiples estimate stock price by using the stock prices of other firms. Therefore, multiples estimate stock price based on the fundamental economic theory: 'The Law of One Number'.

According to The Law of One Number, identical objects should have identical prices, and similar objects should have similar prices. If the prices are different, arbitrageurs will make profits from the difference until the prices become identical. The Law of One Number also applies to firms: identical firms should have identical prices, and similar firms should have similar prices. Therefore, a target firm can be valued based on the stock prices of its peer firms. For example, if peer firms are assumed to be firms in the same industry and the average industry price-to-earnings ratio is 15, a target firm with earnings per share of $5 will have a target price of $75.

By using the stock prices of other firms, multiples implicitly assume the Efficient Market Hypothesis and indirectly use expected future cash flows and discount rates that are determined by the market. Such an advantage allows multiples to avoid the estimations of future cash flows and discount rates, which inevitably involve large estimation errors. Due to this advantage and simplicity, multiples have become a dominant valuation model in practice (Arnold and Moizer, 1984; Barker, 1999a; Block, 1999; Bradshaw, 2002; Demirakos, Strong and Walker, 2004; Imam, Barker and Clubb, 2008), especially when valuing young firms such as initial public offering (IPO) firms that do not have a long history of earnings (Kim and Ritter, 1999).

Baker and Ruback (1999) and Palepu, Healy and Peek (2013) argue that there are three common issues when using multiples: 1) finding comparable or peer firms, 2) selecting a value driver that best reflects firm's performance, and 3) estimating the unit price (i.e. multiple) of a value driver. These are empirical issues and, therefore, explained in more detail in the methodology section of the first project.

2.3. Forecasting Future Cash Flows

All theory-based valuation models require the forecasts of two factors: future cash flows and discount rates. This section and the next section explain the common methods used to forecast future cash flows and discount rates, respectively. Forecasting future cash flows often means forecasting future earnings because several studies have found that earnings explain stock price movements better than dividends or cash flows (Ball and Brown, 1968; Biddle, Seow and Siegel, 1995; Francis, Schipper and Vincent, 2003). In practice, three methods are widely used to forecast future cash flows: 1) the time series of earnings, 2) analyst forecasts, and 3) management earnings forecasts.

2.3.1. Time Series of Earnings

The time series of earnings are widely studied from 1968 to 1987 (Bradshaw et al., 2012). However, Kothari (2001, Page 145) states that "this literature is fast becoming extinct. The main reason is the easy availability of a better substitute: analysts' forecasts are available at a low cost in machine-readable form for a large fraction of publicly traded firms".

There are four main findings in the literature. First, annual earnings follow a random walk or a random walk with drift (Little, 1962; Little and Rayner, 1966; Ball and Watts, 1972; Albrecht, Lookabill and McKeown, 1977; Watts and Leftwich, 1977). Second, there is a mild mean reversion in annual earnings (Brooks and Buckmaster, 1976; Ramakrishnan and Thomas, 1992; Lipe and Kormendi, 1994; Fama and French, 2000). Third, quarterly earnings are largely explained by Box-Jenkins autoregressive integrated moving average (ARIMA) models (Foster, 1977; Griffin, 1977; Brown and Rozeff, 1979). Last, analyst forecasts are more accurate than earnings forecasts from time-series models (Brown and Rozeff, 1978; Collins and Hopwood, 1980; Brown et al., 1987; Kross, Ro and Schroeder, 1990; Branson, Lorek and Pagach, 1995).

Fried and Givoly (1982) and O'Brien (1988) attribute the superiority of analyst forecasts over time-series models to an information advantage that analysts have. In practice, analysts can use more information than past earnings in their earnings forecasts. In fact, analysts can estimate the time series of earnings by themselves as an additional information set. Brown et al. (1987), Lys and Soo (1995), Hopwood and McKeown (1990), and Bradshaw et al. (2012) find that the accuracy of analyst forecasts decreases as a forecast horizon lengthens (i.e. when more distant future earnings are estimated). They interpret the stronger performance of analyst forecasts in a shorter horizon as an evidence of a timing advantage. Since analysts can use information after the last earnings announcements, they utilise more information than time-series models, and this advantage is stronger when a forecast horizon is shorter.

2.3.2. Analyst Forecasts

The initial reason for studying analyst forecasts was to examine the usefulness of analyst forecasts as a surrogate for time-series earnings. Since then, interest in analysts has grown rapidly and now analysts are considered as an important economic agent in the capital market (Bradshaw, 2011).

As explained above, several studies have found that analyst forecasts are generally more accurate than time-series earnings forecasts. Therefore, analyst forecasts are mainly used for future expected earnings in valuation models. However, analyst forecasts have some drawbacks. First, analyst forecasts are expensive and have only limited coverage, especially for large public firms. Second, analyst forecasts are positively biased (Barefield and Comiskey, 1975; Crichfield, Dyckman and Lakonishok, 1978; Stickel, 1990; Abarbanell, 1991; Ali, Klein and Rosenfeld, 1992; Richardson, Teoh and Wysocki, 1999; Easterwood and Nutt, 1999). Thirdly, analyst forecasts are not fully efficient. Analysts overreact to past earnings changes (De Bondt and Thaler, 1990), underreact to past stock price changes (Lys and Sohn, 1990), and underestimate the serial correlation of quarterly earnings, resulting in a post-earnings announcement drift (Mendenhall, 1991; Abarbanell and Bernard, 1992).

The reasons for a positive bias in analyst forecasts are widely studied. The most widely accepted reason is that analysts have economic incentives, such as investment banking fees, to generate positive forecasts (Lin and McNichols, 1998; Michaely and Womack, 1999). Because firms prefer to choose investment banks that issue favourable reports about them, analysts have economic incentives to generate positive forecasts to attract investment banking businesses. Second, Francis and Philbrick (1993) explain that analysts issue positive forecasts to maintain a good relationship with management. This helps them to gain primary information about the firm and have an information advantage over the others. Third, Affleck-Graves, Davis and Mendenhall (1990) and McNichols and O'Brien (1997) explain that the positive bias of analyst forecasts is due to self-selection bias, which means that analysts simply choose not to report negative forecasts at all. Fourth, Elton, Gruber and Gultekin (1984) and Easterwood and Nutt (1999) argue that the positive bias comes from the cognitive behavioural bias of analysts. They claim that analysts overreact to good news and underreact to bad news, resulting in a positive bias in their forecasts. Last, Cowen, Groysberg and Healy (2006) and Jacob, Rock and Weber (2008) explain that the positive bias is due to analysts' incentives to generate transactions. Considering the fact that persuading investors to buy stocks is much easier than persuading them to sell stocks (or short-sell stocks that they do not own), issuing positive forecasts induces transactions and generates transaction fees to a trading office.

2.3.3. Management Forecasts

Management earnings forecasts are voluntary forecasts by management and are often issued after earnings announcements (Kothari, 2001). Studies have found that management forecasts have information content and are positively related to stock returns (Patell, 1976; Nichols and Tsay, 1979; Waymire, 1984; Pownall, Wasley and Waymire, 1993). Penman (1980) attributes the information content of management forecasts to a timing advantage, which management can issue forecasts only when they have an information advantage compared to the market.

However, management forecasts are not widely used in valuation models because they are mostly forecasts for the short-term and issued irregularly. In addition, management forecasts are voluntary in nature and hence have an economic motivation (Kothari, 2001). Skinner (1994), Francis, Philbrick and Schipper (1994), and Kasznik and Lev (1995) argue that management is vulnerable to the threat of litigation and hence is more likely to issue negative forecasts to mitigate litigation risk.

2.3.4. Cross-Sectional Models

Recently, Hou, van Dijk and Zhang (2012) develop a cross-sectional model to estimate earnings forecasts based on the cross-sectional profitability model of Fama and French (2000) and Fama and French (2006). By using a cross-sectional model, Hou, van Dijk and Zhang (2012) argue that their model, the HVZ model, suffers less from survivorship bias and have higher statistical power than time-series models. They find that earnings forecasts from their cross-sectional model outperform analyst forecasts in terms of coverage, forecast bias and earnings response coefficient (ERC). However, in accuracy, analyst forecasts still outperform the HVZ model.

Li and Mohanram (2014) extend the findings of Hou, van Dijk and Zhang (2012) by introducing another cross-sectional model. Their model is based on the finding that the HVZ model does not perform better than a random walk model (Gerakos and Gramacy, 2013). Based on valuation theory and the residual income model, Li and Mohanram (2014) propose the RI model and show that the RI model performs better than the HVZ model in bias, accuracy and ERC. However, Li and Mohanram (2014) do not include the performance of analyst forecasts and, therefore, it is unknown whether the RI model performs better than analyst forecasts in accuracy.

Although cross-sectional models have some advantages over analyst forecasts and time-series models, they suffer from one fundamental problem: the sacrifice of firm-specific information when forecasts are made (Kothari, 2001). This means that all firms use the same coefficients (i.e. the same earnings persistence and future prospects) from the cross-sectional model to estimate their earnings forecasts. The third project of this thesis addresses this issue and proposes a new model, which allows firms to have different earnings coefficients in their earnings estimations.

2.4. Forecasting Discount Rates

Forecasting discount rates means forecasting the cost of equity or capital. Since forecasting the cost of equity is developed from the modern portfolio theory (Markowitz, 1952), studies on the cost of equity are mostly conducted in finance literature under the theme of asset pricing. In this literature review, only the two most fundamental but still most widely used asset pricing models are explained. For both models, constant discount rates are assumed over time.

The first model is the Capital Asset Pricing Model (CAPM). The CAPM estimates the expected stock returns along the capital allocation line (i.e. the line between the risk-free rate and the tangency portfolio on the efficient frontier line). Therefore, the CAPM assumes that investors have a diversified portfolio and only need to consider the systematic risk of stocks. The CAPM estimates the cost of equity as the risk-free rate, plus beta times the market risk premium as: $r_i = r_f + \beta_i(r_m - r_f)$. Beta represents the systematic risk of stocks and the market risk premium represents the expected return of stocks over the expected return of risk-free assets such as government bonds. Due to its simplicity and theoretical foundation, the CAPM has received huge popularity and still remains as the most widely used asset pricing model. However, several studies have found that there are abnormalities that cannot be explained by the CAPM. Basu (1977) finds that firms with low P/E ratios tend to have higher returns than expected by the CAPM. Similarly, Banz (1981) finds that small firms tend to have higher returns than expected, and Litzenberger and Ramaswamy (1979) find that firms with high dividend yields have higher returns than expected by the CAPM.

The second model is the Fama and French three-factor model. Fama and French (1993) and Fama and French (1996) find that most of the abnormalities in the CAPM can be explained by their three-factor model, which adds size and value indicators to the CAPM. However, although the Fama and French three-factor model can improve the explanatory power of the CAPM, the three-factor model suffers from a fundamental problem: the three-factor model is not a theory-based model but an empirical model. The explanation for why size and value indicators are included is not provided. Fama and French (1993) state that “but our work leaves many open questions. Most glaring, we have not shown how the size and book-to-market factors in returns are driven by the stochastic behaviour of earnings. How does profitability, or any other fundamental, produce common variation in returns associated with size and BE/ME that is not picked up by the market return?” This makes the use of size and value indicators somewhat arbitrary. However, due to its simplicity and high explanatory power, the three-factor model remains as one of the most widely used asset pricing models.

2.5. Empirical Tests

Valuation models are generally tested in terms of 1) pricing error (i.e. the distance between target price and stock price), 2) explanatory power (i.e. how much variation in stock price or stock return is explained by variation in independent variables), and 3) future return generation (i.e. how much abnormal returns can be made following a trading strategy based on target prices). The first two performance criteria assume the Efficient Market Hypothesis. By comparing target price with stock price, the two performance criteria identify which valuation model explains stock price most. On the other hand, the third performance criterion, future return generation, assumes an inefficient market. In an inefficient market, stock prices can deviate from intrinsic values in the short-term, but are assumed to converge to intrinsic values in the long-term. Future return generation assumes that target prices from valuation models are intrinsic values. Therefore, if stock prices converge to intrinsic values in the long-term, investors can gain positive abnormal returns by trading based on target prices from valuation models.

2.5.1. Pricing Error

Pricing error is measured as target price minus stock price divided by stock price or earnings per share (Bradshaw et al., 2012). Kaplan and Ruback (1995) compare a discount cash flow model and a multiple using earnings before interest, taxes, depreciation and amortization (EBITDA) in management buyouts, and find that the median pricing error of a discount cash flow model is less than 10% of the completed transaction value. However, when a multiple using EBITDA is estimated based on comparable transactions, it performs as well as the discount cash flow model. Berkman, Bradbury and Ferguson (2000) find similar results to those of Kaplan and Ruback (1995) in IPOs in New Zealand. They find that both discount cash flow model and price-to-earnings (P/E) ratio generate pricing errors of around 20% of market prices. Cheng and McNamara (2000) compare a P/E ratio, a price-to-book (P/B) ratio and the combined model, which combines target prices from the P/E and P/B ratios equally. The results show that the combined model has the smallest pricing error, followed by a P/E ratio and a P/B ratio, sequentially. They conclude that earnings have more information on stock price than book value, but both earnings and book value have value relevant information and neither dominates the other completely. Liu, Nissim and Thomas (2007) compare multiples based on dividends, operating cash flows and earnings in ten countries. They find that a P/E ratio dominates a price-to-dividend (P/D) ratio and a price-to-operating cash flow ratio (P/CFO).

Penman and Sougiannis (1998) compare the performance of the dividend discount model, discount cash flow model and residual income model by using *ex post* values. Penman and Sougiannis (1998) explain that there are two ways to test theory-based valuation models: 1) by using *ex post* values, and 2) by using *ex ante* forecasts. Although using *ex ante* forecasts is ideal, Penman and Sougiannis (1998) argue that not many firms have forecasts for dividends, cash flows and earnings. Therefore, they use *ex post* values assuming that measurement errors in *ex ante* forecasts will average out at zero in a portfolio level. Penman and Sougiannis (1998) find that the residual income model consistently generates smaller pricing errors than the dividend discount model or discount cash flow model. They attribute the outperformance of the residual income model over the other models to accrual earnings, which reflect firms' performance in a timelier manner than cash flows or dividends.

Francis, Olsson and Oswald (2000) instead use *ex ante* forecasts to compare the performance of the dividend discount model, discount cash flow model and residual income model. They use forecasts from Value Line and estimate the accuracy of pricing error (i.e. the absolute value of pricing error), instead of the bias. They argue that bias is a performance criterion for a portfolio (i.e. indicating where target price locates compared to stock price on average), while accuracy is a performance criterion for an individual stock (i.e. indicating how close target price is to stock price). Francis, Olsson and Oswald (2000) find a similar result to that of Penman and Sougiannis (1998): the residual income model generates smaller pricing errors than the dividend discount model or discount cash flow model. However, they attribute the superiority of the residual income model to the use of book value. In the residual income model, book values account for 72% of target prices, while in the dividend discount model and discount cash flow model, terminal values account for 65% and 82% of target prices, respectively. In addition, Francis, Olsson and Oswald (2000) find that the performance of valuation models does not entirely depend on the accuracy of future cash flow estimations. For example, while dividends can be forecasted more accurately than cash flows or earnings, the dividend discount model performs worse than the discount cash flow model or residual income model.

Despite extensive research, most studies have examined only a few valuation models in different contexts, such as IPOs or management buyouts. Therefore, it is difficult to determine which valuation models or factors generally explain stock prices most. To address this issue, Liu, Nissim and Thomas (2002) examine the pricing errors of 17 value drivers including residual income models in multiples, and find that multiples using earnings forecasts perform the best, followed by multiples using the residual income model, and multiples using current accounting values, sequentially.

The second project of this thesis investigates the finding of Liu, Nissim and Thomas (2002) further and explains 1) how multiples using earnings forecasts outperform multiples using the residual income model. Liu, Nissim and Thomas (2002) state a potential reason why multiples using earnings forecasts outperform multiples using the residual income model as "we investigate these results further and *feel* that these results indicate the trade-off that exists between signal and noise when more complex but theoretically correct structures are imposed". The second project of this thesis *explains* mathematically how Liu, Nissim and Thomas (2002) find this puzzling result.

2.5.2. Explanatory Power

Explanatory power is often estimated by the coefficient of determination (i.e. R^2) or the earnings response coefficient. The earnings response coefficient is estimated as the coefficient of a regression of stock value on value drivers. For stock value, stock price or stock return is widely used. Landsman and Magliolo (1988) explain that there is no optimal choice between stock price and stock return. Instead, the decision should be made based on the econometric properties of models such as whether OLS assumptions are violated or not. Barth, Beaver and Landsman (2001) argue that the choice between stock price and stock return should be determined by the economic purpose of research. If research aims to find the determinants of firm value, stock price should be used. On the other hand, if research aims to find the determinants of the change in firm value, stock return should be used.

Kothari and Zimmerman (1995) explain that earnings have an unbiased coefficient when stock price is used, while they have a downward-biased coefficient when stock return is used. This is because earnings have two components: expected earnings and unexpected earnings. Expected earnings do not affect stock return. Therefore, when stock return is used for stock value, earnings contain an unnecessary component (i.e. measurement error in an independent variable), resulting in a coefficient to be biased toward zero. On the other hand, stock price contains cumulative information on both components and hence does not lead to a biased earnings coefficient. However, the use of stock return makes a dependent variable more stationary and hence satisfies OLS assumptions better.

For value drivers, three accounting values are widely used: 1) earnings, 2) residual income, and 3) the book value of equity.

2.5.2.1. Explanatory Power of Earnings

The studies of Ball and Brown (1968) and Beaver (1968) are believed to be the first research to examine the value relevance of earnings. By conducting event studies, Ball and Brown (1968) find that the change in earnings (i.e. unexpected earnings) correlates with abnormal stock returns around earnings announcements. Similarly, Beaver (1968) finds that there are significant increases in trading volume and return volatility during the week of earnings announcements compared to the non-reporting periods. The results of both studies indicate that there is information content in earnings to explain stock returns.

Various studies support the findings of Ball and Brown (1968) and Beaver (1968). Rayburn (1986) finds that both accruals and cash flow components of earnings have value relevant information on stock returns. Barth, Cram and Nelson (2001) find that accruals are related to stock returns and future cash flows. Biddle, Seow and Siegel (1995) find that earnings, sales and cash flows all have incremental value relevance, but among them, earnings have the highest value relevance, followed by sales and cash flows, sequentially. Francis, Schipper and Vincent (2003) find that earnings dominate EBITDA and cash flows in explaining stock returns. Kim, Lim and Park (2009) find that an earnings increase supported by a sales increase has a higher explanatory power than an earnings increase not supported by an increase in sales.

Dechow (1994) finds that earnings are more value relevant than cash flows, especially when firms experience considerable changes in working capital, investments or financing activities. She explains that this is because earnings are estimated based on the matching principle of accounting, while cash flows are not. Similarly, Basu (1997) finds that earnings reflect bad news more quickly than cash flows. He attributes the superiority of earnings to cash flows to conservatism in accounting.

Sloan (1996) finds that the accrual component of earnings has a lower persistence than the cash flow component of earnings. He explains that investors fail to distinguish between the two components and, as a result, have negative abnormal returns after trading based on earnings announcements driven by the accrual component of earnings. Lev and Nissim (2006) argue that investors still cannot gain abnormal profits based on the finding of Sloan (1996) because of significant information and transaction costs involved in distinguishing the cash flow component from the accrual component.

Kim and Ritter (1999) examine the explanatory powers of multiples in IPOs. By comparing the multiples of target firms with the multiples of comparable firms, they find that multiples based on current accounting values including a P/E ratio have limited explanatory powers for the target firms' multiples. Kim and Ritter (1999) explain that this is because comparable firms are young in IPOs and hence their multiples have a high variation. When forecasted earnings are used, however, the adjusted R^2 of the multiple increases significantly.

2.5.2.2. Explanatory Power of Residual Income

Since the development of the residual income model by Ohlson (1995) and Feltham and Ohlson (1995), interest in residual income has increased. Bernard (1995) finds that residual income explains 68% of the variation in price, while dividend explains 29%. Biddle, Bowen and Wallace (1997) examine the explanatory powers of earnings, economic value added (EVA), residual income and cash flows in explaining stock returns. By using *ex post* values, they find that earnings have the highest explanatory power, followed by residual income, EVA and cash flows, sequentially. They find that residual income and EVA have only marginal incremental value beyond earnings. Forker and Powell (2008) revisit the findings of Biddle, Bowen and Wallace (1997) by estimating the pricing errors of valuation models for horizons more than a year. In contrast to the findings of Biddle, Bowen and Wallace (1997), Forker and Powell (2008) find that valuation models using residual income and EVA generate smaller pricing errors than earnings and cash flows, indicating that the capital adjustments to earnings in order to calculate residual income and EVA add value relevant information.

2.5.2.3. Explanatory Power of Book Value

Barth, Beaver and Landsman (1998) find that the explanatory power of book value in explaining stock prices increases when firms are in financial difficulties, while the explanatory power of earnings increases when firms have high intangible assets. Barth, Beaver and Landsman (1998) argue that book value and earnings play a different role in explaining stock prices and omitting one causes omitted variable bias. Collins, Pincus and Xie (1999) argue that book value plays a role of a liquidation value or normal earnings and hence has incremental information beyond earnings. Dechow, Hutton and Sloan (1999) find a similar result that book value adds additional information beyond earnings in explaining stock prices. However, when forecasted earnings are used, the incremental value of book value diminishes dramatically.

2.5.3. Future Return Generation

While examining performance in pricing error or explanatory power assumes an efficient market, the examination of performance in future return generation assumes an inefficient market. Frankel and Lee (1998) examine the future returns of trading strategies based on target prices from the residual income model and a P/B ratio. They find that the buy-and-hold return of a trading strategy based on the residual income model is more than twice as high as that of a P/B ratio in three years. Lee, Myers and Swaminathan (1999) argue that stock prices are efficient only if transaction costs are low enough for arbitrageurs to make spontaneous transactions. Therefore, with an inefficient market assumption, they examine the future returns of trading strategies based on the residual income model, P/E, P/B and P/D ratios and find that a trading strategy based on the residual income model generates higher future returns than those based on the multiples. They explain that the use of time-varying interest rates is crucial in the residual income model to maximise its future returns. Bradshaw (2004) compares the future returns of trading strategies based on the residual income model, a price-earnings-to-growth (PEG) ratio and analysts' long-term earnings growth rate forecasts. He finds that a trading strategy based on the residual income model generates higher future returns than those based on a PEG ratio and long-term earnings growth rate forecasts. However, analyst recommendations are better explained by a PEG ratio and long-term earnings growth rate forecasts than the residual income model. Therefore, the relative performance of valuation models depends on by which performance criteria performance is measured.

2.5.4. Model Combination

Several studies have shown that different accounting values have different information content (Rayburn, 1986; Barth, Beaver and Landsman, 1998; Dechow, Hutton and Sloan, 1999; Barth, Cram and Nelson, 2001; Forker and Powell, 2008). Therefore, it is reasonable to believe that models can improve their performance by combining more than one accounting variable. Penman (1998a) combines P/B and P/E ratios with different weights and finds that some combinations perform better than the individual multiples. He explains that the optimal weights between the two multiples depend on the relative size of book value to earnings. Courteau et al. (2006) combine the residual income model and a P/E ratio with equal weights and find that the combined model outperforms the individual models in terms of both pricing error and future return generation. Yoo (2006) estimates an optimal combination between multiples based on a regression analysis. Similarly, his optimal multiple produces a smaller pricing error than the individual multiples. However, when the optimal multiple is estimated based on multiples using earnings forecasts, the optimal model does not have incremental information beyond the individual multiples.

Although an idea of combining models to improve performance sounds attractive, there is a caveat in application. Because combining models is not based on theory, the combination is inherently arbitrary and there is no optimal rule in how to combine different models. For example, in Yoo (2006), the optimal multiple is estimated by using 63% of P/E ratio, 17% of P/B ratio, 10% of P/EBITDA ratio and -4% of P/S ratio with an intercept of 2.75. Such a combination is difficult to rationalise, not to mention that the use of a negative weight for a P/S ratio makes no sense in practice.

2.5.5. Identical Models and Identical Target Prices

Although the dividend discount model, discount cash flow model and residual income model perform differently in practice, academics generally agree that three models are theoretically identical (Penman, 1998b; Kothari, 2001). Penman (1998b) explains that a difference in performance between models is due to a difference in terminal value estimation. If models estimate future cash flows indefinitely, the three models generate identical target prices. However, because only finite forecasts can be estimated in practice and hence a terminal value should be estimated for earnings forecasts beyond the forecast horizon, models use different terminal values and these generate different target prices.

Courteau, Kao and Richardson (2001) examine Penman (1998b)'s argument by using the Value Line target prices at the end of the forecast horizon as terminal values. They find that, when identical terminal values are used, the residual income model and discount cash flow model produce the same target prices, supporting Penman (1998b)'s argument. However, when ad hoc terminal values are used (i.e. terminal values are estimated based on ad hoc long-term growth rates), the residual income model performs better than the discount cash flow model, consistent with the findings of Penman and Sougiannis (1998) and Francis, Olsson and Oswald (2000).

Lundholm and O'Keefe (2001) argue that the outperformance of the residual income model over the dividend discount model or discount cash flow model (Penman and Sougiannis, 1998; Francis, Olsson and Oswald, 2000) is due to model misspecification. They explain that accounting values are linked to each other based on pro forma financial statements and, if consistent accounting values based on the identical pro forma financial statements are used, the three models perform exactly the same theoretically and empirically. For example, when book value and earnings are assumed to grow at 5% each year, it is easy to assume that dividend and residual income will also grow at 5%, assuming the constant dividend payout ratio. However, the correct future dividends and residual incomes should be $DIV_{t+r} = E_{t+r} - (B_{t+r} - B_{t+r-1})$ and $RI_{t+r} = E_{t+r} - rB_{t+r-1}$, respectively. Therefore, the use of ad hoc growth rates (e.g. 5% per annum) violates this accounting mechanism and applies inconsistent accounting values between the models, generating a difference between the models.

Although the argument of Lundholm and O'Keefe (2001) is plausible, there still remains an application issue: forecasting pro forma financial statements requires the forecasts of at least two accounting variables (i.e. two out of book value, earnings or dividends). This means that forecasting pro forma financial statements is more difficult than forecasting accounting variables for an individual model (Dechow, Hutton and Sloan, 1999). Therefore, in practice, target prices are still estimated based on the forecasts of individual accounting variables rather than the forecasts of pro forma financial statements.

2.5.6. Usage of Valuation Models in Practice

Despite the extensive research on theory-based valuation models, surveys find that practitioners generally prefer to use multiples as a main valuation model (Arnold and Moizer, 1984; Barker, 1999a; Barker, 1999b; Block, 1999; Bradshaw, 2002; Demirakos, Strong and Walker, 2004; Asquith, Mikhail and Au, 2005).

In the US, DeAngelo (1990) finds that investment bankers use more than one valuation model to obtain less biased target prices. The most widely used models are: P/E, P/B and P/S ratios, the discount cash flow model and asset-based valuation (i.e. valuation based on liquidation values). Block (1999) finds that only 15% of financial professionals use theory-based valuation models. He explains that this is because target prices from theory-based valuation models are too sensitive to the assumptions used in the model. In addition, Block (1999) find that practitioners generally do not believe in an efficient market although they use multiples as a main valuation model. In the surveys, 72% of financial professionals respond that P/E ratios and dividend yields will converge to the industry means in the next decade. Bradshaw (2002) finds that analysts use a P/E ratio (76% of analyst reports) or long-term earnings growth prospects (37% of analyst reports) when they justify favourable recommendations, while use qualitative statements such as industry conditions or earnings surprises when justifying unfavourable recommendations.

Similarly, in the UK, Arnold and Moizer (1984) find that analysts use a P/E ratio (73%) mainly, while only 31% of analysts use the discount cash flow model. For information source, analysts consider income statements as the main information source, while cash flow statements are ranked the fifth. Barker (1999a) explains that different sectors prefer different multiples. For example, a P/E multiple is preferred in the service, industrial and consumer goods sectors, while a P/D multiple is preferred in the financial and utility sectors. He explains that practitioners prefer a P/D ratio to the dividend discount model because 1) the dividend discount model is too sensitive to the assumptions used in the model, 2) the marginal cost of forecasting dividends is higher than the marginal benefit, especially for small firms, and 3) practitioners prefer to use a valuation model that is also used by other practitioners because they believe stock prices are determined by market participants' belief rather than the objective forecasts of future cash flows. Barker (1999b) interviews financial analysts and fund managers and finds that equity valuation consists of two stages. In the first stage, practitioners estimate target prices for a finite forecast horizon. Valuation models are used in this stage and practitioners prefer to use P/E and P/D ratios while the dividend discount model and discount cash flow model are used the least. In the second stage, a terminal value is estimated for the period after the forecast horizon. In this stage, practitioners use their "own assessment of management" as the most important information in estimating a terminal value. They believe that management who kept their words in the past are superior management and therefore will deliver superior performance in the future. Therefore, Barker (1999b) argues that equity valuation is a mixture of objective valuation in the first stage and subjective valuation in the second stage.

Demirakos, Strong and Walker (2004) find that a P/E ratio is often complemented by other valuation models such as a P/S ratio or the discount cash flow model. They find that, although a P/E ratio is still most widely used (89%), the discount cash flow model (39%) and a P/S ratio (50%) have become popular as well. However, the residual income model is still rarely used (1.9%). Demirakos, Strong and Walker (2004) explain that the choice of valuation models depends on analysts' familiarity with the model, clients' preference for the model, and the popularity of the model in industry. Imam, Barker and Clubb (2008) find similar results to those of Demirakos, Strong and Walker (2004), and explain that analysts start valuation by using multiples to assess market sentiment, followed by the discount cash flow model to evaluate assumptions used by the market. The assumptions used in the discount cash flow model are then adjusted to the information analysts have about firms. Imam, Barker and Clubb (2008) explain that the discount cash flow model is becoming more popular due to two reasons. First, clients prefer a valuation model that is based on theory. Second, analysts find it easier to manipulate input variables in the discount cash flow model to justify their target price. Deloof, De Maeseneire and Inghelbrecht (2009) find that the discount cash flow model is most widely used in estimating the target prices of IPO firms in the EU. They find that the discount cash flow model generates unbiased target prices, while the dividend discount model generates underestimated target prices. When multiples are used, investment bankers mostly use multiples based on forecasted earnings or cash flows.

3. Do Multiples Using Earnings Forecasts Outperform Multiples Using Residual Income Model?

3.1. Introduction

This project investigates the results of Liu, Nissim and Thomas (2002) and examines whether their finding that multiples using earnings forecasts outperform multiples using the residual income model in pricing error is prevalent in price estimation. Their finding undermines the validity of the residual income model, which originates from valuation theory and hence is considered more theoretically correct and sophisticated than earnings forecasts. If the outperformance is prevalent, it warrants an investigation into how such a result happens, the puzzle still remains unresolved in price estimation (Cooper and Lambertides, 2014). Therefore, this project lays the groundwork for the second project.

The project extends the methods of Liu, Nissim and Thomas (2002) in four dimensions. First, in time, it analyses periods after 2000, as well as before 2000 when Liu, Nissim and Thomas (2002)'s sample ends. Second, in countries, UK firms are also analysed as well as US firms. Third, in calculation methods, mean and value-weighted mean methods are also employed as well as harmonic mean and median methods. Last, in performance criteria, pricing errors are estimated in terms of accuracy as well as bias.

The main finding of this project is that the outperformance of multiples using earnings forecasts over multiples using the residual income model is a dominant result in price estimation. The result is consistent across all four dimensions: time, countries, calculation methods and performance criteria. Rank correlation coefficients confirm that the outperformance is statistically consistent across dimensions.

The project contributes to the literature by demonstrating that the outperformance of multiples using earnings forecasts over multiples using the residual income model in pricing error is not a sample-specific, but a dominant result in price estimation. Therefore, an explanation for how the outperformance occurs advances knowledge in price estimation and hence the project lays the groundwork for the second project.

This project is structured as follows. Section 2 explains the methodology used for four dimensions. Section 3 describes the data for the US and UK samples. Section 4 reports the results of the rank correlation coefficient and pricing error. The project is concluded in Section 5.

3.2. Methodology

3.2.1. Four Dimensions

The project extends the methods of Liu, Nissim and Thomas (2002) in four dimensions: a) time; b) countries; c) calculation methods; and d) performance criteria. For a) time, the project reports the results from 1987 to 1999 and from 2000 to 2010, as well as for the overall period. The sample is divided in 1999/2000 because the sample period of Liu, Nissim and Thomas (2002) ends in 1999. Therefore, the first period matches with the sample period of Liu, Nissim and Thomas (2002) and hence provides the validity of the methodology used in this project. On the other hand, the second period examines whether the puzzling result is still observed outside the sample period of Liu, Nissim and Thomas (2002). For b) countries, the UK sample is also analysed as well as the US sample. Several studies have found that US market-based research results are not applicable to the UK firms (Ali and Pope, 1995; Barth and Clinch, 1996; Green, Stark and Thomas, 1996; O'sullivan, 2000; Toms, 2002; Sudarsanam and Mahate, 2003; Agarwal and Taffler, 2008). By analysing UK firms as well as US firms, the project examines whether the results of Liu, Nissim and Thomas (2002) are common outside the US. For c) calculation methods, Liu, Nissim and Thomas (2002) calculate multiples based on mean and median methods. Because a harmonic mean method is the mathematically correct method to average ratios, it results in zero mean biases for multiples. The same is true for a median method for median biases. By making mean and median biases zero, Liu, Nissim and Thomas (2002) focus on the dispersion of pricing error (i.e. interquartile range) to measure the performance of multiples. In this project, multiples are estimated not only by harmonic mean and median methods but also by mean and value-weighted mean methods (Baker and Ruback, 1999). The latter two methods do not result in zero mean (or median) biases. Therefore, this project examines both central tendency (i.e. the mean and median of pricing error) and dispersion (i.e. the interquartile range and standard deviation of pricing error) to measure the performance of multiples. Lastly, for d) performance criteria, Liu, Nissim and Thomas (2002) summarise pricing errors in bias only. However, several research papers argue that bias is only one side of pricing error and accuracy is the other side (Francis, Olsson and Oswald, 2000; Hou, van Dijk and Zhang, 2012; Li and Mohanram, 2014). Francis, Olsson and Oswald (2000) argue that bias is a performance criterion for a portfolio, while accuracy is a criterion for an individual stock. This project measures the performance of multiples in bias and accuracy, and examines whether the puzzling result still occurs in accuracy as well as in bias.

3.2.2. Multiples

Consistent with Liu, Nissim and Thomas (2002), target prices are estimated by multiples. The main characteristic of multiples is that they are relative valuation models, which means that multiples estimate target prices based on the stock prices of other firms. The estimation of a target price by a multiple is straightforward. First, the unit prices (i.e. the prices of a value driver per unit, in other words, multiples) of comparable firms are estimated and averaged. Second, the average unit price is multiplied by the value driver of a target firm to estimate a target price. For instance, if the average price-to-earnings ratio of comparable firms is 15 and a target firm has earnings-per-share of $5, a target price is $75. If the number of employees is used as a value driver and the average price-to-employee of comparable firms is $0.3, a firm with 1,000 employees has a target price of $300. Although the estimation process looks straightforward, determining which value driver to use, how comparable firms are chosen, and how the average unit price is calculated are not straightforward. Therefore, they are discussed further below.

3.2.2.1. Value Driver

As the examples above demonstrate, multiples are not restricted to one value driver. In fact, any piece of information that is value relevant can be a value driver. For instance, in the hotel and model industry, the number of rooms or even the number of windows can be a value driver. Such flexibility gives multiples both an advantage and a disadvantage. On the one hand, multiples can incorporate non-accounting information in valuation, which is not possible in theory-based valuation models. On the other hand, multiples are exposed to a wide range of choices in value driver and selecting the most relevant one can be difficult and subjective.

In this project, three types of value drivers are used for multiples: 1) current accounting values, 2) earnings forecasts, and 3) residual income models. 1) For current accounting values, a) book value, b) cash flow from operations, c) earnings, d) earnings before interest, taxes, depreciation and amortisation (EBITDA), and e) sales are used. First, a) book value is used as it is one of the most widely used value drivers in practice (Demirakos, Strong and Walker, 2004; Imam, Barker and Clubb, 2008). A multiple using book value is often referred to as a market-to-book ratio. Book value represents the accounting value of firms and is often used as a proxy for the market value of firms when firms have little information about their future prospects. Second, b) cash flow from operations is used as it is often considered as a 'real' value driver. Cash flow from operations represents 'hard' cash and hence is less susceptible to accounting manipulation and more related to firms' survivals in difficult periods (Koller, Goedhart and Wessels, 2005). Third, c) earnings are the most widely used value driver in practice (Arnold and Moizer, 1984; Barker, 1999a; Block, 1999; Bradshaw, 2002; Demirakos, Strong and Walker, 2004; Imam, Barker and Clubb, 2008). Earnings represent accounting profit, which subsequently determines cash flow from operations and dividend. Fourth, d) EBITDA measures earnings before major discretionary expenses. Therefore, EBITDA is considered as a better performance measure between firms that have different capital structures and accounting policies. Last, e) sales are the second most popular value driver in practice (Demirakos, Strong and Walker, 2004). Because sales are positive most of the time, they are used as an alternative to other value drivers when other value drivers are negative and hence cannot be used for multiples.

To be precise, EBITDA and sales are items before interest payment. This means that they include a portion of earnings that are attributed to debt holders as well as to equity holders. Therefore, multiples using EBITDA and sales are supposed to estimate the total value of firms, instead of the equity value. This project estimates the total value of firms, as well as the equity value, by using multiples based on EBITDA and sales. When the total value is estimated, the book value of debt is deducted from the total value to estimate the equity value.

2) For earnings forecast value drivers, a) earnings, b) earnings forecasts and c) earnings-growth are used. Earnings forecast value drivers are obtained from IBES.[3] In contrast to accounting earnings, a) the IBES earnings represent earnings from continuing operations, excluding the impact of extraordinary items and discontinued operations. b) For earnings forecasts, one-, two- and three-year ahead earnings forecasts are used to reflect the future expectations of earnings. If three-year ahead earnings forecasts are missing, they are estimated as two-year ahead earnings forecasts multiplied by one plus long-term earnings growth rates: $EPS3 = EPS2 \times (1 + LTG)$. Last, c) earnings-growth (EG) is calculated as the product of two-year ahead earnings forecasts and long-term earnings growth rates: $EG = EPS2 \times LTG$. A multiple using EG (i.e. a P/EG ratio) is considered as an extension of a P/E ratio by taking into account

[3] IBES is the Institutional Brokers' Estimate System. IBES collects earnings, analyst forecasts, long-term earnings growth rates, target prices and recommendations for firms internationally. Analyst forecasts are estimated for up to five years ahead. The IBES earnings and analyst forecasts are estimated based on firms' continuing operations.

the growth rate of earnings, as well as the level of earnings. As a rule of thumb, a firm with a P/EG ratio above one is considered overvalued.

3) For residual income models, the same residual income models in Liu, Nissim and Thomas (2002) are used. They are explained in Section 3.2.3.

3.2.2.2. Comparable Firms

If an identical firm can be found, the unit price of the identical firm should be used to estimate a target price. However, because an identical firm is difficult to find, if not impossible, similar or comparable firms are used instead to estimate a target price. Three options are widely used to identify comparable firms in practice: 1) selecting comparable firms manually, 2) considering firms in the same industry as comparable firms, and 3) considering firms of similar size as comparable firms.[4]

This project chooses the second option to identify comparable firms, consistent with Liu, Nissim and Thomas (2002). This is because a) the first option is suitable only for a small dataset as it chooses comparable firms manually and hence is not suitable for a big dataset; b) industry is a better measure of classifying similar firms than size because industry by definition classifies firms with similar business activities together; and c) industry data are widely available for most firms.

For industry classification, the IBES industry level is used (Liu, Nissim and Thomas, 2002). IBES has three levels in industry classification: sector, industry and group. Sector is the broadest category with the largest number of firms but the least homogeneous. Group is the narrowest category with the smallest number of firms but

[4] Berkman, Bradbury and Ferguson (2000) find that multiples estimate more accurate target prices if comparable firms are chosen from a more homogeneous group.

the most homogeneous. This project uses the middle level, industry, balancing the quality (i.e. homogeneity) and quantity (i.e. to have at least five observations in each firm-year) between sector and group. As a robustness test, industry classification based on the first two digits of SIC codes were also used. However, the results were qualitatively the same and hence not reported here.

3.2.2.3. Unit Price (Multiple)

If a target price is estimated based on the unit prices of more than one comparable firms, the unit prices have to be averaged to estimate a target price. In this project, unit prices are averaged by harmonic mean, mean, median and value-weighted mean methods. The average unit price is estimated on an out-of-sample basis (i.e. the unit price of a target firm is excluded when estimating the average unit price of the industry).

First, a harmonic mean method is the mathematically correct method to average unit prices because unit prices are in fact ratios. A harmonic mean method first inverses the unit prices of comparable firms, averages them, and re-inverses the average unit price. The average unit price by a harmonic mean method is expressed as:

$$E\left({P_{it}}/{X_{it}}\right) = 1/E({X_{jt}}/{P_{jt}}) \tag{1}$$

where P_{it} is the stock price of a target firm *i* at time *t*, X_{it} is the per share value driver of a target firm *i* at time *t*, P_{jt} is the stock price of a comparable firm *j* at time *t*, and X_{jt} is the per share value driver of a comparable firm *j* at time *t*. A target price is estimated as:

$$E(P_{it}) = E\left({P_{it}}/{X_{it}}\right) \times X_{it} \tag{2}$$

For multiples that estimate the total value of a firm (i.e. EBITDA/FV and SALE/FV), a target price is calculated as the total value of a firm minus the book value of debt, divided by the number of shares outstanding as:

$$E(P_{it}) = \left[\left\{1/E\left({Y_{jt}}/{FV_{jt}}\right)\right\} Y_{it} - Debt_{it}\right] /(Number\ of\ Shares\ Outstanding)_{it} \quad (3)$$

where Y_{jt} is the unscaled (i.e. total) value driver of a comparable firm j at time t, and FV_{jt} is the total value of a comparable firm j. The total value of a firm is calculated as the sum of the market value of equity and the book value of debt. The book value of debt is used instead of the market value of debt because data for the market value are not available.

Second, a mean method is believed to be the most widely used method to average unit prices. However, mathematically, a mean method is not the correct method to average ratios. A mean method averages the unit prices of comparable firms without inversion. Therefore, a target price is estimated as:

$$E(P_{it}) = E\left({P_{jt}}/{X_{jt}}\right) \times X_{it} \quad (4)$$

A target price from multiples estimating the total value of a firm is calculated as:

$$E(P_{it}) = \left\{E\left({FV_{jt}}/{Y_{jt}}\right) Y_{it} - Debt_{it}\right\} /(Number\ of\ Shares\ Outstanding)_{it} \quad (5)$$

Third, a median method uses the median unit price of comparable firms to average unit prices. A median method is less susceptible to outlying values and, therefore, more suitable when there are extreme unit prices in industry. However, a median method uses the unit price(s) of only one (or two) comparable firm(s) in the middle, hence, it loses information on most firms in the industry.

Last, a value-weighted mean method averages unit prices by applying weights based on the relative market values of comparable firms in the industry. The average unit price is calculated as:

$$E\left({}^{P_{jt}}\!\big/_{X_{jt}}\right) = \sum_{j=1}^{J}\left(\frac{MV_{jt}}{\sum_{j=1}^{J} MV_{jt}}\frac{P_{jt}}{X_{jt}}\right) \tag{6}$$

where MV_{jt} is the market value of equity of a comparable firm *j* at time *t*, calculated as the product of stock price and the number of shares outstanding. $\sum_{j=1}^{J} MV_{jt}$ is the sum of the market values in the industry where a comparable firm *j* belongs to, and $\frac{P_{jt}}{X_{jt}}$ is the unit price of a comparable firm *j*.

The advantage of a value-weighted mean method is that it takes into account the size of firms in the industry when estimating the average unit price. However, when industry is highly concentrated, the average unit price can be dominated by the unit prices of a few firms.

3.2.3. Residual Income Model

In contrast to multiples, the residual income model is an absolute valuation model, which estimates a target price based on the information of a target firm. Since stock price is defined as the discounted present value of expected future cash flows, the residual income model requires the estimations of future cash flows and discount rates. These estimations incur measurement errors to the residual income model.

The residual income model is derived from the dividend discount model, which defines stock price as the discounted present value of expected future dividends. Under the clean surplus relation, the residual income model becomes identical to the dividend discount model. The derivation is shown in Appendix 1. The residual income model defines stock price as the sum of book value and discounted expected future residual incomes:

$$P_{i,t} = B_{i,t} + \frac{E_{i,t+1} - r_i B_{i,t}}{(1+r_i)} + \frac{E_{i,t+2} - r_i B_{i,t+1}}{(1+r_i)^2} + \frac{E_{i,t+3} - r_i B_{i,t+2}}{(1+r_i)^3} + \cdots \quad (7)$$

where $P_{i,t}$ is the stock price of a target firm *i* at time *t*, $B_{i,t}$ is the book value, $E_{i,t+s}$ is the earnings at time *t*+*s*, and *r* is the cost of equity.

The project uses the residual income model as a representative of theory-based valuation models due to three reasons. First, the project adopts the view of Lundholm and O'Keefe (2001), which demonstrate that all theory-based valuation models are identical theoretically and empirically if consistent information is employed. Second, given the equivalence between models, earnings forecasts are more widely estimated than dividend forecasts or cash flow forecasts. Last, the residual income model is more widely studied and used than the abnormal earnings growth model in the literature.

Two residual income models used in Liu, Nissim and Thomas (2002) are used in this project. RIM1 has a forecast horizon of five years and a terminal value. It assumes a perpetual earnings growth rate of 0% at the end of the forecast horizon and a discount rate based on the Capital Asset Pricing Model (CAPM).

$$RIM1 = B_{it} + \sum_{s=1}^{s=5} \left[\frac{E\left(E_{i,t+s} - r_i B_{i,t+s-1}\right)}{(1+r_i)^s} \right] + \frac{E(E_{i,t+5} - r_i B_{i,t+4})}{r_i(1+r_i)^5} \quad (8)$$

On the other hand, RIM2 has a forecast horizon of five years but no terminal value. It also uses a CAPM discount rate.

$$RIM2 = B_{it} + \sum_{s=1}^{s=5} \left[\frac{E\left(E_{i,t+s} - r_i B_{i,t+s-1}\right)}{(1+r_i)^s}\right] \quad (9)$$

In the UK, a forecast horizon of three years is used, instead of five years, to preserve a number of observation.

All variables in the residual income model are estimated on a per share basis. Earnings forecasts are obtained from IBES. If three-, four- and five-year ahead earnings forecasts are missing, they are calculated as the product of the previous period earnings forecasts and one plus long-term earnings growth rates. For example, four-year ahead earnings forecasts are calculated as three-year ahead earnings forecasts multiplied by one plus long-term earnings growth rates. Future book value is estimated based on the clean surplus relation as:

$$B_{i,t+s} = B_{i,t+s-1} + E_{i,t+s} - DIV_{i,t+s} \quad (10)$$

where $B_{i,t+s}$ is the book value of equity of a target firm *i* at time *t*+*s*, $E_{i,t+s}$ is the earnings, and $DIV_{i,t+s}$ is the dividend.

Future dividend is calculated as earnings forecasts multiplied by the current dividend payout ratio. The current dividend payout ratio is used based on the findings of Lintner (1956) and Skinner and Soltes (2011) that a payout ratio is often determined by a firm’s payout policy and hence does not change significantly over time. However, current dividend payout ratios are winsorized at 10% and 50% to reflect the long-term dividend payment tendency. As a robustness test, the current dividends were also used for future dividends (Brav et al., 2005). The results were almost identical and, therefore, only the results based on the current dividend payout ratio are reported.

A CAPM discount rate is calculated as:

$$r_{it} = r_{ft} + \beta_{it}(RP) \tag{11}$$

where r_{ft} is the risk-free rate at time *t*, β_{it} is the beta coefficient of a target firm *i* at time *t*, and *RP* is the market risk premium. The US ten-year Treasury bond yields are used for the risk-free rate, and 5% is used for the market risk premium based on the finding of Dimson, Marsh and Staunton (2003). β_{it} is calculated based on the market model. Specifically, β_{it} is the slope coefficient of a regression of stock monthly return on S&P 500 monthly return based on the past 60-month data. To mitigate the impact of extreme betas, betas are truncated at the 1^{st} and 99^{th} percentiles and, after that, the median betas of deciles in each year are used instead of the original betas.

In the UK, the UK ten-year government bond yields from the Bank of England are used for the risk-free rate. In addition, 4% is used for the market risk premium based on the finding of Dimson, Marsh and Staunton (2003).

3.2.4. Performance Criteria

Pricing error is used to measure the performance of multiples. Pricing error is estimated as:

$$Z_{i,t} = \frac{\{E(P_{it}) - P_{it}\}}{P_{it}} \tag{12}$$

where $Z_{i,t}$ is the pricing error of a firm *i* at time *t*, $E(P_{it})$ is the target price, and P_{it} is the stock price.

Pricing error measures how close a target price is to a stock price. The closer a target price is to a stock price, the smaller a pricing error is, and the more accurate a multiple is. Bias summarises pricing errors and indicates where a target price locates compared to a stock price. On the other hand, accuracy summarises the absolute values of pricing error and indicates how close a target price is to a stock price.

3.2.5. Rank Correlation Coefficient

The consistency of performance across time, countries, calculation methods and performance criteria is measured by the rank correlation coefficient. The rank correlation coefficient is preferred to the difference in performance, because the former measures the consistency of performance while the latter measures the change in performance. The rank of multiples in pricing error is estimated based on interquartile ranges. A multiple with the narrowest interquartile range is ranked first. Rank correlation coefficients were also estimated based on mean pricing errors. The results were generally consistent and, therefore, not tabulated in the project.[5]

3.3. Data

3.3.1. US Sample

The sample consists of non-financial US firms listed on the NYSE, Amex or NASDAQ from 1987 to 2010. Firms with a share code of 10 or 11 in CRSP are only chosen, excluding ADRs, REITs and closed-end funds. Both active and inactive firms are

[5] In this case, a multiple with the smallest *absolute* mean pricing error is ranked first because mean pricing errors can be either positive or negative.

included to mitigate survivorship bias. Accounting data are obtained from Compustat. Prices and returns are obtained from CRSP, and earnings forecasts are obtained from IBES. Accounting data are as of the fiscal year end. Prices, the number of shares outstanding and earnings forecasts are as of four months after the fiscal year end, considering the lag between the announcement date and fiscal year end. Time series are based on fiscal years.

Consistent with Liu, Nissim and Thomas (2002), five conditions are imposed on the sample: 1) each firm-year observation has non-missing values for all multiples, except multiples estimating the total value of firms; 2) all multiples estimate positive target prices; 3) prices are truncated at $2 and the 99th percentile; 4) all per share value drivers are truncated at the 1st and 99th percentiles in the pooled distribution, followed by the identical truncation for their multiples; and 5) there are at least five firms in each industry-year.

The first condition makes a common sample across multiples, so the multiples are compared on a level field. Multiples estimating the total value of firms are not included because they are not of main interest. The second condition makes target prices be comparable with stock prices. The third and fourth conditions mitigate the impact of outliers. For price, a cut-off point of $2 is used, instead of $1, to be consistent with Liu, Nissim and Thomas (2002). Results based on a cut-off point of $1 were also estimated, but the results were consistent. Therefore, only the results based on a cut-off point of $2 are reported. Histograms show that multiples still have extreme values after the truncations of price and individual value drivers. Therefore, multiples are also truncated on a pooled sample in the fourth condition. Truncation is used, instead of winsorization, to avoid having heavy tails in distribution, which can affect statistical inferences. The fifth condition makes target prices be estimated based on at least four comparable firms.

The five conditions imposed are likely to remove smaller firms. Therefore, the sample may not be representative of small firms. The final sample covers 3,440 firms with 18,616 firm-year observations. All value drivers are measured on a per share basis, except for multiples estimating the total value of firms. Per share value drivers are calculated as value drivers divided by the current number of shares outstanding. The current number of shares outstanding is used, instead of the average number of shares outstanding for the previous and current years, because they are similar in most cases. The use of the average number of shares outstanding produces qualitatively the same results but reduces the sample size as it requires values in the previous year as well.

<Figure 1 here>

Figure 1 illustrates the number of firms in the sample in each year. It shows that the number of firms follows the market conditions in the US. The number of firms increases until 1997 and decreases as the market cools down. It again increases until 2007 and decreases as the economy slows down. The number of firms becomes more stable since 1993 and, therefore, the results of the second period (i.e. from 2000 to 2010) might be more representative of the US firms at present. The average number of firms in each year is 776 firms.

<Table 1 here>

Panel A of Table 1 shows that the sample mainly comprises large firms. The average market value of equity is $2 billion and the book value of equity is $812 million. The same inference is drawn from other variables. Among earnings forecasts, forecasts for the more distant future have higher means and medians than those for the nearer future. This indicates that analysts are more optimistic when forecasting the more distant future, consistent with the findings of La Porta (1996), Dechow and Sloan (1997), and Rajan and Servaes (1997). Analysts' optimism is also evidenced by a long-term earnings growth rate. The mean and median growth rates are 16.4% and 15.0% respectively, significantly higher than the average US GDP growth rate of 2.6% over the same period.[6]

Panel B of Table 1 presents the distributions of multiples. On average, book value per share is about half the size of stock price, and earnings per share are less than one-tenth of stock price. RIM1/P has an average close to one because RIM1 is an absolute valuation model, which estimates target prices comparable with stock prices.

EBITDA/FV and SALE/FV (i.e. multiples estimating the total value of firms) have distributions similar to those of EBITDA/P and SALE/P (i.e. multiples estimating the equity value), respectively. The project investigates the reason for the similarity and finds that this is because the book value of debt is relatively minor compared to the market value of equity, resulting in minor difference between the total value of firms and the market value of equities. The correlation coefficient between the total value of firms and the market value of equities is one (not tabulated).

Panel C of Table 1 reports the correlation coefficients between value drivers. The IBES current earnings and earnings forecasts are highly correlated, with all correlation coefficients above 0.89. RIM1 has lower correlation coefficients with current

[6] The average US GDP growth rate from 1987 to 2010 is manually calculated based on data from the World Bank.

accounting variables than RIM2 does. This indicates that a terminal value has little commonality with current accounting variables. RIM2 has a correlation coefficient of 0.908 with book value, indicating that a residual income model without a terminal value is mainly dominated by book value, consistent with the finding of Francis, Olsson and Oswald (2000).

3.3.2. UK Sample

The UK sample consists of non-financial firms in the Worldscope database from 1987 to 2010. Both active and inactive firms are included. The sample period starts from 1987 because IBES started collecting earnings forecasts for non-US firms from 1987. Accounting data, prices and the number of shares outstanding are obtained from Worldscope, and earnings forecasts are obtained from IBES. Accounting data are as of the fiscal year end, prices, the number of shares outstanding and earnings forecasts are as of four months after the fiscal year end. All variables are denominated in pounds sterling (not in pence).

Although the UK has the third largest accounting data set in the world after the US and Japan, the UK sample size is about one-tenth of the US sample size. Therefore, less stringent conditions are imposed on the UK sample to preserve a sample size: 1) each firm-year observation has non-missing values for multiples using BV, EBITDA, SALES, EPS0, EPS1, EPS2 and EPS3; 2) all multiples have positive target prices; 3) prices are truncated at £0.1 (ten pence) and the 99th percentile; 4) all per share value drivers are truncated at £0.1 (ten pence) and the 99th percentile in the pooled distribution, followed by a subsequent truncation at the 1st and 99th percentiles for multiples; and 5) there are at least five firms in each industry-year.

The first condition is to make a common sample across multiples. Only seven multiples are used for a common sample because the inclusion of the other multiples reduces a sample size considerably. While requiring only seven multiples preserves a sample size, it makes the other multiples be estimated based on different observations. Therefore, the direct comparison between the seven key multiples and the other non-key multiples becomes unfeasible. The third condition truncates prices at ten pence, instead of at £1, to preserve a sample size. Cut-off points of 30 pence, 50 pence and £1 were also tested, but the results were consistent (not tabulated). For the fourth condition, truncations at ten pence is in fact a stricter condition than truncations at the 1st percentile because most value drivers have less than ten pence at the 1st percentile. A cut-off point of ten pence is used considering the difficulty in estimating earnings forecasts less than ten pence in practice. The final UK sample covers 204 firms with 1,239 firm-year observations.

<Figure 2 here>

Figure 2 illustrates the number of firms in the UK sample in each year. The average number of firms in each year is 52 firms, much smaller than that in the US. The number of firms increases until 1998 and decreases afterward. The number increases again since 2002. The number of firms in the first period (i.e. an average of 22 firms from 1987 to 1999) is considerably different from that in the second period (i.e. an average of 86 firms from 2000 to 2010). Therefore, the results of the second period might be more representative of the UK firms at present.

<Table 2 here>

Panel A of Table 2 shows that the characteristics of the UK sample are similar to those of the US sample, although the direct comparison between the two countries is difficult due to a currency mismatch. The main difference is observed in earnings per share (EPS): the average EPS in the UK is £0.37 while that in the US is $1.16. The project investigates the reason for the difference and finds that it is due to the difference in the average number of shares outstanding between the two countries, rather than the difference in earnings. The average number of shares outstanding in the UK is 497 million, while that in the US is 100 million. The average long-term earnings growth rate forecast in the UK is 9.04%, much lower than that in the US.

Panel B of Table 2 reports the distributions of multiples in the UK. Book value per share is about half the size of stock price, and earnings per share are about one-tenth of stock price. The total value of firms and the market value of equities are also similar in the UK, due to the relatively small size of the book value of debt compared to the market value of equity. The correlation coefficient between the total value of firms and the market value of equities is 0.97 in the UK (not tabulated).

Panel C of Table 2 demonstrates that the correlation coefficients between value drivers in the UK are also similar to those in the US. The correlation coefficients between earnings forecasts are close to one. RIM1 has lower correlation coefficients with current accounting variables than RIM2 does. RIM2 has a high correlation coefficient with book value. However, in the UK, the correlation coefficients between EPS and earnings forecasts are lower than those in the US, indicating that UK analysts estimate earnings forecasts less based on the current accounting earnings than US analysts do.

3.4. Results

The main results are presented in Tables 3 and 4. Table 3 reports the rank correlation coefficients of the performance of multiples across time periods (i.e. between the periods from 1987 to 1999 and from 2000 to 2010). Table 4 reports rank correlation coefficients across calculation methods, performance criteria and countries.

<Table 3 here>

Table 3 demonstrates that the performance of multiples in pricing error is consistent across the two time periods. The performance is also consistent across calculation methods and countries. All rank correlation coefficients are close to one and statistically significant at the 1% level. Only the rank correlation coefficient of accuracy under a harmonic mean method in the UK is less than 0.8, possibly due to the non-key multiples that are not based on the common sample. When only the pricing errors of the key multiples are examined, all rank correlation coefficients are above 0.85. Overall, Table 3 demonstrates that the performance of multiples in pricing error is consistent across time periods.

<Table 4 here>

Table 4 demonstrates that the performance of multiples in pricing error is also consistent across calculation methods, performance criteria and countries. Rank correlation coefficients show that the performance of multiples is consistent across all dimensions. Panel A of Table 4 shows that all rank correlation coefficients are close to one in the US. In addition, the performances between bias and accuracy are also highly correlated and statistically significant at the 1% level. Panel B of Table 4 reports similar results for the UK sample. All rank correlation coefficients are close to one and statistically significant at the 1% level, although they are not as high as those in the US. This is possibly due to the non-key multiples that are not based on the common sample. When only the pricing errors of the key multiples are examined, all rank correlation coefficients increase to close to one (presented in Appendix 2). Panel C of Table 4 shows that the performance is also consistent between the US and UK. All rank correlation coefficients are close to one and statistically significant at the 1% level. Rank correlation coefficients increase further when only the pricing errors of the key multiples are examined (Appendix 2). In summary, Table 4 demonstrates that the performance of multiples in pricing error is consistent across calculation methods, performance criteria and countries both statistically and economically.

3.4.1. US Results

Tables 5 and 6 report the pricing errors of multiples by harmonic mean and mean methods, respectively. Results are similar when multiples are measured by median and value-weighted mean methods. Therefore, the results of median and value-weighted mean methods are presented in Appendices 3 and 4, respectively.

<Table 5 here>

Panel A of Table 5 reports the performance of harmonic mean multiples for the overall period. As explained above, the harmonic mean method produces mean biases close to zero. Means, medians and interquartile ranges all show that multiples using earnings forecasts perform the best, followed by multiples using residual income models and current accounting values, sequentially. The result is consistent for both bias and accuracy. The pricing errors of EBITDA/FV and SALE/FV are similar to those of

EBITDA/P and SALE/P, respectively. This is because the total value of firms is similar to the market value of equities, as explained above.

Panels B and C report the performances of multiples in two time periods (i.e. from 1987 to 1999 and from 2000 to 2010), respectively. Mean biases are close to zero under a harmonic mean method. Consistent with the results in Panel A of Table 5, multiples using earnings forecasts perform better than multiples using residual income models and current accounting variables in both periods. In addition, the pricing errors of multiples are similar between the two periods.

<Table 6 here>

Table 6 reports the pricing errors of mean multiples. Consistent with the results of harmonic mean multiples, multiples using earnings forecasts perform the best, followed by multiples using residual income models and current accounting values, sequentially. Since the mean method is not a mathematically correct method to average ratios, mean biases are no longer close to zero under the mean method. However, the relative performance of multiples remains the same. Under the mean method, pricing errors are also similar between the two time periods (Panels B and C of Table 6).

3.4.2. UK Results

Tables 7 and 8 present the pricing errors of multiples by harmonic mean and mean methods, respectively, for the UK sample. The results of multiples by median and value-weighted mean methods are similar and, therefore, presented in Appendices 5 and 6, respectively.

<Table 7 here>

Table 7 presents the pricing errors of harmonic mean multiples. Consistent with the results of the US sample, multiples using earnings forecasts perform the best, followed by multiples using residual income models and current accounting values, sequentially. The results are consistent in mean, median and interquartile range for both bias and accuracy. In addition, pricing errors are also similar between the two time periods (Panels B and C of Table 7). Mean biases are less close to zero in the UK, possibly because pricing errors are calculated based on a smaller sample. However, the relative performance of multiples remains the same.

<Table 8 here>

Consistent results are observed when multiples are calculated by a mean method in Table 8. As expected, mean biases are no longer close to zero. However, this does not affect the relative performance of multiples. Panels B and C of Table 8 show that the pricing errors of multiples are less similar between the two time periods. However, the relative performance of multiples still remains the same.

3.5. Conclusion

The main finding of this project is that the outperformance of multiples using earnings forecasts over multiples using the residual income model and current accounting values in pricing error is prevalent in price estimation. The results of the rank correlation coefficient indicate that the results are consistent across time, countries, calculation methods and performance criteria both statistically and economically.

The project contributes to the literature by demonstrating that the puzzling result, the outperformance of multiples using earnings forecasts over multiples using the residual income model, is a dominant result. Therefore, the understanding of how this happens advances knowledge in equity valuation and, hence, the project lays the groundwork for the second project.

There are two main limitations in this project. First, the UK sample includes only the seven multiples in the common sample. Therefore, the direct comparison between the key multiples and non-key multiples is not feasible. However, the results show that consistent performance is observed in the US and UK, although the non-key multiples are estimated based on different observations in the UK. Second, the results may not represent the performance of small firms. This is due to the stringent conditions imposed on the samples to make target prices comparable with stock prices. Therefore, a caution should be taken when applying the results to small firms.

Figure 1

Number of US Firms

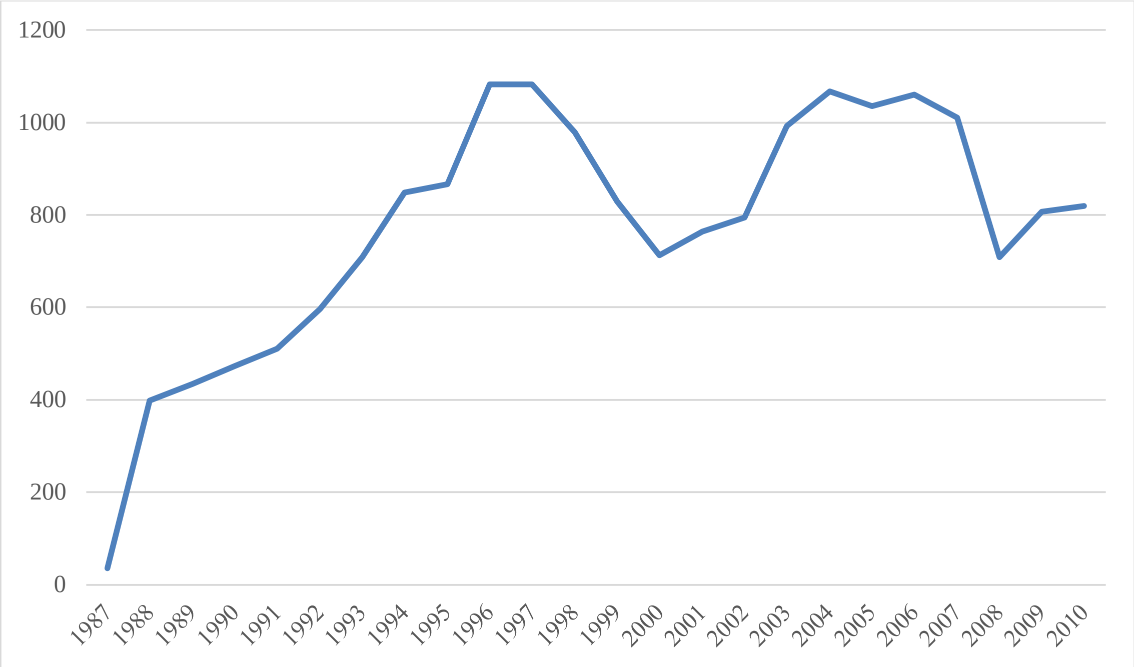

Figure 2

Number of UK Firms

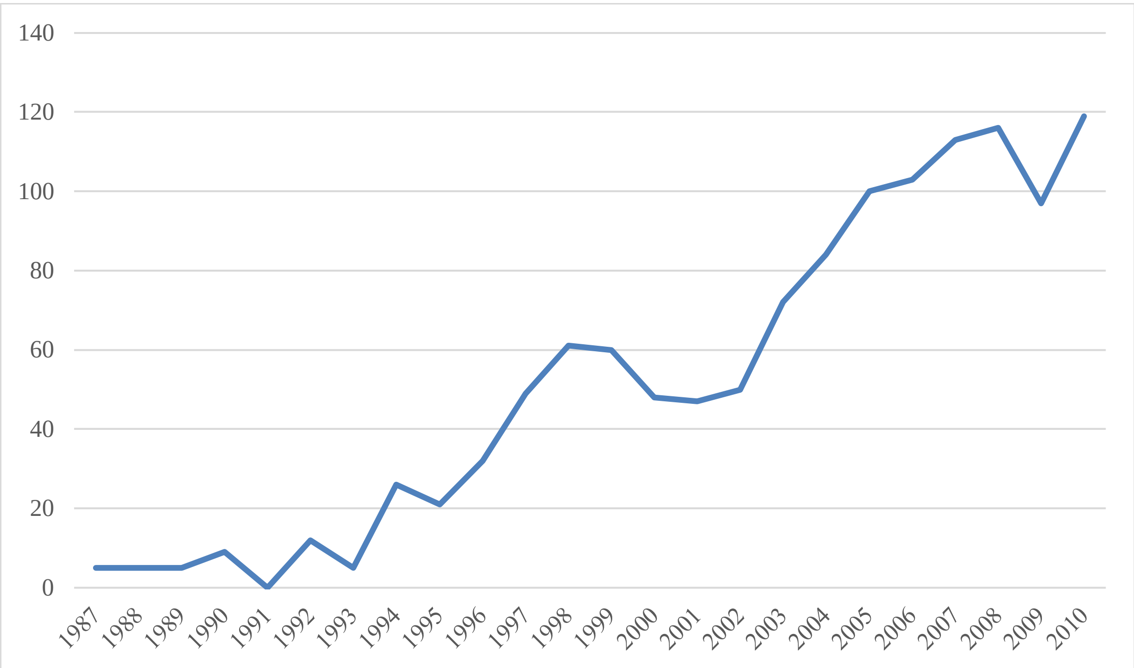

Table 1

Descriptive Statistics (US)

Panel A: Firm level								(in $ mil, except per share values)	
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
MV	2,088	826	3,256	40	85	311	2,256	9,318	16,566
B	812	319	1,357	19	36	122	874	3,368	7,281
CFO	215	70	392	2	5	23	212	953	2,088
EBITDA	301	103	538	4	9	35	298	1,350	2,825
SALE	1,882	658	3,292	27	59	230	1,917	8,415	17,405
E	119	39	223	2	4	14	117	530	1,150
EPS	1.16	0.92	0.93	0.08	0.17	0.49	1.56	3.01	4.40
EPS0	1.17	0.97	0.85	0.10	0.21	0.54	1.57	2.88	4.05
EPS1	1.31	1.12	0.90	0.15	0.27	0.65	1.74	3.09	4.30
EPS2	1.54	1.33	0.99	0.21	0.37	0.81	2.00	3.49	4.84
EPS3	1.77	1.55	1.11	0.25	0.44	0.97	2.30	3.95	5.52
LTG (%)	16.40	15.00	7.28	3.94	6.29	11.67	20.00	30.00	40.00

Panel B: Multiples									
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
B/P	0.450	0.395	0.265	0.076	0.130	0.258	0.584	0.963	1.338
CFO/P	0.101	0.084	0.073	0.010	0.022	0.053	0.129	0.238	0.370
EPS/P	0.055	0.050	0.032	0.007	0.015	0.034	0.069	0.113	0.169
EBITDA/P	0.144	0.124	0.092	0.023	0.040	0.081	0.182	0.320	0.475
SALE/P	1.121	0.795	1.132	0.103	0.176	0.428	1.381	3.204	5.943
EPS0/P	0.056	0.052	0.027	0.011	0.020	0.038	0.069	0.107	0.149
EPS1/P	0.063	0.059	0.026	0.018	0.028	0.045	0.076	0.111	0.145
EPS2/P	0.075	0.071	0.028	0.028	0.038	0.056	0.088	0.128	0.165
EPS3/P	0.087	0.081	0.032	0.035	0.046	0.066	0.102	0.148	0.191
EG/P	0.012	0.010	0.006	0.003	0.004	0.008	0.014	0.023	0.033
EBITDA/FV	0.144	0.124	0.092	0.023	0.040	0.081	0.183	0.321	0.476
SALE/FV	1.131	0.802	1.140	0.104	0.178	0.431	1.394	3.250	5.957
RIM1/P	0.880	0.771	0.455	0.252	0.341	0.556	1.085	1.801	2.421
RIM2/P	0.554	0.519	0.229	0.193	0.247	0.383	0.684	0.990	1.240

Panel C: Correlation coefficients between value drivers												
	B	CFO	EPS	EBITDA	SALE	EPS0	EPS1	EPS2	EPS3	EG	RIM1	RIM2
B		0.715	0.677	0.780	0.683	0.711	0.707	0.722	0.705	0.428	0.626	0.904
CFO	0.700		0.729	0.860	0.651	0.754	0.737	0.736	0.711	0.404	0.645	0.779
EPS	0.663	0.696		0.830	0.623	0.904	0.857	0.844	0.822	0.554	0.710	0.801
EBITDA	0.764	0.856	0.793		0.783	0.857	0.841	0.836	0.809	0.466	0.713	0.860
SALE	0.565	0.533	0.486	0.633		0.644	0.647	0.649	0.624	0.337	0.540	0.697
EPS0	0.689	0.717	0.879	0.821	0.510		0.941	0.930	0.908	0.615	0.777	0.861
EPS1	0.679	0.694	0.836	0.797	0.509	0.941		0.982	0.960	0.695	0.819	0.884
EPS2	0.687	0.686	0.819	0.785	0.516	0.923	0.982		0.987	0.749	0.834	0.899
EPS3	0.666	0.657	0.792	0.754	0.499	0.892	0.952	0.982		0.790	0.842	0.889
EG	0.371	0.349	0.515	0.398	0.250	0.574	0.673	0.731	0.772		0.659	0.611
RIM1	0.550	0.551	0.636	0.617	0.385	0.721	0.766	0.777	0.786	0.609		0.878
RIM2	0.908	0.745	0.780	0.826	0.565	0.848	0.870	0.879	0.866	0.569	0.823	

The sample consists of non-financial US firms listed on the NYSE, Amex or NASDAQ from 1987 to 2010. The sample covers 3,440 firms with 18,616 firm-year observations. All value drivers are estimated on a per share basis. In panel C, values below the diagonal are pairwise correlation coefficients, and those above the diagonal are Spearman rank correlation coefficients.

MV is the market value of equity, calculated as the product of stock price and the number of shares outstanding; BV is equity; CFO is cash flow from operations; EBITDA is earnings before interest, taxes, depreciation and amortisation; SALE is sales; E is earnings before extraordinary items; EPS is earnings per share, calculated as net income divided by the current number of shares outstanding; EPS0 is the IBES current earnings per share; EPS1 (EPS2) is the IBES one-year (two-year) ahead earnings per share forecasts; EPS3 is three-year ahead earnings per share forecasts. If EPS3 is missing in IBES, it is calculated as EPS2 multiplied by one plus a long-term earnings growth rate (LTG); LTG is long-term earnings growth rate forecasts from IBES; P is stock price; EG is calculated as *(EPS2×LTG)*; FV is the total value of firms, calculated as the sum of the market value of equity and the book value of debt; RIM1 and RIM2 are calculated as below. A discount rate, *r*, is calculated according to the CAPM.

$$RIM1 = B_{it} + \sum_{s=1}^{s=5}\left[\frac{E\left(E_{i,t+s} - r_i B_{i,t+s-1}\right)}{(1 + r_i)^s}\right] + \frac{E(E_{i,t+5} - r_i B_{i,t+4})}{r_i(1 + r_i)^5}$$

$$RIM2 = B_{it} + \sum_{s=1}^{s=5}\left[\frac{E\left(E_{i,t+s} - r_i B_{i,t+s-1}\right)}{(1 + r_i)^s}\right]$$

Table 2

Descriptive Statistics (UK)

Panel A: Firm level								(in £ mil, except per share values)	
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
MV	1,698	613	2,698	36	79	257	1,976	6,994	14,980
B	813	217	1,392	8	20	73	906	3,954	6,608
CFO	274	70	625	1	5	25	248	1,083	3,127
EBITDA	338	96	780	7	16	42	318	1,186	4,273
SALE	2,305	679	4,486	34	94	297	2,004	10,392	27,217
E	198	58	468	1	3	17	172	800	2,435
EPS	0.37	0.25	0.35	0.10	0.11	0.16	0.43	1.05	1.78
EPS0	0.36	0.27	0.28	0.10	0.12	0.17	0.44	0.98	1.38
EPS1	0.38	0.28	0.28	0.11	0.12	0.18	0.46	1.00	1.39
EPS2	0.41	0.31	0.30	0.12	0.14	0.20	0.50	1.09	1.49
EPS3	0.45	0.34	0.33	0.13	0.15	0.22	0.54	1.19	1.61
LTG (%)	9.04	8.00	5.02	0.50	3.00	6.00	11.00	17.00	25.00

Panel B: Multiples									
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
B/P	0.436	0.339	0.346	0.055	0.088	0.205	0.567	1.102	1.789
CFO/P	0.101	0.086	0.064	0.024	0.035	0.061	0.123	0.219	0.317
EPS/P	0.069	0.060	0.040	0.020	0.028	0.046	0.081	0.136	0.198
EBITDA/P	0.171	0.147	0.098	0.059	0.075	0.108	0.209	0.335	0.508
SALE/P	1.487	1.060	1.652	0.224	0.325	0.592	1.776	4.175	7.427
EPS0/P	0.090	0.078	0.045	0.035	0.044	0.061	0.106	0.181	0.261
EPS1/P	0.093	0.082	0.041	0.040	0.050	0.066	0.108	0.173	0.260
EPS2/P	0.102	0.090	0.043	0.047	0.056	0.073	0.117	0.189	0.265
EPS3/P	0.111	0.099	0.047	0.054	0.062	0.080	0.127	0.208	0.286
EG/P	0.009	0.008	0.006	0.002	0.003	0.005	0.011	0.020	0.032
EBITDA/FV	0.132	0.119	0.060	0.044	0.064	0.093	0.154	0.240	0.337
SALE/FV	1.111	0.857	0.965	0.146	0.243	0.505	1.320	3.212	4.909
RIM1/P	1.014	0.939	0.440	0.396	0.478	0.679	1.245	1.933	2.359
RIM2/P	0.559	0.501	0.250	0.214	0.253	0.371	0.690	1.081	1.283

Panel C: Correlation coefficients between value drivers												
	B	CFO	EPS	EBITDA	SALE	EPS0	EPS1	EPS2	EPS3	EG	RIM1	RIM2
B		0.605	0.558	0.667	0.423	0.565	0.542	0.524	0.512	0.232	0.518	0.885
CFO	0.594		0.734	0.861	0.520	0.752	0.745	0.739	0.733	0.475	0.745	0.779
EPS	0.514	0.745		0.858	0.465	0.838	0.848	0.842	0.837	0.644	0.763	0.770
EBITDA	0.625	0.856	0.868		0.514	0.860	0.860	0.850	0.844	0.576	0.838	0.866
SALE	0.278	0.569	0.406	0.518		0.450	0.444	0.448	0.454	0.341	0.443	0.493
EPS0	0.644	0.726	0.670	0.781	0.448		0.980	0.969	0.956	0.661	0.884	0.842
EPS1	0.613	0.717	0.666	0.777	0.443	0.970		0.994	0.985	0.727	0.898	0.835
EPS2	0.602	0.715	0.660	0.771	0.453	0.956	0.993		0.995	0.751	0.899	0.824
EPS3	0.590	0.714	0.653	0.765	0.459	0.939	0.980	0.992		0.770	0.898	0.814
EG	0.428	0.534	0.511	0.565	0.352	0.701	0.761	0.788	0.807		0.627	0.502
RIM1	0.552	0.736	0.640	0.745	0.411	0.845	0.866	0.867	0.867	0.657		0.827
RIM2	0.936	0.750	0.653	0.778	0.487	0.864	0.853	0.840	0.825	0.575	0.793	

The sample consists of non-financial UK firms in Worldscope from 1987 to 2010. The sample covers 204 firms with 1,239 firm-year observations. All value drivers are denominated in pounds sterling and measured on a per share basis. In panel C, values below the diagonal are pairwise correlation coefficients, and those above the diagonal are Spearman rank correlation coefficients.

MV is the market value of equity, calculated as the product of stock price and the number of shares outstanding; BV is equity; CFO is cash flow from operations; EBITDA is earnings before interest, taxes, depreciation and amortisation; SALE is sales; E is earnings before extraordinary items; EPS is earnings per share, calculated as net income divided by the current number of shares outstanding; EPS0 is the IBES current earnings per share; EPS1 (EPS2) is the IBES one-year (two-year) ahead earnings per share forecasts; EPS3 is three-year ahead earnings per share forecasts. If EPS3 is missing in IBES, it is calculated as EPS2 multiplied by one plus a long-term earnings growth rate (LTG); LTG is long-term earnings growth rate forecasts from IBES; P is stock price; EG is calculated as *(EPS2×LTG)*; FV is the total value of firms, calculated as the sum of the market value of equity and the book value of debt;

RIM1 and RIM2 are calculated as below. Residual income models in the UK use a three-year forecast horizon, instead of a five-year forecast horizon. A discount rate, r, is calculated according to the CAPM.

$$RIM1 = B_{it} + \sum_{s=1}^{s=3}\left[\frac{E\left(E_{i,t+s} - r_i B_{i,t+s-1}\right)}{(1+r_i)^s}\right] + \frac{E(E_{i,t+3} - r_i B_{i,t+2})}{r_i(1+r_i)^3}$$

$$RIM2 = B_{it} + \sum_{s=1}^{s=3}\left[\frac{E\left(E_{i,t+s} - r_i B_{i,t+s-1}\right)}{(1+r_i)^s}\right]$$

Table3

Rank Correlation Coefficients across Two Time Periods

		Harmonic mean		Mean		Median		Value-weighted mean	
		Bias	Accuracy	Bias	Accuracy	Bias	Accuracy	Bias	Accuracy
US	All Multiples	0.98***	0.98***	0.99***	0.97***	0.99***	0.97***	0.99***	0.96***
UK	All Multiples	0.93***	0.70***	0.93***	0.83***	0.91***	0.89***	0.87***	0.86***
	Key Multiples	0.96***	0.95***	1.00***	0.86**	0.96***	0.96***	0.88***	0.92***

The rank correlation coefficients of the performance of multiples between the two time periods (from 1987 to 1999 and from 2000 to 2010) are estimated. The rank of multiples is based on the interquartile ranges of pricing error. Harmonic mean, mean, median and value-weighted mean indicate calculation methods used to estimate the average industry multiple. Bias summarises pricing errors, and accuracy summarises the absolute values of pricing error. In the UK, key multiples indicate BV/P, EBITDA/P, SALES/P, EPS0/P, EPS1/P, EPS2/P and EPS3/P. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4

Rank Correlation Coefficients across Calculation Methods, Performance Criteria and Countries

Panel A: Within the US

		Bias				Accuracy			
		H.Mean	Mean	Median	VW.Mean	H.Mean	Mean	Median	VW.Mean
Bias	H. Mean								
	Mean	0.98 ***							
	Median	1.00 ***	0.98 ***						
	VW. Mean	0.98 ***	0.99 ***	0.98 ***					
Accuracy	H. Mean	0.98 ***	1.00 ***	0.98 ***	0.99 ***				
	Mean	0.97 ***	0.99 ***	0.98 ***	0.99 ***	0.99 ***			
	Median	0.98 ***	0.99 ***	0.98 ***	0.98 ***	0.99 ***	0.99 ***		
	VW. Mean	0.96 ***	0.99 ***	0.96 ***	0.99 ***	0.99 ***	0.98 ***	0.97 ***	

Panel B: Within the UK

		Bias				Accuracy			
		H.Mean	Mean	Median	VW.Mean	H.Mean	Mean	Median	VW.Mean
Bias	H. Mean								
	Mean	1.00 ***							
	Median	0.99 ***	0.99 ***						
	VW. Mean	0.94 ***	0.93 ***	0.94 ***					
Accuracy	H. Mean	0.93 ***	0.93 ***	0.91 ***	0.91 ***				
	Mean	0.96 ***	0.96 ***	0.93 ***	0.91 ***	0.98 ***			
	Median	0.96 ***	0.96 ***	0.94 ***	0.92 ***	0.98 ***	1.00 ***		
	VW. Mean	0.89 ***	0.88 ***	0.89 ***	0.92 ***	0.94 ***	0.90 ***	0.90 ***	

Panel C: Between the US and UK

			US							
			Bias				Accuracy			
			H.Mean	Mean	Median	VW.Mean	H.Mean	Mean	Median	VW.Mean
UK	Bias	H. Mean	0.82 ***	0.80 ***	0.80 ***	0.81 ***	0.80 ***	0.80 ***	0.81 ***	0.82 ***
		Mean	0.81 ***	0.79 ***	0.79 ***	0.81 ***	0.79 ***	0.79 ***	0.80 ***	0.82 ***
		Median	0.82 ***	0.80 ***	0.80 ***	0.81 ***	0.80 ***	0.79 ***	0.80 ***	0.83 ***
		VW. Mean	0.91 ***	0.87 ***	0.89 ***	0.87 ***	0.87 ***	0.86 ***	0.87 ***	0.89 ***
	Accuracy	H. Mean	0.79 ***	0.80 ***	0.78 ***	0.80 ***	0.80 ***	0.80 ***	0.81 ***	0.82 ***
		Mean	0.80 ***	0.81 ***	0.79 ***	0.81 ***	0.81 ***	0.81 ***	0.82 ***	0.82 ***
		Median	0.81 ***	0.82 ***	0.80 ***	0.81 ***	0.82 ***	0.82 ***	0.83 ***	0.83 ***
		VW. Mean	0.79 ***	0.79 ***	0.78 ***	0.81 ***	0.79 ***	0.77 ***	0.79 ***	0.82 ***

Panels A, B and C report rank correlation coefficients of the performance of multiples within the US, within the UK, and between the US and UK, respectively. The rank of multiples is based on the interquartile ranges of pricing error. Harmonic mean, mean, median and value-weighted mean indicate calculation methods used to estimate the average industry multiple. Bias summarises pricing errors, and accuracy summarises the absolute values of pricing error. H.Mean indicates harmonic mean, and VW.Mean indicates value-weighted mean. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5

Pricing Errors of Multiples by Harmonic Mean (US)

Panel A: 1987 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.020	-0.106	0.606	0.674	11	0.442	0.356	0.414	0.414	11
CFO/P	0.027	-0.121	0.714	0.701	12	0.483	0.376	0.526	0.433	12
EPS/P	0.017	-0.070	0.570	0.584	8	0.400	0.304	0.406	0.396	10
EBITDA/P	0.018	-0.097	0.587	0.599	9	0.410	0.318	0.421	0.383	8
SALE/P	0.048	-0.226	1.046	0.782	13	0.620	0.461	0.844	0.473	14
EPS0/P	0.012	-0.049	0.461	0.507	6	0.337	0.260	0.315	0.345	7
EPS1/P	0.008	-0.036	0.386	0.431	3	0.283	0.220	0.263	0.286	3
EPS2/P	0.007	-0.039	0.350	0.390	2	0.256	0.201	0.238	0.255	2
EPS3/P	0.006	-0.043	0.341	0.379	1	0.250	0.195	0.231	0.251	1
EG/P	0.012	-0.083	0.464	0.474	4	0.327	0.255	0.329	0.298	4
EBITDA/FV	0.016	-0.102	0.588	0.602	10	0.411	0.320	0.420	0.384	9
SALE/FV	0.044	-0.231	1.048	0.782	13	0.622	0.464	0.844	0.472	13
RIM1/P	0.013	-0.085	0.493	0.528	7	0.357	0.282	0.340	0.340	6
RIM2/P	0.009	-0.055	0.402	0.478	5	0.305	0.248	0.262	0.306	5

Panel B: 1987 – 1999

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.021	-0.106	0.608	0.661	11	0.440	0.351	0.420	0.412	11
CFO/P	0.034	-0.142	0.794	0.759	12	0.527	0.408	0.595	0.463	12
EPS/P	0.017	-0.070	0.555	0.583	8	0.394	0.302	0.391	0.389	10
EBITDA/P	0.020	-0.106	0.592	0.612	9	0.417	0.325	0.420	0.383	8
SALE/P	0.055	-0.233	1.084	0.787	13	0.637	0.467	0.879	0.482	13
EPS0/P	0.012	-0.051	0.456	0.507	6	0.336	0.259	0.309	0.347	7
EPS1/P	0.008	-0.039	0.382	0.432	3	0.282	0.221	0.257	0.289	3
EPS2/P	0.007	-0.042	0.352	0.406	2	0.262	0.209	0.235	0.264	2
EPS3/P	0.007	-0.045	0.343	0.393	1	0.256	0.203	0.229	0.256	1
EG/P	0.012	-0.081	0.451	0.477	4	0.322	0.255	0.316	0.295	4
EBITDA/FV	0.019	-0.110	0.592	0.619	10	0.419	0.328	0.419	0.384	9
SALE/FV	0.054	-0.235	1.086	0.789	14	0.638	0.470	0.881	0.484	14
RIM1/P	0.014	-0.087	0.497	0.511	7	0.354	0.276	0.349	0.333	6
RIM2/P	0.010	-0.054	0.413	0.485	5	0.312	0.253	0.271	0.319	5

Panel C: 2000 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.019	-0.105	0.604	0.688	12	0.445	0.362	0.409	0.416	12
CFO/P	0.020	-0.104	0.633	0.658	11	0.444	0.346	0.452	0.408	11
EPS/P	0.017	-0.071	0.583	0.585	8	0.406	0.306	0.419	0.406	10
EBITDA/P	0.016	-0.088	0.583	0.590	9	0.403	0.312	0.421	0.384	8
SALE/P	0.042	-0.217	1.011	0.778	14	0.605	0.454	0.811	0.464	13
EPS0/P	0.011	-0.046	0.466	0.507	6	0.338	0.261	0.321	0.343	6
EPS1/P	0.008	-0.033	0.390	0.430	3	0.283	0.220	0.268	0.286	3
EPS2/P	0.006	-0.038	0.348	0.375	2	0.251	0.194	0.241	0.249	2
EPS3/P	0.006	-0.041	0.339	0.365	1	0.245	0.189	0.234	0.245	1
EG/P	0.012	-0.087	0.475	0.473	5	0.331	0.255	0.340	0.302	5
EBITDA/FV	0.013	-0.095	0.585	0.590	9	0.405	0.314	0.422	0.384	8
SALE/FV	0.036	-0.226	1.011	0.775	13	0.607	0.458	0.809	0.464	13
RIM1/P	0.012	-0.083	0.490	0.545	7	0.361	0.289	0.332	0.346	7
RIM2/P	0.008	-0.056	0.392	0.472	4	0.299	0.243	0.254	0.296	4

The average industry multiple is calculated by a harmonic mean method as: $E\left({P_{it}}/{X_{it}}\right) = 1/E({X_{jt}}/{P_{jt}})$, where P_{it} is the stock price of a target firm *i* at time *t*, X_{it} is the per share value driver of a target firm *i* at time *t*, P_{jt} is the stock price of a comparable firm *j* at time *t*, and X_{jt} is the per share value driver of a comparable firm *j* at time *t*. A target price is estimated as: $E(P_{it}) = E\left({P_{it}}/{X_{it}}\right) \times X_{it}$. SD represents standard deviation and IQR represents interquartile range. Rank is estimated based on the interquartile ranges. The sample and value drivers are explained in Table 1.

Table 6

Pricing Errors of Multiples by Mean (US)

Panel A: 1987 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.392	0.178	0.869	0.924	11	0.629	0.408	0.716	0.577	11
CFO/P	0.551	0.262	1.176	1.081	12	0.786	0.469	1.033	0.706	12
EPS/P	0.396	0.217	0.859	0.833	10	0.609	0.401	0.724	0.576	10
EBITDA/P	0.323	0.144	0.793	0.790	8	0.549	0.354	0.657	0.491	9
SALE/P	0.773	0.267	1.854	1.290	14	1.037	0.511	1.720	0.826	14
EPS0/P	0.247	0.137	0.608	0.644	7	0.447	0.310	0.480	0.439	7
EPS1/P	0.158	0.083	0.471	0.503	3	0.341	0.241	0.360	0.337	3
EPS2/P	0.114	0.050	0.397	0.434	2	0.287	0.205	0.296	0.282	2
EPS3/P	0.105	0.039	0.382	0.416	1	0.276	0.197	0.284	0.270	1
EG/P	0.174	0.056	0.546	0.543	4	0.374	0.249	0.434	0.340	5
EBITDA/FV	0.321	0.140	0.796	0.791	9	0.550	0.355	0.659	0.490	8
SALE/FV	0.765	0.259	1.855	1.287	13	1.034	0.509	1.720	0.815	13
RIM1/P	0.213	0.075	0.603	0.628	6	0.426	0.285	0.477	0.388	6
RIM2/P	0.153	0.068	0.468	0.551	5	0.352	0.258	0.344	0.338	4

Panel B: 1987 – 1999

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.375	0.164	0.859	0.898	11	0.611	0.396	0.710	0.551	10
CFO/P	0.669	0.313	1.375	1.264	12	0.913	0.529	1.227	0.861	12
EPS/P	0.362	0.195	0.799	0.820	10	0.577	0.388	0.660	0.556	11
EBITDA/P	0.321	0.131	0.792	0.805	8	0.551	0.350	0.654	0.491	8
SALE/P	0.822	0.272	1.964	1.340	13	1.090	0.519	1.829	0.869	13
EPS0/P	0.236	0.126	0.597	0.644	7	0.438	0.305	0.469	0.431	7
EPS1/P	0.151	0.075	0.462	0.498	3	0.336	0.237	0.351	0.331	3
EPS2/P	0.117	0.047	0.402	0.452	2	0.295	0.211	0.298	0.290	2
EPS3/P	0.109	0.039	0.387	0.436	1	0.284	0.203	0.285	0.281	1
EG/P	0.166	0.050	0.528	0.546	4	0.367	0.248	0.415	0.334	4
EBITDA/FV	0.320	0.127	0.795	0.808	9	0.552	0.351	0.655	0.493	9
SALE/FV	0.820	0.266	1.970	1.347	14	1.090	0.519	1.834	0.872	14
RIM1/P	0.204	0.063	0.606	0.596	6	0.416	0.272	0.486	0.369	6
RIM2/P	0.160	0.073	0.483	0.565	5	0.362	0.261	0.357	0.346	5

Panel C: 2000 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.408	0.194	0.877	0.951	11	0.645	0.420	0.721	0.599	11
CFO/P	0.444	0.227	0.948	0.952	12	0.672	0.425	0.803	0.615	12
EPS/P	0.427	0.237	0.909	0.844	10	0.638	0.413	0.775	0.595	10
EBITDA/P	0.325	0.156	0.794	0.775	8	0.547	0.359	0.660	0.491	9
SALE/P	0.729	0.262	1.748	1.251	14	0.990	0.504	1.615	0.794	14
EPS0/P	0.257	0.147	0.617	0.642	6	0.455	0.315	0.490	0.449	7
EPS1/P	0.165	0.090	0.478	0.507	3	0.346	0.244	0.368	0.344	4
EPS2/P	0.111	0.051	0.391	0.418	2	0.281	0.200	0.294	0.275	2
EPS3/P	0.102	0.040	0.377	0.400	1	0.269	0.190	0.283	0.259	1
EG/P	0.182	0.059	0.562	0.541	4	0.380	0.250	0.451	0.346	5
EBITDA/FV	0.323	0.153	0.798	0.775	8	0.548	0.359	0.663	0.487	8
SALE/FV	0.715	0.252	1.741	1.245	13	0.982	0.500	1.606	0.774	13
RIM1/P	0.221	0.092	0.600	0.655	7	0.436	0.297	0.467	0.404	6
RIM2/P	0.147	0.063	0.453	0.541	4	0.342	0.254	0.331	0.334	3

A target price is calculated as: $E(P_{it}) = E\left({P_{jt}}/{X_{jt}}\right) \times X_{it}$, where P_{jt} is the stock price of a comparable firm *j* at time *t*, X_{jt} is the per share value driver of a comparable firm *j* at time *t*, and X_{it} is the per share value driver of a target firm *i* at time *t*. SD represents standard deviation and IQR represents interquartile range. Rank is estimated based on the interquartile ranges. The sample and value drivers are explained in Table 1.

Table 7

Pricing Errors of Multiples by Harmonic Mean (UK)

Panel A: 1987 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.063	-0.139	0.799	0.924	13	0.578	0.479	0.555	0.467	13
CFO/P	0.058	-0.088	0.638	0.688	11	0.450	0.353	0.456	0.357	8
EPS/P	0.054	-0.047	0.667	0.507	6	0.384	0.268	0.548	0.358	9
EBITDA/P	0.027	-0.078	0.519	0.578	7	0.368	0.295	0.367	0.333	6
SALE/P	0.094	-0.204	1.122	0.853	12	0.640	0.481	0.926	0.434	12
EPS0/P	0.022	-0.079	0.462	0.470	4	0.320	0.249	0.335	0.285	5
EPS1/P	0.017	-0.058	0.411	0.390	3	0.280	0.209	0.301	0.269	3
EPS2/P	0.016	-0.055	0.397	0.372	2	0.269	0.201	0.292	0.259	2
EPS3/P	0.016	-0.053	0.396	0.371	1	0.266	0.197	0.294	0.249	1
EG/P	0.066	-0.072	0.729	0.654	10	0.468	0.340	0.562	0.429	11
EBITDA/FV	0.018	-0.073	0.645	0.615	8	0.433	0.320	0.478	0.388	10
SALE/FV	0.081	-0.253	1.337	0.980	14	0.808	0.563	1.068	0.607	14
RIM1/P	0.048	-0.039	0.439	0.499	5	0.320	0.250	0.304	0.277	4
RIM2/P	0.056	-0.033	0.510	0.626	9	0.385	0.312	0.339	0.340	7

Panel B: 1987 – 1999

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.054	-0.072	0.670	0.849	14	0.507	0.433	0.440	0.475	14
CFO/P	0.066	-0.084	0.595	0.693	11	0.433	0.346	0.411	0.357	10
EPS/P	0.033	-0.061	0.414	0.442	4	0.283	0.218	0.303	0.217	1
EBITDA/P	0.025	-0.025	0.434	0.556	10	0.333	0.287	0.280	0.290	7
SALE/P	0.083	-0.169	0.854	0.828	13	0.570	0.452	0.640	0.428	13
EPS0/P	0.028	-0.087	0.469	0.447	5	0.325	0.246	0.339	0.288	6
EPS1/P	0.022	-0.070	0.414	0.387	2	0.293	0.213	0.293	0.290	7
EPS2/P	0.021	-0.058	0.404	0.390	3	0.286	0.219	0.286	0.284	5
EPS3/P	0.023	-0.061	0.424	0.380	1	0.290	0.226	0.309	0.270	2
EG/P	0.079	-0.062	0.711	0.553	8	0.455	0.310	0.551	0.413	11
EBITDA/FV	0.030	-0.056	0.445	0.466	7	0.333	0.252	0.296	0.302	9
SALE/FV	0.117	-0.215	1.028	0.816	12	0.655	0.442	0.800	0.424	12
RIM1/P	0.031	-0.055	0.444	0.460	6	0.310	0.242	0.318	0.274	3
RIM2/P	0.028	-0.063	0.438	0.554	9	0.339	0.280	0.278	0.282	4

Panel C: 2000 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.066	-0.159	0.835	0.944	13	0.599	0.490	0.584	0.466	13
CFO/P	0.056	-0.089	0.650	0.679	11	0.455	0.354	0.467	0.358	7
EPS/P	0.064	-0.041	0.760	0.561	6	0.433	0.307	0.628	0.417	9
EBITDA/P	0.027	-0.088	0.543	0.586	7	0.379	0.298	0.389	0.338	6
SALE/P	0.097	-0.226	1.193	0.861	12	0.662	0.490	0.997	0.433	12
EPS0/P	0.020	-0.070	0.461	0.477	4	0.318	0.250	0.334	0.284	4
EPS1/P	0.016	-0.057	0.410	0.392	3	0.276	0.208	0.304	0.259	3
EPS2/P	0.015	-0.054	0.395	0.369	2	0.264	0.198	0.294	0.251	2
EPS3/P	0.014	-0.050	0.387	0.366	1	0.258	0.192	0.289	0.237	1
EG/P	0.063	-0.072	0.735	0.660	8	0.472	0.348	0.566	0.422	10
EBITDA/FV	0.014	-0.078	0.705	0.668	10	0.470	0.335	0.526	0.427	11
SALE/FV	0.067	-0.264	1.435	1.100	14	0.865	0.605	1.146	0.673	14
RIM1/P	0.057	-0.031	0.437	0.512	5	0.325	0.254	0.296	0.296	5
RIM2/P	0.070	-0.021	0.544	0.665	9	0.410	0.334	0.365	0.361	8

The average industry multiple is calculated by a harmonic mean method as: $E\left({P_{it}}/{X_{it}}\right) = 1/E({X_{jt}}/{P_{jt}})$, where P_{it} is the stock price of a target firm *i* at time *t*, X_{it} is the per share value driver of a target firm *i* at time *t*, P_{jt} is the stock price of a comparable firm *j* at time *t*, and X_{jt} is the per share value driver of a comparable firm *j* at time *t*. A target price is estimated as: $E(P_{it}) = E\left({P_{it}}/{X_{it}}\right) \times X_{it}$. SD represents standard deviation and IQR represents interquartile range. Rank is estimated based on the interquartile ranges. The sample and value drivers are explained in Table 2.

Table 8

Pricing Errors of Multiples by Mean (UK)

Panel A: 1987 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.653	0.290	1.319	1.399	14	0.939	0.557	1.132	0.885	14
CFO/P	0.276	0.105	0.785	0.816	11	0.544	0.365	0.630	0.468	10
EPS/P	0.204	0.061	0.844	0.581	6	0.448	0.267	0.743	0.389	8
EBITDA/P	0.202	0.090	0.616	0.662	7	0.431	0.319	0.484	0.355	6
SALE/P	0.653	0.175	1.819	1.319	12	0.944	0.475	1.687	0.784	12
EPS0/P	0.145	0.025	0.512	0.512	4	0.347	0.244	0.404	0.313	5
EPS1/P	0.113	0.024	0.442	0.429	3	0.298	0.207	0.345	0.269	3
EPS2/P	0.103	0.021	0.422	0.405	2	0.284	0.194	0.328	0.239	1
EPS3/P	0.101	0.015	0.421	0.398	1	0.278	0.189	0.332	0.245	2
EG/P	0.294	0.094	0.871	0.783	10	0.575	0.366	0.718	0.503	11
EBITDA/FV	0.196	0.073	0.759	0.705	8	0.498	0.323	0.606	0.445	9
SALE/FV	0.612	0.143	1.844	1.337	13	1.051	0.537	1.634	0.848	13
RIM1/P	0.138	0.034	0.499	0.533	5	0.352	0.253	0.379	0.300	4
RIM2/P	0.171	0.076	0.557	0.706	9	0.427	0.321	0.396	0.373	7

Panel B: 1987 – 1999

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.487	0.226	1.026	1.120	14	0.765	0.509	0.839	0.655	14
CFO/P	0.230	0.080	0.671	0.776	11	0.490	0.374	0.512	0.417	11
EPS/P	0.096	0.027	0.431	0.425	4	0.291	0.206	0.332	0.217	1
EBITDA/P	0.154	0.084	0.486	0.637	9	0.383	0.293	0.336	0.288	6
SALE/P	0.466	0.142	1.147	1.087	13	0.754	0.440	0.981	0.623	13
EPS0/P	0.138	0.007	0.506	0.482	5	0.340	0.235	0.398	0.295	7
EPS1/P	0.114	0.017	0.441	0.420	3	0.306	0.202	0.336	0.249	3
EPS2/P	0.105	0.016	0.423	0.407	2	0.296	0.204	0.320	0.229	2
EPS3/P	0.110	0.005	0.450	0.397	1	0.298	0.191	0.355	0.251	4
EG/P	0.273	0.060	0.833	0.664	10	0.529	0.304	0.698	0.413	10
EBITDA/FV	0.132	0.019	0.490	0.546	7	0.358	0.261	0.359	0.358	9
SALE/FV	0.483	0.131	1.299	0.966	12	0.797	0.440	1.133	0.559	12
RIM1/P	0.112	0.029	0.462	0.504	6	0.319	0.231	0.352	0.253	5
RIM2/P	0.137	0.051	0.489	0.635	8	0.374	0.293	0.343	0.316	8

Panel C: 2000 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.703	0.305	1.392	1.470	13	0.993	0.570	1.203	0.946	13
CFO/P	0.289	0.122	0.813	0.834	10	0.558	0.363	0.658	0.476	9
EPS/P	0.256	0.084	0.979	0.708	7	0.525	0.329	0.865	0.452	8
EBITDA/P	0.216	0.091	0.650	0.678	6	0.446	0.330	0.520	0.372	6
SALE/P	0.711	0.180	1.977	1.352	12	1.002	0.486	1.846	0.816	12
EPS0/P	0.148	0.032	0.515	0.520	4	0.350	0.245	0.405	0.319	5
EPS1/P	0.113	0.025	0.442	0.429	3	0.296	0.207	0.347	0.275	3
EPS2/P	0.102	0.022	0.421	0.407	2	0.281	0.191	0.330	0.244	2
EPS3/P	0.098	0.019	0.412	0.398	1	0.272	0.188	0.325	0.240	1
EG/P	0.300	0.112	0.883	0.843	11	0.588	0.384	0.723	0.529	11
EBITDA/FV	0.220	0.085	0.836	0.755	9	0.549	0.359	0.667	0.487	10
SALE/FV	0.660	0.153	2.008	1.507	14	1.145	0.607	1.776	0.992	14
RIM1/P	0.152	0.041	0.518	0.547	5	0.370	0.266	0.392	0.316	4
RIM2/P	0.189	0.091	0.589	0.752	8	0.456	0.346	0.418	0.377	7

A target price is calculated as: $E(P_{it}) = E\left({}^{P_{jt}}\!/_{X_{jt}}\right) \times X_{it}$, where P_{jt} is the stock price of a comparable firm *j* at time *t*, X_{jt} is the per share value driver of a comparable firm *j* at time *t*, and X_{it} is the per share value driver of a target firm *i* at time *t*. SD represents standard deviation and IQR represents interquartile range. Rank is estimated based on the interquartile ranges. The sample and value drivers are explained in Table 2.

4. Addressing Puzzle about Equity Valuation Using Multiples: How Earnings Forecasts Outperform Residual Income Model in Multiples

4.1. Introduction

What is the best model to estimate the intrinsic value of stocks? This question is one of the most important questions in accounting and finance, leading to decades of extensive research on developing theoretical models that best estimate intrinsic value. Based on the assumption that intrinsic value is the present value of expected future cash flows, several theory-based valuation models have been developed including the dividend discount model, discount cash flow model, residual income model and abnormal earnings growth model. On the other hand, some believe that rule-of-thumb based models such as multiples work better than theory-based models because they avoid estimating future cash flows and discount rates, which contain large estimation errors (Kaplan and Ruback, 1995; Block, 1999; Baker and Ruback, 1999).

To compare the performances of these two types of valuation models, Liu, Nissim and Thomas (2002) examine the performances of multiples using the residual income model and multiples using accounting values in pricing error. They find a surprising result that multiples using earnings forecasts outperform multiples using the residual income model. This finding undermines the validity of theory-based valuation models and has puzzled researchers about how rule-of-thumb based models outperform theory-based valuation models, which in fact contain earnings forecasts as the elements. This puzzle still remains unresolved (Cooper and Lambertides, 2014).

This project explains mathematically how Liu, Nissim and Thomas (2002) find the puzzling result and shows that the majority of residual income models (i.e. well-chosen residual income models) actually outperform multiples using earnings forecasts in pricing error. The reason why Liu, Nissim and Thomas (2002) find the puzzling result is that they accidentally choose residual income models that perform the worst among residual income models, and compare them with multiples that perform the best in pricing error.

Some researchers believe measuring the performance in pricing error, which compares target price with stock price, is less informative because valuation models aim to estimate intrinsic value instead of current stock price. Since intrinsic value is unobservable and therefore cannot be measured directly, they measure future stock return as an indirect way of estimating intrinsic value (Frankel and Lee, 1998; Lee, Myers and Swaminathan, 1999; Bradshaw, 2004; Courteau et al., 2006). Therefore, this project also examines the model performance in future stock return. The results show that the majority of residual income models again outperform multiples using earnings forecasts, indicating the superiority of theory-based valuation models to rule-of-thumb based multiples in price and intrinsic value estimations. A surprising result is that multiples using current accounting values (i.e. the worst performers in pricing error) outperform multiples using earnings forecasts (i.e. the best performers in pricing error) in future return generation. In fact, a multiple using cash flow (i.e. the worst performer in pricing error) performs the best in future return generation, indicating the importance of accounting fundamentals, especially cash flows, in estimating intrinsic value.

Another puzzling result in Liu, Nissim and Thomas (2002) is that EBITDA and sales multiples that estimate equity value directly (i.e. EBITDA/P and SALE/P) outperform the corresponding multiples that estimate firm value (i.e. EBITDA/FV and SALE/FV). Since EBITDA and sales include a portion of earnings that are attributed to debt holders, the theoretically correct way to use these multiples is to estimate firm value instead of equity value. This project shows that, when intrinsic value is estimated by future stock returns, EBITDA/FV and SALE/FV outperform EBITDA/P and SALE/P respectively, providing another evidence that theory-based models are superior to rule-of-thumb based models.

This project contributes to the literature by addressing the decade-old puzzle about equity valuation using multiples. First, the project explains mathematically why Liu, Nissim and Thomas (2002) find the puzzling result. Second, the project rectifies the previous misunderstanding and demonstrates that theory-based valuation models are in fact superior to rule-of-thumb based multiples in price and intrinsic value estimations. Last, by demonstrating the outperformance of multiples using accounting fundamentals over multiples using earnings forecasts in future stock return, the project emphasises the importance of accounting fundamentals, which are often overshadowed by earnings forecasts (Ohlson, 2005; Ohlson and Juettner-Nauroth, 2005; Penman, 2005).

The project proceeds in the following order: Section 2 explains the mechanism of how pricing error of a multiple is determined by the correlation coefficient between price and a value driver. Section 3 describes the sample, and the results of valuation models in pricing error and future stock return are reported in Section 4. The project is concluded in Section 5.

4.2. Methodology

4.2.1. Mechanism of Pricing Error of Multiple

To understand how Liu, Nissim and Thomas (2002) find the result that multiples using earnings forecasts outperform multiples using the residual income model, it is necessary to understand the mechanism of how pricing error of a multiple is determined. Pricing error is measured as the difference between target price and stock price, divided by stock price (Liu, Nissim and Thomas, 2002):

$$Z_i = \frac{E(P_i) - P_i}{P_i} \tag{1}$$

where Z_i denotes a pricing error of a firm *i*, P_i is a stock price of a firm *i*, and $E(P_i)$ is an expected value of stock price from a multiple, or a target price. For simplicity, a time notation *t* is omitted but all variables are at time *t*.

A target price from a multiple, $E(P_i)$, is calculated as the product of a value driver and the average multiple in the industry as:

$$E(P_i) = X_i \cdot E\left(\frac{P_I}{X_I}\right) \tag{2}$$

where X_i is a value driver of a firm *i*, and $E\left(\frac{P_I}{X_I}\right)$ is the average multiple of X_i in an industry *I* where a firm *i* belongs to.

Replacing $E(P_i)$ in Equation (1) with Equation (2), a pricing error of a firm *i* is obtained as:

$$Z_i = \frac{X_i}{P_i} \cdot E\left(\frac{P_I}{X_I}\right) - 1 \tag{3}$$

The average industry pricing error, Z_I, is the average of the pricing errors of individual firms in the industry:

$$Z_I = E(Z_i) = \frac{\sum_{i=1}^{N} Z_i}{N} \tag{4}$$

where Z_I is the average industry pricing error, and *N* is the total number of firms in the industry.

Replacing Z_i in Equation (4) with Equation (3) results in:

$$Z_I = \frac{1}{N}\left\{E\left(\frac{P_I}{X_I}\right) \cdot \left(\frac{X_1}{P_1} + \frac{X_2}{P_2} + \frac{X_3}{P_3} + \cdots + \frac{X_N}{P_N}\right) - N\right\} \tag{5}$$

Given that $E\left(\frac{P_I}{X_I}\right)$ is the average multiple in an industry *I*, it can be described as:

$$E\left(\frac{P_I}{X_I}\right) = \frac{1}{N} \cdot \sum_{i=1}^{N} \left(\frac{P_i}{X_i}\right) \tag{6}$$

Substituting Equation (6) into Equation (5) results in:

$$Z_I = \frac{1}{N^2}\left\{\left(\frac{P_1}{X_1} + \frac{P_2}{X_2} + \frac{P_3}{X_3} + \cdots + \frac{P_N}{X_N}\right) \cdot \left(\frac{X_1}{P_1} + \frac{X_2}{P_2} + \frac{X_3}{P_3} + \cdots + \frac{X_N}{P_N}\right)\right\} - 1 \tag{7}$$

Each term in the first bracket is the reciprocal of a term in the second bracket. From now on, for simplicity in illustration, I assume that there are only three firms in the industry (*N* = 3) but the same logic applies to the case of *N* firms in the industry. Resolving Equation (7):

$$Z_I = \frac{1}{3^2}\left\{\left(1 + \frac{P_1}{X_1} \cdot \frac{X_2}{P_2} + \frac{P_1}{X_1} \cdot \frac{X_3}{P_3}\right) + \left(\frac{P_2}{X_2} \cdot \frac{X_1}{P_1} + 1 + \frac{P_2}{X_2} \cdot \frac{X_3}{P_3}\right) + \left(\frac{P_3}{X_3} \cdot \frac{X_1}{P_1} + \frac{P_3}{X_3} \cdot \frac{X_2}{P_2} + 1\right)\right\} - 1 \tag{8}$$

Rearranging Equation (8) by clustering terms with the same notations together:

$$Z_I = \frac{1}{3^2}\left\{3 + \left(\frac{P_1}{X_1} \cdot \frac{X_2}{P_2} + \frac{P_2}{X_2} \cdot \frac{X_1}{P_1}\right) + \left(\frac{P_1}{X_1} \cdot \frac{X_3}{P_3} + \frac{P_3}{X_3} \cdot \frac{X_1}{P_1}\right) + \left(\frac{P_2}{X_2} \cdot \frac{X_3}{P_3} + \frac{P_3}{X_3} \cdot \frac{X_2}{P_2}\right)\right\} - 1 \tag{9}$$

Finally, rearranging Equation (9), the average industry pricing error becomes:

$$Z_I = \frac{1}{3^2}\left\{3 + \left(\frac{X_1}{X_2}\cdot\frac{P_2}{P_1} + \frac{X_2}{X_1}\cdot\frac{P_1}{P_2}\right) + \left(\frac{X_1}{X_3}\cdot\frac{P_3}{P_1} + \frac{X_3}{X_1}\cdot\frac{P_1}{P_3}\right) + \left(\frac{X_2}{X_3}\cdot\frac{P_3}{P_2} + \frac{X_3}{X_2}\cdot\frac{P_2}{P_3}\right)\right\} - 1 \quad (10)$$

The second term in each bracket is the reciprocal of the first term. Therefore, by denoting the first term in each bracket as W_1, W_2 and W_3, respectively, Equation (10) can be simplified as:

$$Z_I = \frac{1}{3^2}\left\{3 + \left(W_1 + \frac{1}{W_1}\right) + \left(W_2 + \frac{1}{W_2}\right) + \left(W_3 + \frac{1}{W_3}\right)\right\} - 1 \quad (11)$$

where $W_1 = \frac{X_1}{X_2}\cdot\frac{P_2}{P_1}$, $W_2 = \frac{X_1}{X_3}\cdot\frac{P_3}{P_1}$, and $W_3 = \frac{X_2}{X_3}\cdot\frac{P_3}{P_2}$.

Since prices and value drivers are always positive, W_1, W_2 and W_3 are also always positive. Therefore, the average industry pricing error is minimum when $\left(W_1 + \frac{1}{W_1}\right)$, $\left(W_2 + \frac{1}{W_2}\right)$ and $\left(W_3 + \frac{1}{W_3}\right)$ are minimum.

<Figure 1 here>

Figure 1 illustrates the graph of $Y = \left(W + \frac{1}{W}\right)$. It is a convex curve with a minimum of 2 at $W = 1$. When $W \neq 1$, Y is not at its minimum and Y increases as W increases above or decreases below 1. There are three cases W_1, W_2 and W_3 can have:

	W		
	W_1	W_2	W_3
$W = 1$	$\frac{X_1}{X_2} \cdot \frac{P_2}{P_1} = 1 \Rightarrow \frac{P_1}{X_1} = \frac{P_2}{X_2}$: The slopes of (X_1, P_1) and (X_2, P_2) are the same.	$\frac{X_1}{X_3} \cdot \frac{P_3}{P_1} = 1 \Rightarrow \frac{P_1}{X_1} = \frac{P_3}{X_3}$: The slopes of (X_1, P_1) and (X_3, P_3) are the same.	$\frac{X_2}{X_3} \cdot \frac{P_3}{P_2} = 1 \Rightarrow \frac{P_2}{X_2} = \frac{P_3}{X_3}$: The slopes of (X_2, P_2) and (X_3, P_3) are the same.
$W > 1$	$\frac{X_1}{X_2} \cdot \frac{P_2}{P_1} > 1 \Rightarrow \frac{P_2}{X_2} > \frac{P_1}{X_1}$: The slope of (X_2, P_2) is greater than that of (X_1, P_1).	$\frac{X_1}{X_3} \cdot \frac{P_3}{P_1} > 1 \Rightarrow \frac{P_3}{X_3} > \frac{P_1}{X_1}$: The slope of (X_3, P_3) is greater than that of (X_1, P_1).	$\frac{X_2}{X_3} \cdot \frac{P_3}{P_2} > 1 \Rightarrow \frac{P_3}{X_3} > \frac{P_2}{X_2}$: The slope of (X_3, P_3) is greater than that of (X_2, P_2).
$W < 1$	$\frac{X_1}{X_2} \cdot \frac{P_2}{P_1} < 1 \Rightarrow \frac{P_2}{X_2} < \frac{P_1}{X_1}$: The slope of (X_2, P_2) is smaller than that of (X_1, P_1).	$\frac{X_1}{X_3} \cdot \frac{P_3}{P_1} < 1 \Rightarrow \frac{P_3}{X_3} < \frac{P_1}{X_1}$: The slope of (X_3, P_3) is smaller than that of (X_1, P_1).	$\frac{X_2}{X_3} \cdot \frac{P_3}{P_2} < 1 \Rightarrow \frac{P_3}{X_3} < \frac{P_2}{X_2}$: The slope of (X_3, P_3) is smaller than that of (X_2, P_2).

<Figure 2 here>

Figure 2 depicts the three cases of W_1, but the same inference can be drawn for W_2 and W_3.

1) When (X_2, P_2) is on the same slope as (X_1, P_1), $W_1 = 1$ and $\left(W_1 + \frac{1}{W_1}\right) = 2$, the minimum value.
2) When (X_2, P_2) is above the slope of (X_1, P_1), $W_1 > 1$ and $\left(W_1 + \frac{1}{W_1}\right) > 2$. The greater (X_2, P_2) is above the slope of (X_1, P_1), $W_1 \gg 1$ and $\left(W_1 + \frac{1}{W_1}\right) \gg 2$.
3) When (X_2, P_2) is below the slope of (X_1, P_1), $W_1 < 1$ and $\left(W_1 + \frac{1}{W_1}\right) > 2$. The greater (X_2, P_2) is below the slope of (X_1, P_1), $W_1 \ll 1$ and $\left(W_1 + \frac{1}{W_1}\right) \gg 2$.

In both 2) and 3), when the slope of (X_2, P_2) is not equal to the slope of (X_1, P_1), $\left(W_1 + \frac{1}{W_1}\right) > 2$ and $Z_I > 0$.

Figure 2 indicates four implications about $\left(W_1+\frac{1}{W_1}\right)$: a) $\left(W_1+\frac{1}{W_1}\right)$ depends on the inter-relationship between slopes of $(X_i,\, P_i), i=\{1,2\}$; b) $\left(W_1+\frac{1}{W_1}\right)$ reaches the minimum point of 2 when $(X_i,\, P_i), i=\{1,2\}$, are on the same slopes; c) $\left(W_1+\frac{1}{W_1}\right)$ increases as $(X_i,\, P_i), i=\{1,2\}$, diverge from each other. The greater $(X_i,\, P_i), i=\{1,2\}$, diverge from each other, the greater $\left(W_1+\frac{1}{W_1}\right)$ becomes; d) the actual slopes of $(X_i,\, P_i), i=\{1,2\}$, are not important. What is important for $\left(W_1+\frac{1}{W_1}\right)$ and the average industry pricing error is the inter-relationship between the two slopes. The same logic applies to the cases of W_2 and W_3.

When there are N firms in an industry, the average industry pricing error is:

$$Z_I=\frac{1}{N^2}\left\{N+\sum_{j=1}^{\frac{N^2-N}{2}}\left(W_j+\frac{1}{W_j}\right)\right\}-1, j=\{1,2,3,\cdots,\frac{N^2-N}{2}\} \tag{12}$$

In general, the average industry pricing error is determined by how close $(X_i,\, P_i), i=\{1,2,3,\cdots,N\}$, are to each other around a common slope line. A special case occurs when all $(X_i,\, P_i)$, $i=\{1,2,3,\cdots,N\}$, are on the same slope. Then, $\frac{P_1}{X_1}=\frac{P_2}{X_2}=\frac{P_3}{X_3}=\frac{P_i}{X_i}=\cdots=\frac{P_N}{X_N}$, resulting in all $W_j=1$ and $\left(W_j+\frac{1}{W_j}\right)=2$, $j=\left\{1,2,3,\cdots,\frac{N^2-N}{2}\right\}$. In this case, $Z_I=0$ in Equation (12). This special case is depicted in Figure 3.

<Figure 3 here>

The closeness of $(X_i,\, P_i), i=\{1,2,3,\cdots,N\}$, to each other around a common slope line can simply be measured by the correlation coefficient between price and a value driver, henceforth, price correlation coefficient (PCC). This project will use PCC to explain how Liu, Nissim and Thomas (2002) find the outperformance of multiples using earnings forecasts over multiples using the residual income model in pricing error.

4.2.2. Choice of Multiples

The project chooses six current accounting values and three earnings forecasts for value drivers of multiples. 1) The book value of equity (B) is chosen as it is one of the most widely used value drivers in practice (Demirakos, Strong and Walker, 2004; Imam, Barker and Clubb, 2008). The book value of equity represents the accounting value of a firm and is often used as a proxy for the market value of a firm when the firm has little information about its future prospects. A multiple using the book value of equity is also called a market-to-book ratio. 2) Cash flow from operations (CFO) is chosen because cash flow is considered as a 'real' value driver of a firm. Cash flow represents 'hard' cash, which is less susceptible to accounting manipulation and more important for firms in financial difficulties (Koller, Goedhart and Wessels (2005)). 3) Earnings before interest, taxes, depreciation and amortisation (EBITDA) measure earnings before major discretionary expenses. Therefore, EBITDA is considered as a better earnings measure between firms that have different capital structures and accounting policies. 4) Sales (SALE) are the second most popular value driver among analysts in practice (Demirakos, Strong and Walker, 2004). Because sales have positive values most of the time, they are used as an alternative to other value drivers when other value drivers have negative values. 5) Earnings per share (EPS) are by far the most widely used value driver in practice (Arnold and Moizer, 1984; Barker, 1999; Block, 1999; Bradshaw, 2002; Demirakos, Strong and Walker, 2004; Imam, Barker and Clubb, 2008). Earnings have gained its popularity because a large amount of research support a strong relation between earnings and stock return (Ball and Brown, 1968; Beaver, 1968; Rayburn, 1986; Biddle, Seow and Siegel, 1995; Barth, Cram and Nelson, 2001; Francis, Schipper and Vincent, 2003). Earnings represent accounting profit, which subsequently determines cash flow from operations and dividend. 6) Earnings per share from IBES (EPS0) are often called 'street earnings' in practice. Earnings from IBES represent earnings from continuing operations, excluding the impact of extraordinary items and discontinued operations. 7) One-year ahead earnings forecast from IBES (EPS1) is included due to the outstanding performance of its multiple (Kim and Ritter, 1999; Liu, Nissim and Thomas, 2002; Yee, 2004). 8) Two-year ahead earnings forecast from IBES (EPS2) is also included for the same reason as one-year ahead earnings forecast. 9) Three-year ahead earnings forecast from IBES (EPS3) is calculated as two-year ahead earnings forecast multiplied by one plus a long-term earnings growth rate from IBES (LTG), $EPS3 = EPS2 \times (1 + LTG)$, if three-year ahead earnings forecasts are missing in IBES.

To be precise, EBITDA and sales are values before interest payment. Because they include a portion of earnings that are attributed to debt holders as well as equity holders, theoretically EBITDA and sales multiples should be used to estimate total firm value instead of equity value. This project estimates total firm value (FV) as well as equity value by using EBITDA and sales multiples. When total firm value is estimated, the book value of debt is subsequently deducted from the total firm value to estimate stock price as:

$$E(P_i) = \left\{E\left({}^{FV_I}/_{Y_I}\right)Y_i - DEBT_i\right\}/SHOUT_i \tag{13}$$

where $E\left({}^{FV_I}/_{Y_I}\right)$ is the average ratio of total firm value to a value driver in an industry I, FV_I is the total firm value calculated as the sum of the market value of equity and the book value of debt, Y_i is an unscaled (i.e. total) value driver of a firm i, $DEBT_i$ is the book value of debt, and $SHOUT_i$ is the number of shares outstanding.

4.2.3. Residual Income Model

The development of the residual income model is widely accredited to Ohlson (1995) and Feltham and Ohlson (1995), although the original concept starts from Edwards and Bell (1961) and Peasnell (1982). The residual income model defines stock price as the sum of book value and discounted expected residual incomes:

$$P_{i,t} = B_{i,t} + \frac{E(E_{i,t+1} - r_i B_{i,t})}{(1+r_i)} + \frac{E(E_{i,t+2} - r_i B_{i,t+1})}{(1+r_i)^2} + \frac{E(E_{i,t+3} - r_i B_{i,t+2})}{(1+r_i)^3} + \cdots \tag{14}$$

where $P_{i,t}$ is the stock price of a firm *i* at time *t*, $B_{i,t}$ is the book value, $E_{i,t+s}$ is the earnings at time t+s, and *r* is the cost of equity.

In this project, the residual income model is estimated with a forecast horizon of five years and a terminal value as:

$$P_{i,t} = B_{i,t} + \sum_{s=1}^{5} \left[\frac{E(E_{i,t+s} - r_i \cdot B_{i,t+s-1})}{(1+r_i)^s} \right] + \frac{[E(E_{i,t+5} - r_i \cdot B_{i,t+4})](1+g_i)}{(r_i - g_i)(1+r_i)^5} \tag{15}$$

where g_i is a perpetual residual income growth rate.

Because the residual income model involves the estimations of future residual incomes and discount rates, different target prices can be reached depending on the estimation assumptions. Unlike most papers that use only a few assumptions and choose a few representative residual income models, this project examines a matrix of residual income models with all plausible assumptions on a discount rate and a perpetual residual income growth rate. Specifically, for a discount rate (r_i), 1% through 12% are used as well as a discount rate estimated based on the Capital Asset Pricing Model

(CAPM). For a perpetual residual income growth rate (g_i), 0% through 5% are examined as well as the case when the residual income model does not have a terminal value.

Two residual income models are chosen based on the price correlation coefficient (PCC). The first residual income model (RIMG0R11) assumes a perpetual residual income growth rate of 0% and a discount rate of 11%. RIMG0R11 is chosen because it has the highest PCC among residual income models (reported in Table 2). The second residual income model (RIMG4RC) assumes a perpetual residual income growth rate of 4% and a discount rate based on the CAPM. RIMG4RC has the lowest PCC (reported in Table 2). Therefore, the results of the two models can demonstrate the best and worst performances residual income models can have.

All variables in the residual income model are estimated on a per share basis. Earnings forecasts are obtained from IBES. If IBES three-, four- and five-year ahead earnings forecasts are missing, they are calculated as the product of the previous period earnings forecasts and one plus long-term earnings growth rates. For example, four-year ahead earnings forecasts are calculated as three-year ahead earnings forecasts multiplied by one plus a long-term earnings growth rate.

The future book value of equity is estimated based on the clean surplus relation as:[7]

$$B_{i,t+s} = B_{i,t+s-1} + E_{i,t+s} - DIV_{i,t+s} \tag{16}$$

[7] The clean surplus relation assumes that all changes in equity are reflected in an income statement in the period, except transactions between owners.

where $B_{i,t+s}$ is the book value of equity of a firm i at time t+s, $E_{i,t+s}$ is the earnings, and $DIV_{i,t+s}$ is the dividend.

Future dividend is calculated as future earnings forecast multiplied by the current dividend payout ratio (Lintner, 1956; Liu, Nissim and Thomas, 2002; Skinner and Soltes, 2011). To reflect a long-term dividend payment behaviour, the current dividend payout ratios are winsorized at 10% and 50%. As a robustness test, current dividend payments were also used as future dividends based on the finding of Brav et al. (2005). However, the results were qualitatively the same so they are not reported in this project.

A CAPM discount rate is calculated as:

$$r_{it} = r_{ft} + \beta_{it}(RP) \tag{17}$$

where r_{ft} is the risk-free rate at time *t*, β_{it} is the beta coefficient of a firm *i* at time *t*, and *RP* is the market risk premium. The project uses the ten-year US Treasury bond yields for the risk-free rate and 5% for the market risk premium (Dimson, Marsh and Staunton, 2003). β_{it} is calculated based on the market model. Specifically, β_{it} is the slope coefficient of a regression of stock monthly return on S&P 500 monthly return based on the past 60 months' data. To mitigate the impact of extreme betas, β_{it} is truncated at the 1st and 99th percentiles and then replaced by the median beta of each decile in each year (Liu, Nissim and Thomas, 2002).

4.2.4. Performance Criteria

The performance of multiples and the residual income model is measured by pricing error and future return generation. Performance in pricing error implicitly assumes the Efficient Market Hypothesis: when stock price reflects all available information in the market, performance in pricing error measures how much information valuation models contain compared to that in the stock price (Kothari, 2001). Bias summarises the signed pricing errors and indicates where target price locates compared to stock price. On the other hand, accuracy summarises the absolute values of pricing error and indicates how close target price is to stock price. Therefore, bias is often considered as a performance criterion for a portfolio of stocks, while accuracy is a performance criterion for an individual stock (Francis, Olsson and Oswald, 2000). The calculation of pricing error is described in Equation (1).

For future stock return, the project employs two measures: a) a relation between future abnormal stock return and target price, and b) buy-and-hold abnormal stock return. a) A relation between future abnormal stock return and target price is similar to the earnings response coefficient. The earnings response coefficient measures the relation between abnormal stock return and earnings (Kothari, 2001), and is calculated as the slope coefficient of a regression of abnormal stock return on earnings (Hou, van Dijk and Zhang, 2012) as:

$$ASR_{i,t} = \alpha + \gamma \cdot E_{i,t} + \varepsilon_{i,t} \tag{18}$$

where $ASR_{i,t}$ is the abnormal stock return of a firm i at time t, $E_{i,t}$ is earnings, and γ is the earnings response coefficient.

The relation between future abnormal stock return and target price replaces $ASR_{i,t}$ and $E_{i,t}$ in Equation (17) with future abnormal stock return and a ratio of target price to stock price, respectively, as:

$$FASR_{i,t}^{T} = \alpha + \gamma \cdot \frac{E(P_{i,t})}{P_{i,t}} + \varepsilon_{i,t} \tag{19}$$

where $FASR_{i,t}^{T}$ is the future abnormal stock return of a firm i at time t for T months into the future, $T = \{3, 6, 9, 12, 24, 36, 48, 60\}$, and $\frac{E(P_{i,t})}{P_{i,t}}$ is the ratio of target price to stock price.

Abnormal stock return is measured as the difference between stock return and S&P 500 index return. To examine the short- and long-term relations, the project uses future abnormal stock returns for 3, 6, 9, 12, 24, 36, 48 and 60 months into the future.

The ratio of target price to stock price measures how much a stock is over/undervalued and hence indicates future abnormal stock return opportunities. However, some valuation models tend to overstate target prices while others understate them depending on the assumptions used in the model. To make the ratios comparable across valuation models and across time, the ratio of target price to stock price is standardised to have a standard deviation of one for each valuation model in each year (Hou, van Dijk and Zhang, 2012).

The second measure for future stock return is buy-and-hold abnormal stock return. Buy-and-hold abnormal stock return is estimated based on a trading strategy that holds 20% of most undervalued stocks and short-sells 20% of most overvalued stocks. Future abnormal stock returns are measured for 3, 6, 9, 12, 24, 36, 48 and 60 months into the future. Overvaluation and undervaluation are determined by the standardised ratio of target price to stock price. A trading strategy based on 10% long and 10% short was also examined as a robustness test. The results were qualitatively the same. Only the results of a trading strategy based on 20% long and 20% short are reported as they present a clearer distinction in performance between models.

4.3. Data

The sample consists of non-financial US firms listed on the NYSE, Amex or NASDAQ from 1982 to 2012. Firms with a share code of 10 or 11 in CRSP are only chosen, excluding ADRs, REITs and closed-end funds. Both active and inactive firms are included to mitigate survivorship bias. Accounting data are obtained from Compustat, prices and returns are obtained from CRSP, and earnings forecasts are obtained from IBES. Accounting data are as of the fiscal year end. Prices, the number of shares outstanding and earnings forecasts are as of four months after the fiscal year end, considering the lag between the announcement date and fiscal year end. Time series are based on firms' fiscal years.

The sample requires four conditions to be met: a) each firm-year has positive target prices for all multiples; b) prices are truncated at $2 and the 99th percentile, and the number of shares outstanding at one million shares and the 99th percentile; c) all value drivers and multiples are truncated at the 1st and 99th percentiles in the pooled distributions, and d) there are at least five firms in each industry-year.

The first condition makes target prices comparable with stock prices. The second and third conditions mitigate the impact of outliers. A cut-off point of $1 for price was also used, but the results were consistent (not reported). In addition, the project uses truncation, instead of winsorization, to remove outlying values. This is to avoid having heavy tails in the distribution, which can affect statistical inferences. The fourth condition ensures that there are at least four comparable firms for each target price estimation.

All valuation models are estimated on a per share basis, except for EBITDA/FV and SALE/FV that estimate total firm values. The final sample covers 4,231 firms with 24,246 firm-year observations.

<Table 1 here>

Table 1 reports the descriptive statistics of the sample. Panel A shows that the sample comprises mainly large firms due to the four restrictions imposed above. The average market value of equity is $2.4 billion and the book value of equity is $790 million. Earnings forecasts for the more distant future have higher means and medians than those for the nearer future. This indicates that analyst forecasts tend to be more optimistic as a forecast horizon lengthens, consistent with the findings of La Porta (1996), Dechow and Sloan (1997), and Rajan and Servaes (1997). Analysts' optimism is also evidenced by a long-term earnings growth rate (LTG). The mean and median growth rates are 17% and 15% respectively, significantly higher than the average US GDP growth rate of 2.8% over the same time period.[8]

Panel B of Table 1 reports the distributions of multiples. On average, book value per share is about half the size of stock price, and earnings per share are less than one-tenth of stock price. EBITDA/FV and SALE/FV have similar distributions to EBITDA/P and SALE/P, respectively. Although RIMG0R11/P and RIMG4RC/P are both residual income models, they have distinctively different distributions indicating that the differences in assumptions used in the model can result in significantly different target prices.

[8] The average US GDP growth rate from 1982 to 2012 is manually calculated based on data from the World Bank.

Panel C of Table 1 reports the correlation coefficients between value drivers. Current earnings from IBES (EPS0) and earnings forecasts are highly correlated with each other with all correlation coefficients above 0.89. Current reported earnings (EPS) and EPS0 are also highly correlated. However, the correlations between EPS and analyst forecasts decrease as a forecast horizon lengthens. RIMG0R11 has high correlations with the book value of equity, current reported earnings and earnings forecasts. However, RIMG4RC has low correlations with all accounting variables due to a significant weight on the terminal value by using a perpetual residual income growth rate of 4%.

4.4. Results

4.4.1. Relation between Price Correlation Coefficient and Performance of Multiples in Pricing Error

Price correlation coefficients (PCCs) are estimated to examine the relation between PCC and the performance of multiples in pricing error. Table 2 reports the PCCs of residual income models.

<Table 2 here>

Table 2 shows that residual income models have a wide distribution of PCC, from 0.119 to 0.753, depending on the assumptions used. Four patterns arise in Table 2 are: a) an increase in a discount rate increases a PCC; b) an increase in a perpetual residual income growth rate decreases a PCC; c) when a terminal value is estimated, the use of a CAPM discount rate decreases a PCC especially when a perpetual residual income growth rate is high; and d) the omission of a terminal value decreases a PCC, except when a CAPM discount rate is used.

The reason why the use of a CAPM discount rate decreases a PCC is another research theme and, therefore, is not discussed in this project. However, Table 2 shows that the use of a CAPM discount rate does not always have a negative impact on PCC as the PCC of residual income models without a terminal value increases when a CAPM discount rate is used.

The PCC peaks at a residual income model with a discount rate of 11% and a perpetual residual income growth rate of 0% (RIMG0R11). On the other hand, the PCC reaches its bottom when a model uses a CAPM discount rate and a perpetual residual income growth rate of 4% (RIMG4RC). These two residual income models are used for multiples to compare their performance with other multiples.

<Table 3 here>

Table 3 reports the pricing errors of multiples based on a mean method (i.e. the average industry multiple is estimated as the mean of individual firms' multiples, except the multiple of a target firm). The results based on the other methods (i.e. harmonic mean, median, value-weighted mean methods) are consistent with the results based on the mean method and hence reported in Appendix 1. Generally, the results are identical to those of Liu, Nissim and Thomas (2002): multiples using earnings forecasts perform the best, followed by multiples using current accounting values. EBITDA/P and SALE/P also outperform EBITDA/FV and SALE/FV, respectively. However, a different result is that RIMG0R11/P outperforms multiples using earnings forecasts (e.g. EPS3/P). When other residual income models with similar PCCs to that of

RIMG0R11 are used, they also outperform EPS3/P suggesting that well-chosen residual income models outperform multiples using earnings forecasts. On the other hand, RIMG4RC/P performs the worst among all multiples in both bias and accuracy. The results suggest that the performance of multiples using residual income models can vary from the best to the worst depending on the assumptions used in the model.

<Table 4 here>

A relation between PCC and the performance of multiples in pricing error is statistically examined by the rank correlation coefficient. The rank correlation coefficient is a non-parametric measure of a relation. A non-parametric measure is used because the purpose of the research is to examine whether PCC and the performance of multiples are positively related, rather than linearly related. In fact, the pricing error of multiples and their PCC have different distributions (i.e. the pricing error has a minimum of zero but no maximum, while PCC distributes from -1 to +1). Therefore, they are likely to be non-linearly related.

Panel A of Table 4 reports the PCCs of value drivers of multiples. Consistent with the results in pricing error in Table 3, RIMG0R11 has the highest PCC, followed by earnings forecasts, current accounting values and RIMG4RC, sequentially. The relation between PCC and the performance of multiples in pricing error is examined in Panel B of Table 4. The results show that the rank correlation coefficients between PCC and the performance of multiples in pricing error are above 0.9 regardless of the calculation methods used for multiples. The rank correlation coefficients are not one because the average industry multiples are estimated on an out-of-sample basis (i.e. the target firm’s multiple is excluded when calculating the average industry multiple).

In addition, rank correlation coefficients differ marginally across the calculation methods because different calculation methods estimate the average industry multiple in a different manner.[9] However, the rank correlation coefficients indicate that PCC and the performance of multiples in pricing error have an almost perfect relation across calculation methods.

The relation between PCC and the performance of multiples in pricing error explains why Liu, Nissim and Thomas (2002) find the puzzling result. Liu, Nissim and Thomas (2002) choose three residual income models: a) a model based on a CAPM discount rate and a perpetual residual income growth rate of 0%; b) a model based on a CAPM discount rate without a terminal value; and c) a model based on a CAPM discount rate with a gradual decrease in future residual incomes. As seen in Table 2, residual income models using a CAPM discount rate have the lowest PCCs in the matrix of residual income models. Although a model without a terminal value has the highest PCC when a CAPM discount rate is used, its PCC is still on the low boundary of the PCCs of other models that use constant discount rates.

By choosing residual income models that use only a CAPM discount rate, Liu, Nissim and Thomas (2002) accidentally choose residual income models that perform the worst among residual income models and compare their results with the best performing multiples. However, as seen in Tables 2 and 3, the majority of residual income models

[9] A mean method estimates the average industry multiple by weighting individual firms' multiples equally. A median method estimates the average industry multiple by using the multiple(s) of only one (or two) comparable firm(s) in the middle. A harmonic mean method estimates the average industry multiple by 1) inversing individual firms' multiples; 2) averaging them; and 3) re-inversing the average. A value-weighted mean method estimates the industry average multiple by applying weights based on firms' market values to individual firms' multiples.

in fact have higher PCCs than earnings forecasts and perform better than earnings forecasts in multiples.

4.4.2. Future Abnormal Stock Return

Pricing error assumes that stock price is intrinsic value and, therefore, measures how close target prices from valuation models are to stock prices. However, equity valuation inherently assumes an inefficient market and aims to exploit misvaluation (Kothari, 2001). Therefore, not everyone agrees to the use of pricing error as a performance criterion of valuation models. Instead, researchers who believe in an inefficient market use future stock return as an alternative performance criterion to estimate intrinsic value. (Frankel and Lee, 1998; Lee, Myers and Swaminathan, 1999; Bradshaw, 2004; Courteau et al., 2006).

<Table 5 here>

Table 5 reports the relation between future abnormal stock return and the ratio of target price to stock price for 3, 6, 9, 12, 24, 36, 48 and 60 months into the future. Rank summarises the average performance across the periods. The most interesting result in Table 5 is the reversal of ranks of multiples: when future abnormal stock return is measured, multiples using current accounting values perform the best, followed by multiples using the two residual income models and earnings forecasts, sequentially. A multiple using cash flow from operations (CFO/P), which performs the worst among multiples in pricing error, performs the best across the periods in Table 5. In addition, SALE/FV (i.e. the second worst performer in pricing error) performs the second best in Table 5. On the other hand, multiples using earnings forecasts are all ranked the bottom on the list.

The consistently outstanding performance of CFO/P implies the importance of cash flow in estimating the intrinsic value of stocks. In addition, the outperformance of EBITDA/FV and SALE/FV over EBITDA/P and SALE/P, respectively, indicates the superiority of the theoretically correct methods of using multiples to the rule-of-thumb based methods.

On the other hand, RIMG0R11/P performs considerably better than EPS3/P only for 60 months' period, while RIMG4RC/P performs mediocre during the periods. The performance of the residual income model will be discussed further later in Tables 7 and 8.

<Table 6 here>

Table 6 reports the buy-and-hold abnormal stock returns of multiples following a trading strategy of buying 20% of most undervalued stocks and short-selling 20% of most overvalued stocks. The results of buy-and-hold abnormal stock returns support the results of the relation between abnormal stock return and target price in Table 5: multiples using current accounting values perform the best, followed by multiples using residual income models and earnings forecasts, sequentially. Among multiples using current accounting values, CFO/P performs the best, followed by EBITDA/FV and SALE/FV. Multiples using earnings forecasts and current earnings perform the worst in buy-and-hold abnormal stock return.

The consistent results across the two measures of future abnormal stock return show the importance of accounting fundamentals, especially cash flow from operations, in estimating the intrinsic value of stocks. On the other hand, while earnings forecasts have high PCCs and perform well in pricing error, they have limited value in generating future abnormal stock returns and estimating intrinsic values.

4.4.3. Future Abnormal Stock Return of Residual Income Model

Although residual income models are previously used through multiples to address the puzzle in Liu, Nissim and Thomas (2002), such a method is not the theoretically correct method to use the residual income model. This is because multiples are relative valuation models while the residual income model is an absolute valuation model. The residual income model is a self-contained model and, therefore, should be used by itself. Tables 7 and 8 report the results of future abnormal stock returns when the residual income model is used by itself.

<Table 7 here>

Table 7 presents the results of a relation between future abnormal stock return and the ratio of target price to stock price. To conserve space, only the results for 60 months' period into the future are reported. The results for the remaining periods are reported in Appendix 2.

Four distinctive patterns arise are: a) as a discount rate decreases, the relation between future abnormal stock return and the ratio of target price to stock price increases; b) an increase in a perpetual residual income growth rate generally increases the relation marginally; c) the omission of a terminal value decreases the relation; and d) the use of a CAPM discount rate decreases the relation.

The relation peaks at 0.109 when a residual income model uses a discount rate of 1% and a perpetual residual income growth rate of 0%. Compared to the results of multiples in Table 5, this figure is higher than that of any other multiple except for CFO/P. The same results are observed for 36 and 48 months into the future (Appendix 2). The results indicate that the majority of residual income models generate higher future abnormal stock returns than multiples using earnings forecasts or multiples using residual income models (i.e. the incorrect method of using the residual income model).

<Table 8 here>

The consistent results are observed when the residual income model is used in a trading strategy. Table 8 reports the 60-month buy-and-hold abnormal stock returns of the residual income model when buying 20% of most undervalued stocks and short-selling 20% of most overvalued stocks based on its target prices. The results for the other periods are reported in Appendix 3. The buy-and-hold abnormal stock return peaks at 0.231 when a residual income model uses a discount rate of 2% and a perpetual residual income growth rate of 1%. A surprising result is that this figure is higher than the buy-and-hold abnormal returns of any other multiples including CFO/P in Table 6. The consistent results are observed for 36 and 48 months into the future.

The results in Tables 7 and 8 demonstrate that the theoretically correct use of the residual income model generates higher future abnormal stock returns than most of multiples including multiples using earnings forecasts and multiples using residual income models. The results support the superiority of theory-based valuation models to rule-of-thumb based valuation models in estimating intrinsic value.

4.5. Conclusion

This project attempts to address the decade-old puzzle about equity valuation using multiples: how simple earnings forecasts outperform the theory-based residual income model in multiples in pricing error. This finding is difficult to understand because the residual income model in fact contains earnings forecasts as its elements. In addition, the finding undermines the validity of theory-based valuation models that have been developed for decades. This project explains mathematically why the puzzling result happens and demonstrates that a theory-based valuation model is in fact better than a rule-of-thumb based multiple in price and intrinsic value estimations.

The main finding of this project is that the residual income model performs better than multiples using earnings forecasts in both pricing error and future abnormal stock return. The reason why Liu, Nissim and Thomas (2002) find the puzzling result is that they accidentally choose residual income models that perform the worst and compare their performance with those of the best performing multiples. The project shows that the majority of residual income models (i.e. well-chosen residual income models) in fact outperform multiples using earnings forecasts in pricing error. In addition, when future abnormal stock return is measured, the residual income model (i.e. the correct use of the residual income model) generates higher future abnormal stock returns than most of multiples including multiples using earnings forecasts and multiples using the residual income model. In addition, EBITDA/FV and SALE/FV also perform better than EBITDA/P and SALE/P, respectively. To sum up, the results demonstrate that theory-based valuation models outperform rule-of-thumb based valuation models in price and intrinsic value estimations.

The project contributes to the literature by addressing the decade-old puzzle about equity valuation using multiples. The project demonstrates that theory-based valuation models are superior to rule-of-thumb based multiples in price and intrinsic value estimations. Therefore, the project supports the validity of theory-based valuation models and encourages future researchers to further develop theory-based valuation models.

Figure 1

A Graph of $Y = \left(W + \frac{1}{W}\right)$

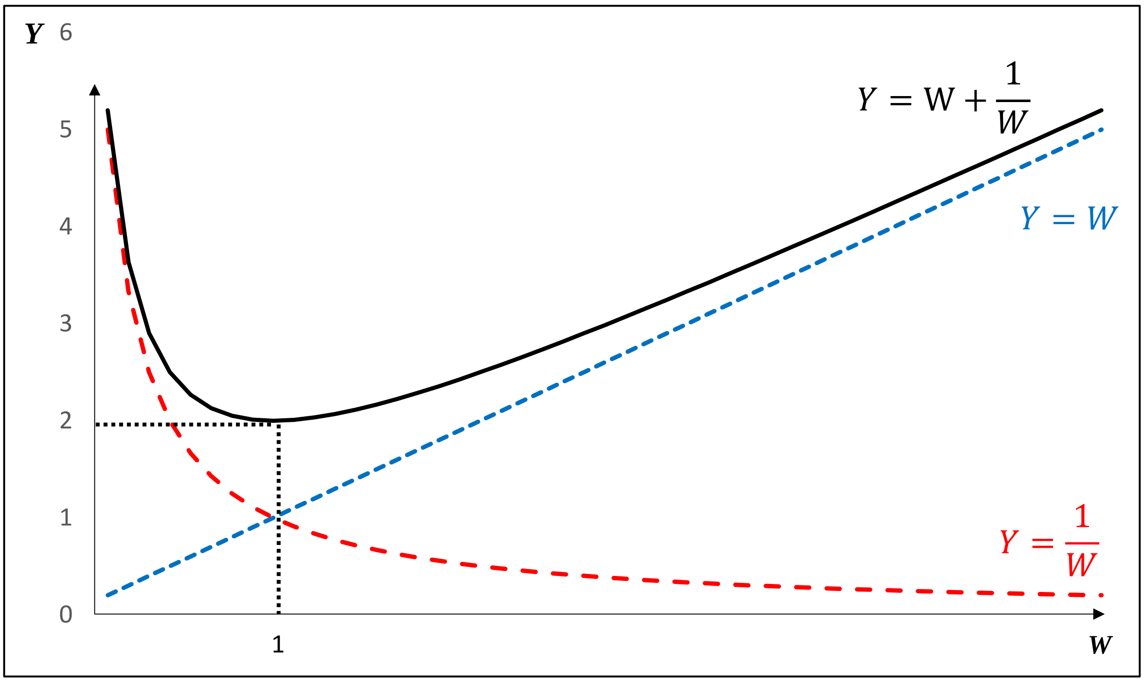

Figure 2

Three cases of W_1

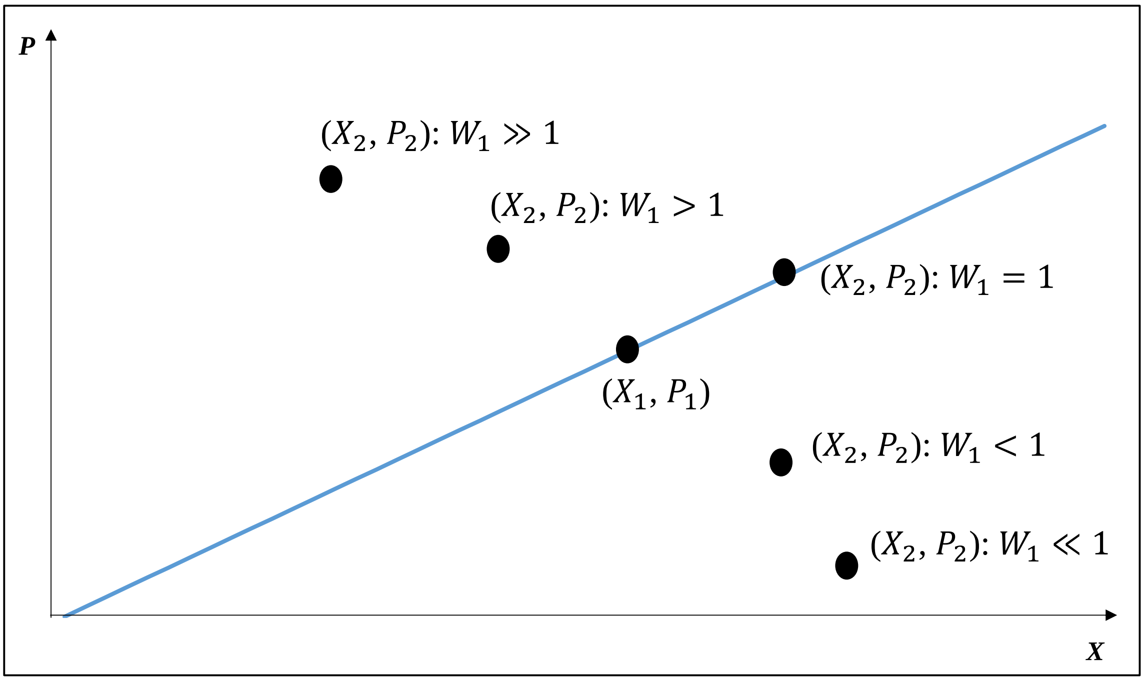

Figure 3

A Case When Pricing Error Equals Zero

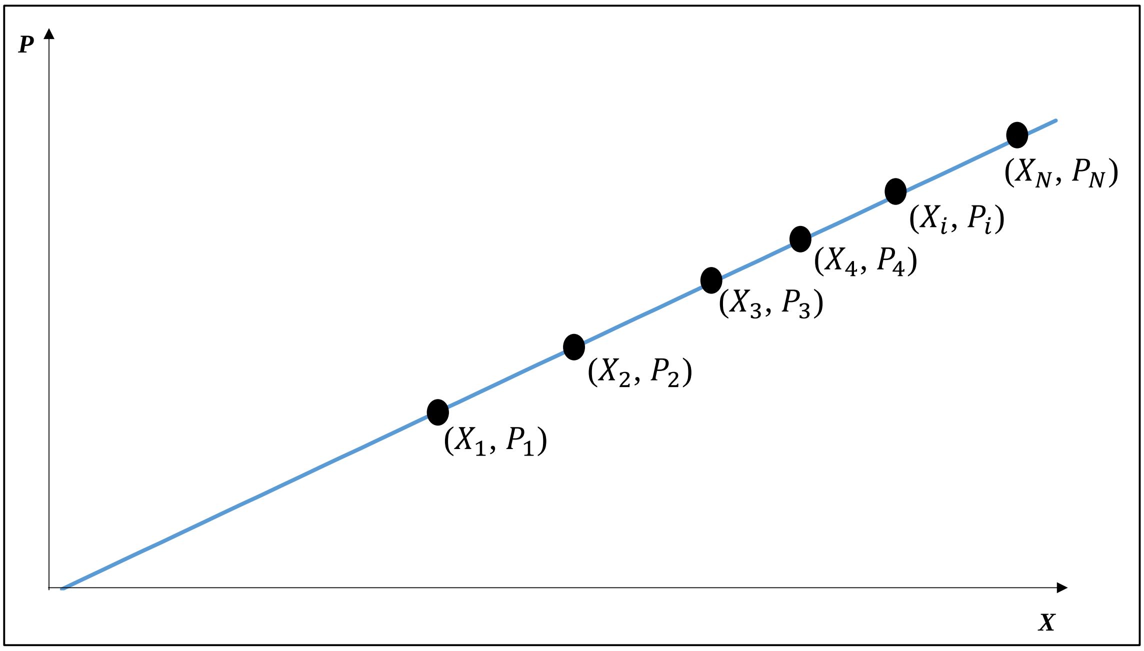

Table 1

Descriptive Statistics

Panel A: Firm level									(in $ mil, except per share values)
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
MV	2394	745	5024	32	69	267	2115	10447	26985
TA	1977	563	4484	25	51	190	1739	8699	23806
B	790	280	1588	15	31	106	779	3119	8223
CFO	217	61	486	1	4	19	192	948	2366
SALE	1978	599	4152	23	52	205	1843	8687	20936
EBITDA	300	89	651	3	8	30	269	1317	3246
E	127	35	306	1	3	12	107	537	1527
EPS	1.16	0.86	1.04	0.06	0.15	0.45	1.53	3.19	5.06
EPS0	1.18	0.91	0.97	0.08	0.18	0.50	1.55	3.13	4.71
EPS1	1.32	1.05	1.02	0.13	0.24	0.60	1.73	3.34	5.02
EPS2	1.56	1.28	1.13	0.19	0.34	0.77	2.01	3.81	5.58
EPS3	1.81	1.50	1.27	0.23	0.41	0.92	2.32	4.32	6.29
LTG	0.17	0.15	0.08	0.05	0.08	0.12	0.20	0.32	0.43

Panel B: Multiples									
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
B/P	0.467	0.394	0.316	0.062	0.116	0.252	0.599	1.053	1.597
CFO/P	0.103	0.082	0.083	0.008	0.019	0.050	0.130	0.258	0.424
EBITDA/P	0.148	0.123	0.106	0.017	0.035	0.080	0.184	0.345	0.548
SALE/P	1.239	0.822	1.353	0.084	0.159	0.417	1.527	3.784	6.818
EPS/P	0.057	0.051	0.036	0.006	0.013	0.033	0.071	0.124	0.187
EPS0/P	0.058	0.052	0.032	0.009	0.018	0.037	0.072	0.119	0.171
EPS1/P	0.065	0.060	0.030	0.014	0.025	0.045	0.079	0.122	0.167
EPS2/P	0.079	0.073	0.034	0.023	0.035	0.056	0.094	0.143	0.195
EPS3/P	0.092	0.084	0.040	0.029	0.043	0.066	0.109	0.167	0.229
EBITDA/FV	0.112	0.105	0.056	0.016	0.034	0.073	0.142	0.213	0.285
SALE/FV	0.920	0.692	0.821	0.081	0.152	0.377	1.174	2.493	4.108
RIMG0R11/P	0.796	0.719	0.357	0.268	0.386	0.567	0.940	1.462	2.047
RIMG4RC/P	2.527	0.958	19.204	0.150	0.301	0.616	1.599	4.413	19.338

Panel C: Correlation coefficient between value drivers											(per share values)
	B	CFO	EBITDA	SALE	EPS	EPS0	EPS1	EPS2	EPS3	RIMG0R11	RIMG4RC
B		0.705	0.773	0.697	0.669	0.709	0.709	0.734	0.721	0.682	0.485
CFO	0.688		0.852	0.654	0.726	0.751	0.736	0.741	0.721	0.675	0.543
EBITDA	0.755	0.851		0.797	0.836	0.858	0.843	0.845	0.824	0.775	0.604
SALE	0.598	0.551	0.673		0.620	0.632	0.640	0.648	0.628	0.583	0.445
EPS	0.662	0.711	0.820	0.509		0.917	0.868	0.853	0.835	0.793	0.619
EPS0	0.685	0.727	0.833	0.510	0.911		0.935	0.925	0.906	0.863	0.671
EPS1	0.685	0.706	0.810	0.508	0.860	0.935		0.980	0.959	0.923	0.711
EPS2	0.704	0.708	0.807	0.516	0.842	0.919	0.982		0.987	0.957	0.721
EPS3	0.692	0.687	0.784	0.503	0.817	0.893	0.954	0.983		0.981	0.734
RIMG0R11	0.648	0.632	0.730	0.470	0.766	0.839	0.908	0.942	0.971		0.741
RIMG4RC	0.061	0.085	0.084	0.040	0.087	0.106	0.112	0.110	0.112	0.114	

The sample consists of non-financial US firms listed on the NYSE, Amex or NASDAQ from 1982 to 2012. The sample covers 4,231 firms with 24,246 firm-year observations. All valuation models are estimated on a per share basis. In panel C, figures below the diagonal are pairwise correlation coefficients, and those above the diagonal are Spearman rank correlation coefficients.

MV is the market value of equity, calculated as the product of stock price and the number of shares outstanding; TA is total asset; B is the book value of equity; CFO is cash flow from operations; SALE is sales; EBITDA is earnings before interest, taxes, depreciation and amortisation; E is earnings before extraordinary items; EPS is current earnings per share calculated as earnings before extraordinary items divided by the number of shares outstanding; EPS0 is current earnings per share from IBES; EPS1 is one-year ahead earnings per share forecast from IBES; EPS2 is two-year ahead earnings per share forecast from IBES; EPS3 is three-year ahead earnings per share forecast from IBES. If EPS3 is missing, it is calculated as EPS2 multiplied by one plus a long-term earnings growth rate; LTG is long-term earnings growth rate from IBES; FV is total firm value, calculated as the sum of the market value of equity plus the book value of debt; RIMG0R11 is a residual income model that uses a discount rate (r) of 11% and a perpetual residual income growth rate (g) of 0%; and RIMG4RC is a residual income model that uses a discount rate (r) based on the CAPM and a perpetual residual income growth rate (g) of 4%. The residual income model is calculated as:

$$P_{i,t} = B_{i,t} + \sum_{s=1}^{5}\left[\frac{E\left(E_{i,t+s} - r_i \cdot B_{i,t+s-1}\right)}{(1+r_i)^s}\right] + \frac{\left[E\left(E_{i,t+5} - r_i \cdot B_{i,t+4}\right)\right](1+g_i)}{(r_i - g_i)(1+r_i)^5}$$

Table 2

Price Correlation Coefficient (PCC) of Residual Income Models

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.694	0.694	0.694	0.694	0.695	0.695	0.695	0.695	0.695	0.695	0.696	0.696	0.721
g=0%	0.751	0.751	0.751	0.752	0.752	0.753	0.753	0.753	0.753	0.753	0.753	0.753	0.692
g=1%		0.747	0.748	0.748	0.748	0.749	0.749	0.749	0.749	0.749	0.749	0.749	0.666
g=2%			0.743	0.743	0.744	0.744	0.745	0.745	0.745	0.745	0.745	0.744	0.622
g=3%				0.738	0.739	0.739	0.739	0.739	0.740	0.740	0.740	0.741	0.525
g=4%					0.730	0.730	0.731	0.732	0.732	0.732	0.733	0.734	0.119
g=5%						0.719	0.721	0.721	0.722	0.723	0.724	0.725	0.294

The price correlation coefficient is the correlation coefficient between price and a value driver (i.e. in this case, a target price from the residual income model). A matrix of residual income models is estimated based on different discount rates and perpetual residual income growth rates. Discount rates (*r*) from 1% to 12% are used as well as a discount rate based on the CAPM. For a perpetual residual income growth rate (*g*), 0% through 5% are used as well as the case when the residual income model has no terminal value (TV) after a five-year forecast horizon.

Table 3

Pricing Error of Multiples

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.492	0.242	1.032	1.060	8	0.732	0.459	0.879	0.668	9
CFO/P	0.738	0.345	1.551	1.255	10	0.969	0.532	1.418	0.869	10
EBITDA/P	0.457	0.204	1.078	0.930	6	0.685	0.410	0.950	0.595	7
SALE/P	0.931	0.326	2.153	1.502	11	1.193	0.561	2.019	1.026	11
EPS/P	0.503	0.296	1.007	0.960	9	0.716	0.460	0.869	0.652	8
EPS0/P	0.331	0.193	0.745	0.738	5	0.534	0.361	0.615	0.504	5
EPS1/P	0.215	0.114	0.577	0.580	4	0.406	0.277	0.463	0.389	4
EPS2/P	0.157	0.067	0.484	0.498	3	0.340	0.235	0.379	0.324	3
EPS3/P	0.148	0.055	0.471	0.486	2	0.331	0.229	0.367	0.316	2
EBITDA/FV	0.481	0.243	1.039	0.892	7	0.677	0.404	0.923	0.628	6
SALE/FV	1.048	0.403	2.290	1.622	12	1.296	0.594	2.159	1.188	12
RIMG0R11/P	0.136	0.035	0.478	0.473	1	0.323	0.219	0.377	0.300	1
RIMG4RC/P	1.521	0.159	15.610	1.054	13	1.779	0.417	15.583	0.654	13

The pricing errors of multiples are estimated based on the mean method (i.e. the average industry multiple is estimated as the mean of individual firms' multiples, except the multiple of a target firm). A pricing error is calculated as $Z_i = \frac{E(P_i)-P_i}{P_i}$, where Z_i denotes a pricing error of a firm i, P_i is a stock price, and $E(P_i)$ is a target price. Bias summarises pricing errors and accuracy summarises the absolute values of pricing error. SD represents standard deviation and IQR represents interquartile range. Rank is based on the mean values of pricing error.

Table 4

Rank Correlation between PCC and Pricing Error

Panel A: PCC of value drivers

	B	CFO	EBITDA	SALE	EPS	EPS0	EPS1	EPS2	EPS3	RIMG0R11	RIMG4RC
PCC	0.534	0.512	0.562	0.307	0.645	0.671	0.723	0.735	0.734	0.753	0.119
Rank	8	9	7	10	6	5	4	2	3	1	11

Panel B: Rank correlation between PCC and pricing error

	Mean Method	Harmonic Mean Method	Median Method	Value-Weighted Mean Method
Bias	0.964***	0.973***	0.918***	0.991***
Accuracy	0.982***	0.964***	0.964***	0.982***

The price correlation coefficient (PCC) is the correlation coefficient between price and a value driver. Panel A reports the PCCs of value drivers of multiples. The definitions of value drivers are explained in Table 1. Panel B reports the rank correlation coefficients between the PCC of value drivers and the pricing error of multiples. For the rank correlation coefficients, a higher PCC is ranked high, and a smaller pricing error is ranked high. Four different calculation methods (i.e. mean, harmonic mean, median and value-weighted mean methods) are used to estimate the average industry multiple. *** indicates significance at the 1% level.

Table 5

Relation between Future Abnormal Stock Return and Target Price of Multiples

	3MTH	6MTH	9MTH	12MTH	24MTH	36MTH	48MTH	60MTH	Rank
B/P	0.003	0.002	0.002	0.006	0.003	0.028	0.029	0.072	5
CFO/P	0.007	0.008	0.010	0.014	0.024	0.047	0.076	0.118	1
EBITDA/P	0.004	0.001	0.001	0.003	-0.003	0.010	0.038	0.085	6
SALE/P	0.003	0.002	0.002	0.006	0.005	0.027	0.041	0.090	3
EPS/P	0.003	0.004	0.001	0.001	-0.005	-0.012	0.002	0.016	10
EPS0/P	0.003	0.004	0.000	0.000	-0.009	-0.005	0.004	0.002	9
EPS1/P	-0.001	-0.002	-0.010	-0.014	-0.037	-0.017	-0.013	-0.007	13
EPS2/P	0.002	0.003	-0.003	-0.005	-0.016	0.020	0.020	0.052	12
EPS3/P	0.003	0.003	-0.003	-0.004	-0.015	0.022	0.023	0.066	10
EBITDA/FV	0.005	0.005	0.004	0.004	-0.002	0.015	0.028	0.076	4
SALE/FV	0.004	0.005	0.005	0.007	0.008	0.029	0.036	0.081	2
RIMG0R11/P	0.003	0.004	-0.002	-0.003	-0.014	0.019	0.023	0.080	7
RIMG4RC/P	0.003	0.003	0.002	0.004	0.008	0.004	0.005	-0.006	8

A relation between future abnormal stock return and target price is estimated as a slope coefficient, γ, in a regression: $FASR_{i,t}^{T} = \alpha + \gamma \cdot \frac{E(P_{i,t})}{P_{i,t}} + \varepsilon_{i,t}$, where $FASR_{i,t}^{T}$ is a future abnormal stock return of a firm *i* at time *t* for *T* months into the future, $T = \{3, 6, 9, 12, 24, 36, 48, 60\}$, and $\frac{E(P_{i,t})}{P_{i,t}}$ is a ratio of target price to stock price. Abnormal stock return is measured as the difference between stock return and S&P 500 index return. The higher is a ratio of target price to stock price, the more undervalued is a stock. The ratio of target price to stock price is standardised to have a standard deviation of one in each year. The relation is estimated for 3, 6, 9, 12, 24, 36, 48 and 60 months into the future, and rank indicates the average performance of multiples across the periods.

Table 6

Buy-and-Hold Abnormal Return of Multiples

	3MTH	6MTH	9MTH	12MTH	24MTH	36MTH	48MTH	60MTH	Rank
B/P	0.007	0.008	0.010	0.023	0.035	0.078	0.091	0.193	7
CFO/P	0.011	0.013	0.022	0.037	0.052	0.089	0.127	0.217	1
EBITDA/P	0.007	0.008	0.011	0.021	0.034	0.051	0.127	0.208	6
SALE/P	0.006	0.006	0.011	0.025	0.036	0.074	0.111	0.202	5
EPS/P	0.006	0.008	0.005	0.009	0.018	0.004	0.057	0.074	13
EPS0/P	0.008	0.010	0.010	0.017	0.025	0.023	0.065	0.059	11
EPS1/P	0.006	0.009	0.005	0.012	0.005	0.022	0.070	0.111	12
EPS2/P	0.008	0.009	0.010	0.020	0.034	0.067	0.093	0.149	8
EPS3/P	0.007	0.007	0.009	0.021	0.035	0.077	0.093	0.162	9
EBITDA/FV	0.011	0.018	0.022	0.030	0.041	0.077	0.118	0.210	2
SALE/FV	0.008	0.011	0.017	0.028	0.037	0.077	0.099	0.214	3
RIMG0R11/P	0.010	0.010	0.012	0.025	0.033	0.079	0.103	0.196	4
RIMG4RC/P	0.009	0.012	0.009	0.015	0.034	0.062	0.065	0.116	10

The buy-and-hold abnormal stock return of multiples is estimated based on a trading strategy buying 20% of most undervalued stocks and short-selling 20% of most overvalued stocks. Abnormal stock return is measured as the difference between stock return and S&P 500 index return. Overvaluation and undervaluation are determined by the ratio of target price to stock price. The ratio of target price to stock price is standardised to have a standard deviation of one in each year. The relation is estimated for 3, 6, 9, 12, 24, 36, 48 and 60 months into the future, and rank indicates the average performance of multiples across the periods.

Table 7

Relation between Future Abnormal Stock Return and Target Price of Residual Income Models

	Discount rate (r)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.064	0.064	0.064	0.063	0.063	0.062	0.062	0.061	0.061	0.060	0.060	0.060	0.056
g=0%	0.109	0.108	0.106	0.104	0.102	0.099	0.097	0.095	0.091	0.089	0.087	0.084	0.054
g=1%		0.107	0.105	0.103	0.101	0.099	0.097	0.095	0.093	0.089	0.087	0.085	0.051
g=2%			0.106	0.104	0.102	0.099	0.097	0.095	0.092	0.090	0.088	0.084	0.045
g=3%				0.104	0.103	0.100	0.098	0.096	0.093	0.091	0.089	0.087	0.040
g=4%					0.105	0.102	0.099	0.097	0.095	0.092	0.089	0.087	-0.017
g=5%						0.103	0.100	0.097	0.095	0.092	0.089	0.087	0.008

The relations between future abnormal stock return and target price for 60 months into the future are reported. The results for the other periods are reported in Appendix 2. The relation between future abnormal stock return and target price is estimated as a slope coefficient, γ, in a regression: $FASR_{i,t}^{T} = \alpha + \gamma \cdot \frac{E(P_{i,t})}{P_{i,t}} + \varepsilon_{i,t}$, where $FASR_{i,t}^{T}$ is a future abnormal stock return of a firm i at time t for T months into the future, $T = \{3, 6, 9, 12, 24, 36, 48, 60\}$, and $\frac{E(P_{i,t})}{P_{i,t}}$ is a ratio of target price to stock price. Abnormal stock return is measured as the difference between stock return and S&P 500 index return. Target prices are estimated from the residual income model by itself, without being estimated through multiples. The ratio of target price to stock price is standardised to have a standard deviation of one in each year. Discount rates (r) from 1% to 12% are used as well as a discount rate based on the CAPM. For a perpetual residual income growth rate (g), 0% through 5% are used as well as the case when the residual income model has no terminal value (TV) after a five-year forecast horizon.

Table 8

Buy-and-Hold Abnormal Return of Residual Income Models

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.133	0.131	0.128	0.130	0.130	0.131	0.129	0.129	0.130	0.129	0.128	0.129	0.138
g=0%	0.226	0.227	0.225	0.218	0.217	0.212	0.203	0.204	0.204	0.202	0.197	0.196	0.122
g=1%		0.231	0.228	0.221	0.212	0.208	0.209	0.211	0.205	0.204	0.204	0.203	0.119
g=2%			0.223	0.223	0.217	0.214	0.215	0.213	0.215	0.206	0.203	0.194	0.110
g=3%				0.212	0.212	0.210	0.210	0.208	0.209	0.210	0.206	0.203	0.105
g=4%					0.204	0.204	0.204	0.204	0.198	0.200	0.197	0.196	0.088
g=5%						0.192	0.193	0.192	0.190	0.189	0.186	0.183	0.079

The buy-and-hold abnormal stock return is estimated based on a trading strategy buying 20% of most undervalued stocks and short-selling 20% of most overvalued stocks. The results for 60 months into the future are reported. The results for the other periods are reported in Appendix 3. Abnormal stock return is measured as the difference between stock return and S&P 500 index return. Overvaluation and undervaluation are determined by the ratio of target price to stock price. The ratio of target price to stock price is standardised to have a standard deviation of one in each year. Discount rates (*r*) from 1% to 12% are used as well as a discount rate based on the CAPM. For a perpetual residual income growth rate (*g*), 0% through 5% are used as well as the case when the residual income model has no terminal value (TV) after a five-year forecast horizon.

5. Estimating Earnings Forecasts Using Conditional Cross-Sectional Model

5.1. Introduction

As stock price is assumed as the present value of expected future cash flows, forecasting future earnings plays a major role in valuation. Extensive research has been carried out to find the best earnings forecast model. Time-series models (i.e. forecasting future earnings based on past earnings) are the first models developed to estimate earnings forecasts (Little, 1962; Little and Rayner, 1966; Ball and Watts, 1972). However, as analyst forecasts become more and more available, the use of time-series models has declined since the late 1980s (Kothari, 2001; Bradshaw et al., 2012). More importantly, researchers have found that analyst forecasts are more accurate than earnings forecasts from time-series models (Brown and Rozeff, 1978; Collins and Hopwood, 1980; Brown et al., 1987; Kross, Ro and Schroeder, 1990; Branson, Lorek and Pagach, 1995) and, therefore, analyst forecasts have become the dominant source of earnings forecasts over decades.

Recently, Hou, van Dijk and Zhang (2012) challenge the dominance of analyst forecasts by introducing a cross-sectional model (henceforth, HVZ model) in estimating earnings forecasts. They develop a cross-sectional model based on profitability models in Fama and French (2000) and Fama and French (2006) and explain that their cross-sectional model suffers less from survivorship bias but has higher statistical power than time-series models as it uses more observations in forecasting. They find that earnings forecasts from the HVZ model outperform analyst forecasts in coverage, bias and earnings response coefficient (ERC), while analyst forecasts outperform the HVZ model only in accuracy. Li and Mohanram (2014) extend the results of Hou, van Dijk and Zhang (2012) by introducing another cross-sectional model based on the residual income model (henceforth, RI model). Li and Mohanram (2014) argue that the RI model outperforms the HVZ model in bias, accuracy and ERC.

However, several questions still need to be answered. First, both HVZ and RI models are cross-sectional models and, therefore, they have the advantages and disadvantages of cross-sectional models. As Hou, van Dijk and Zhang (2012) explain, the advantages of cross-sectional models are wide coverage, lower cost of estimation compared to analyst forecasts, and smaller survivorship bias and higher statistical power than time-series models. However, a fundamental disadvantage of cross-sectional models is that the loss of firm-specific information on the time-series properties (Kothari, 2001). In other words, the same coefficients are applied to all firms to estimate their earnings forecasts.

This problem is more noticeable when a simpler cross-sectional model is used to estimate earnings forecasts. For example, when a cross-sectional model estimates one-year ahead earnings forecasts using only current earnings, $E_{t+1} = \alpha + \beta \cdot E_t + \varepsilon$, the cross-sectional model applies the same α and β to all firms to estimate their one-year ahead earnings forecasts. With the sample dataset in this project, one-year ahead earnings forecasts made in 2005 is calculated as \$5.3 million (α) plus 0.976 (β) times the current earnings of firms in 2005 (results not tabulated).[10] The β of 0.976 is the

[10] Coefficients are manually calculated based on Compustat data from 1956 to 2012. The sample is explained in more detail in Section 3.

average earnings persistence in a cross section. The problem of estimating future earnings based on this model is that all firms apply the same β (0.976) to estimate their earnings in 2006 no matter firms are high-growth or mature firms. In reality, some firms are high-growth firms such as Apple or Google in 2005 and deserve β of more than 0.976. On the other hand, some firms are mature or declining firms such as Chrysler or Kodak and deserve β of less than 0.976. What cross-sectional models do is to average future prospects of individual firms in a cross section and apply the average future prospects to all firms to estimate their earnings forecasts.

Increasing the number of variables on the right hand side does not change the inference. The difference is that the average future prospects are estimated based on different variables other than current earnings. As long as earnings forecasts are estimated based on a cross-sectional model, the average future prospects are applied to all firms. Similarly, increasing the number of years in a pooled sample does not change the inference either. The only difference is that the average future prospects are estimated based on observations for more than one year. The model still applies the average future prospects of a cross section to all firms. This problem can only be resolved when coefficients are allowed to vary across firms.

The second issue in Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014) is that models are not estimated on a level field. In Hou, van Dijk and Zhang (2012), the HVZ model is estimated on unscaled dollar value while its benchmark, analyst forecasts, is estimated on per share level. Similarly, in Li and Mohanram (2014), the HVZ model and a random walk model are estimated on unscaled dollar value while the RI model and the earnings persistence model are estimated on per share level. Although earnings forecasts from the models based on unscaled dollar value are in the end scaled by the market value to calculate bias and accuracy, several papers explain that the effect of scaling in regressions is not trivial (Akbar and Stark, 2003; Barth and Clinch, 2009; Goncharov and Veenman, 2013). Therefore, it is not known what the scaling effects are in Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014).

The third issue is the use of different benchmarks in each paper. The purpose of Hou, van Dijk and Zhang (2012) is to introduce a cross-sectional model in earnings estimation. Therefore, they compare their model with analyst forecasts, the dominant method for estimating future earnings. On the other hand, Li and Mohanram (2014) develop the RI model based on the finding that the HVZ model underperforms a naïve random walk model (Gerakos and Gramacy, 2013). Therefore, they compare the RI model with the HVZ model and a random walk model. However, by omitting analyst forecasts from benchmarks, Li and Mohanram (2014) make the comparison between the RI model and analyst forecasts unfeasible and hence it is not known whether the RI model outperforms analyst forecasts in accuracy. To make matters worse, the performance of analyst forecasts is measured compared to future street earnings, while the performance of the HVZ model is measured compared to future accounting earnings in Hou, van Dijk and Zhang (2012). This inconsistency in the use of benchmarks makes the comparison between models difficult.

This project develops Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014) by addressing these three issues. First, the project introduces a conditional cross-sectional model that allows the coefficient on earnings to vary across firms. Therefore, different future prospects are applied to different firms in estimating their future earnings. Second, the project estimates both unscaled and scaled earnings forecasts. Therefore, the performances of models are compared on a level field. Third, the project uses both a random walk model and analyst forecasts as benchmarks. As a result, the project eliminates the inconsistency in benchmarks.

The difference between this project and Hou, van Dijk and Zhang (2012) and Li and Mohanram (2014) is that this project adopts the perspective of valuation model users. Kothari (2001) states that equity valuation inherently assumes an inefficient market and aims to discover under-/over-valued stocks in order to make abnormal profits. Following this perspective, the project does not assume that the market price is the intrinsic value and hence does not calculate the implied cost of capital. Instead, the project focuses on estimating different types of earnings forecasts, which are widely estimated in practice. Specifically, the project examines the performance of cross-sectional and conditional cross-sectional models in estimating a) unscaled dollar earnings, b) reported earnings per share, and c) street earnings per share. Therefore, the results of this project are informative to various model users regardless of the types of earnings they estimate.

The results show that conditional cross-sectional models improve the performance of cross-sectional models in bias, accuracy and ERC across unscaled earnings, reported earnings per share and street earnings per share. The results indicate that, by improving model specification, conditional cross-sectional models use the same amount of information as cross-sectional models do and hence keep the advantages of cross-sectional models but improve their performance. The results of robustness tests confirm that the improvement is widely observed across various subsamples and, therefore, is not a sample specific result.

Other results are: a) between a random walk model and the HVZ model, the project finds the consistent result with Gerakos and Gramacy (2013) that the HVZ model underperforms a random walk model for unscaled earnings estimation. However, when the HVZ model is used to estimate reported earnings per share, the HVZ model outperforms a random walk model, implying the merit of the HVZ model for reported earnings per share estimation; b) between the HVZ and RI models, the RI model generally outperforms the HVZ model consistent with the result of Li and Mohanram (2014). However, the outperformance is much smaller than in Li and Mohanram (2014) when the models are estimated on a level field, indicating that the results in Li and Mohanram (2014) are partly driven by scaling effects; c) the RI model performs similarly to the HVZ model in street earnings per share estimation: the HVZ and RI models underperform analyst forecasts in accuracy and ERC for one- and two-year ahead earnings forecasts. However, conditional cross-sectional models reduce the underperformance and produce better earnings forecasts than analyst forecasts in bias, accuracy and ERC for the long forecast horizons (i.e. four- and five-year ahead forecasts); and d) between the conditional HVZ model and conditional RI model, both models perform similarly and it is difficult to conclude which model performs better. However, in general, the conditional RI model is better in bias and accuracy while the conditional HVZ model is better in ERC.

The project contributes to the literature by proposing a new model, a conditional cross-sectional model, which improves a cross-sectional model in model specification and performance. By allowing the coefficient on earnings to vary across firms, a conditional cross-sectional model makes firms use different earnings persistence and future prospects in their earnings forecasts. The results of robustness tests confirm that the improvement is observed across various subsamples, implying that valuation model users can benefit from a conditional cross-sectional model regardless of the types of earnings they estimate.

The project is structured in the following order: Section 2 explains the cross-sectional models and conditional cross-sectional models. Section 3 explains the sample used to estimate unscaled earnings, reported earnings per share and street earnings per share. Section 4 presents the results of model performance in bias, accuracy and ERC. Section 5 reports the results of robustness tests, and Section 6 concludes the project.

5.2. Methodology

5.2.1. Conditional Cross-Sectional Model

Conditional models are first developed to improve time-series models in estimating beta (i.e. systematic risk) in the Capital Asset Pricing Model (Chan and Chen, 1988; Ferson and Schadt, 1996), and further used in the Asset Pricing literature (Shanken, 1990; Jagannathan and Wang, 1996; Gregory, Harris and Michou, 2003). One of the problems of the traditional Capital Asset Pricing Model (CAPM) is that it estimates unconditional beta, which does not vary over time as expected returns and risks change. Conditional models are developed to overcome this problem by making beta conditional on other factors and change over time. Ferson and Schadt (1996) allow beta to change conditional on the dividend yield of the CRSP index, a Treasury yield spread, the yield on a short-term Treasury bill, a corporate bond spread and a dummy variable for Januarys. On the other hand, Chan and Chen (1988) make beta to change conditional on the market risk premium.

In Ferson and Schadt (1996), the unconditional (i.e. traditional) CAPM is estimated as:

$$r_{p,t+1} = \alpha_p + \beta_{1p} r_{m,t+1} + \varepsilon_{p,t+1} \qquad (1)$$

where $r_{p,t+1}$ is the expected excess return of a portfolio *p* at time *t+1*, and $r_{m,t+1}$ is the expected excess market risk premium.

On the other hand, the conditional CAPM is estimated as:

$$r_{p,t+1} = \alpha_p + \beta_{1p} r_{m,t+1} + \beta_{2p}\left(z_t r_{m,t+1}\right) + \varepsilon_{p,t+1} \qquad (2)$$

where z_t is a vector of predetermined information variables at time *t*.

By adding $\beta_{2p}\left(z_t r_{m,t+1}\right)$ to the unconditional CAPM in Equation (1), the conditional CAPM allows $r_{m,t+1}$ to interact with a vector of predetermined information variables (i.e. the dividend yield of the CRSP index, a Treasury yield spread, the yield on a short-term Treasury bill, a corporate bond spread and a dummy variable for Januarys) that have shown a relation between stock return and risk over time. Therefore, the conditional CAPM estimates the future expected portfolio return as:

$$E\left(r_{p,t+1}\right) = \alpha_p + \left(\beta_{1p} + \beta_{2p} z_t\right) E\left(r_{m,t+1}\right) \qquad (3)$$

β_{1p} indicates the unconditional relation between portfolio return and the market risk premium, and $\beta_{2p} z_t$ indicates adjustments to the unconditional relation between return and risk as market conditions change.

This project employs a similar mechanism to cross-sectional models. As far as the author is aware, this is the first paper that applies the conditioning mechanism to cross-sectional models. As explained in Section 1, cross-sectional models suffer from a similar problem to that of time-series models but in a different dimension: cross-sectional models estimate unconditional coefficients that do not vary across firms. In the earnings estimation literature, this means that all firms use the same coefficients to estimate their earnings forecasts. The project addresses this problem by conditioning the earnings coefficient to factors that affect earnings persistence, so different earnings coefficients are applied to firms to estimate their earnings forecasts.

The project chooses the two cross-sectional models that are used in the earnings estimation literature: a) the HVZ model and b) the RI model. The HVZ model is developed based on the profitability models in Fama and French (2000) and Fama and French (2006) and includes total assets, dividends, earnings and accruals as factors to determine future earnings. On the other hand, the RI model is developed based on the residual income model, and estimates future earnings based on current earnings, current and lagged book values, and capital expenditures (Feltham and Ohlson, 1996). Although different factors are used in each model to estimate future earnings, they are both cross-sectional models and, therefore, can be expressed in a general cross-sectional model form:

$$E_{i,t+s} = \delta_0 + \delta_{1t}E_{i,t} + \delta_{2t}z_{i,t} + \varepsilon_{i,t+s} \quad (4)$$

where $E_{i,t+s}$ is the earnings of firm i at time t+s (s = 1 to 5), and $z_{i,t}$ is the vector of factors that determine future earnings.

Conditional cross-sectional models in this project interacts earnings and the vector of factors to allow the earnings coefficient to vary based on the values of the factors of each firm:

$$E_{i,t+s} = \delta_0 + \delta_{1t}E_{i,t} + \delta_{2t}z_{i,t} + \delta_{3t}(z_{i,t}E_{i,t}) + \varepsilon_{i,t+s} \quad (5)$$

Therefore, earnings forecasts from conditional cross-sectional models are estimated as:

$$E(E_{i,t+s}) = \delta_0 + (\delta_{1t} + \delta_{3t}z_{i,t})E_{i,t} + \delta_{2t}z_{i,t} \quad (6)$$

In Equation (6), δ_{1t} measures the unconditional earnings persistence, δ_{2t} measures the direct impact of the factors on future earnings, and δ_{3t} measures the indirect impact of the factors on future earnings through the change in earnings persistence. Therefore, the conditional cross-sectional model allows the factors to determine future earnings directly and indirectly, and through this indirect influence, firms use different earnings coefficients (i.e. different earnings persistence) to estimate their future earnings.

5.2.2. Model Specification

5.2.2.1. The HVZ Model

The HVZ model is developed based on the profitability models of Fama and French (2000), Fama and French (2006), Hou and Robinson (2006), and Hou and van Dijk (2011). Hou, van Dijk and Zhang (2012) argue that the HVZ model has less survivorship bias and more statistical power than time-series models. They estimate the HVZ model as:

$$E_{i,t+s} = \alpha_0 + \alpha_1 TA_{i,t} + \alpha_2 DIV_{i,t} + \alpha_3 DD_{i,t} + \alpha_4 E_{i,t} + \alpha_5 NegE_{i,t} + \alpha_6 AC_{i,t} + \varepsilon_{i,t+s} \quad (7)$$

where $E_{i,t+s}$ is the earnings of a firm *i* at time *t+s*, $TA_{i,t}$ is the total asset, $DIV_{i,t}$ is the dividend, $DD_{i,t}$ is a binary variable that is one for firms paying dividends and zero for non-payers, $NegE_{i,t}$ is a binary variable that is one for firms with negative earnings and zero otherwise, and $AC_{i,t}$ is the accruals. As Hou, van Dijk and Zhang (2012), accruals before 1988 are calculated as the change in current assets excluding cash, minus the change in current liabilities excluding short-term debt and tax payable, minus depreciation and amortization expenses.[11] This is mainly due to the lack of data on cash flow from operations before 1988. From 1988, accruals are calculated as earnings minus cash flow from operations.

The HVZ model estimates future earnings based on the past ten years' data available at time *t*. For example, to estimate the one-year ahead earnings forecasts ($E_{i,t+1}$) in 1987, the model uses data from 1977 to 1986 on the right hand side of Equation (7), and data from 1978 to 1987 on the left hand side. To estimate the three-year ahead earnings forecasts ($E_{i,t+3}$) in 1987, the model uses data from 1975 to 1984 on the right hand side, and data from 1978 to 1987 on the left hand side. By using data only available at time *t*, the HVZ model avoids look-ahead bias. Future earnings are estimated as the expected values of Equation (7) by using the coefficients estimated based on the past data and the values of the factors at time *t*. The project presents the results of earnings estimation up to five years ahead.

5.2.2.2. The RI Model

The RI model is proposed as an alternative cross-sectional model to the HVZ model based on the finding that the HVZ model does not perform better than a random walk model (Gerakos and Gramacy, 2013). The RI model estimates future earnings based

[11] Specifically, accruals before 1988 are calculated as: $AC_{i,t} = \Delta\left(Current\ Asset_{i,t} - Cash_{i,t}\right) - \Delta\left(Current\ Liabilities_{i,t} - Short\ Term\ Debt_{i,t} - Tax\ Payable_{i,t}\right) - Depreciation\&Amortization_{i,t}$

on the valuation theory (i.e. the residual income model) and uses earnings, book value and accruals as the determinants of future earnings (Li and Mohanram, 2014):

$$E_{i,t+s} = \omega_0 + \omega_1 NegE_{i,t} + \omega_2 E_{i,t} + \omega_3 NegE_{i,t} \cdot E_{i,t} + \omega_4 B_{i,t} + \omega_5 AC_{i,t} + \varepsilon_{i,t+s} \quad (8)$$

where $E_{i,t+s}$ is the earnings of a firm *i* at time t+s, $NegE_{i,t}$ is a binary variable that is one for firms with negative earnings and zero otherwise, $B_{i,t}$ is the book value of equity, and $AC_{i,t}$ is the accruals. By adding the interaction term of $NegE_{i,t}$ and $E_{i,t}$, the RI model allows the earnings persistence to be different between profit and loss firms. The same estimation procedure as for the HVZ model is used for the RI model.

5.2.2.3. The CHVZ Model (Conditional HVZ Model)

The CHVZ model is the conditional version of the HVZ model. The CHVZ model allows total assets, dividends, accruals, a binary variable of dividend payment and a binary variable of loss firms to interact with earnings, so the coefficient on earnings varies across firms based on these factors. Specifically, the CHVZ model is estimated as:

$$E_{i,t+s} = \gamma_0 + \gamma_1 E_{i,t} + \gamma_2 TA_{i,t} \cdot E_{i,t} + \gamma_3 DIV_{i,t} \cdot E_{i,t} + \gamma_4 AC_{i,t} \cdot E_{i,t} + \gamma_5 DD_{i,t} \cdot E_{i,t} +$$
$$\gamma_6 NegE_{i,t} \cdot E_{i,t} + \gamma_7 TA_{i,t} + \gamma_8 DIV_{i,t} + \gamma_9 AC_{i,t} + \gamma_{10} DD_{i,t} + \gamma_{11} NegE_{i,t} + \varepsilon_{i,t+s} \quad (9)$$

The coefficient on earnings is ($\gamma_1 + \gamma_2 TA_{i,t} + \gamma_3 DIV_{i,t} + \gamma_4 AC_{i,t} + \gamma_5 DD_{i,t} + \gamma_6 NegE_{i,t}$) in future earnings estimation. By allowing the coefficient on earnings to vary based on the other factors, the CHVZ model applies different earnings persistence to different firms and avoids the problem of cross-sectional models that all firms use the same future prospects in their earnings forecasts.

The same estimation procedure as for the cross-sectional models is used for the conditional cross-sectional models. The CHVZ model uses the same information as the HVZ model does. Therefore, the CHVZ model has the same coverage as the HVZ model and keeps the advantages of cross-sectional models without further data requirement.

5.2.2.4. The CRI Model (Conditional RI Model)

The CRI model is the conditional version of the RI model. The CRI model interacts book value, accruals and a binary variable of loss firms with earnings. The CRI model is estimated as:

$$E_{i,t+s} = \theta_0 + \theta_1 E_{i,t} + \theta_2 B_{i,t} \cdot E_{i,t} + \theta_3 AC_{i,t} \cdot E_{i,t} + \theta_4 NegE_{i,t} \cdot E_{i,t} + \theta_5 B_{i,t} + \theta_6 AC_{i,t} + \theta_7 NegE_{i,t} + \varepsilon_{i,t+s} \quad (10)$$

The coefficient on earnings becomes $\left(\theta_1 + \theta_2 B_{i,t} + \theta_3 AC_{i,t} + \theta_4 NegE_{i,t}\right)$ in future earnings estimation, indicating that firms have different earnings persistence based on their book values, accruals and the loss of earnings. By having the interaction terms, the CRI model allows book value, accruals and a binary variable of loss firms to influence future earnings directly and indirectly through the change in earnings persistence.

The CRI model uses the same amount of information as the RI model does. Therefore, the CRI model has all the advantages of the RI model but allows earnings persistence to change across firms.

5.2.2.5. The RW Model (Random Walk Model)

The RW model is used as a benchmark against the cross-sectional and conditional cross-sectional models. The simplest random walk model (i.e. the martingale) is used in this project as:

$$E_{i,t+s} = E_{i,t} + \varepsilon_{i,t+s} \tag{11}$$

The RW model assumes that earnings follow a random walk and hence are not predictable and, as a result, the best estimate for the future earnings is the current earnings (Little, 1962; Ball and Watts, 1972; Albrecht, Lookabill and McKeown, 1977; Watts and Leftwich, 1977). This project estimates three different measures of earnings: unscaled earnings, reported earnings per share and street earnings per share. Therefore, a different type of current earnings is used for each earnings measure. Specifically, for future unscaled earnings, current unscaled earnings are used for the RW model; for future reported earnings per share, current reported earnings per share are used; and for future street earnings per share, current street earnings per share are used for the RW model.

5.2.3. Performance Criteria

The performance of the models is examined by three criteria: bias, accuracy and earnings response coefficient (ERC). Bias is calculated as forecasted future earnings minus actual future earnings, divided by market value (when future earnings are unscaled earnings) or stock price (when future earnings are earnings per share). Therefore, a positive bias means that forecasted future earnings are higher than actual future earnings.

Accuracy is measured as the absolute difference between forecasted future earnings and actual future earnings, divided by market value (when future earnings are unscaled earnings) or stock price (when future earnings are earnings per share). While bias measures how much a model tends to over-/under-estimate future earnings relative to actual earnings, accuracy measures how close forecasted earnings are to actual earnings.

On the other hand, ERC measures a relation between future abnormal return and earnings surprise. If forecasted earnings from a model are the expected earnings by the market, an earnings surprise (i.e. the difference between actual earnings and the expected earnings) will result in abnormal returns. Therefore, a higher ERC means that a model's forecasted earnings are closer to the expected earnings by the market. An ERC is estimated as the slope coefficient of a regression of future abnormal return on earnings surprise. For future abnormal return, the project uses the sum of quarterly earnings announcement returns from -1 day to +1 day of earnings announcements, adjusted to S&P 500 index returns, over one through five years' forecast horizons. When quarterly earnings announcement returns are missing, they are replaced by the average value during the year. Earnings surprise is calculated as actual earnings minus forecasted earnings divided by market value (when future earnings are unscaled earnings) or stock price (when future earnings are earnings per share). However, some models may tend to generate earnings forecasts that are higher or lower than those from other models. Therefore, earnings surprises are standardised to have a unit variance in each year, so ERCs are comparable between models and across years.

5.3. Data

The sample consists of non-financial US firms listed on NYSE, AMEX or NASDAQ from 1956 to 2012. Only firms with a share code of 10 or 11 in CRSP are selected, excluding ADRs, REITs and closed-end funds. Both active and inactive firms are included to alleviate survivorship bias, resulting in 13,541 firms with 154,653 firm-year observations in the sample. Yearly accounting data are obtained from Compustat, prices and returns are obtained from CRSP, and analyst forecasts are obtained from IBES. Accounting data are as of the fiscal year end. Prices, returns, the number of shares outstanding and analyst forecasts are as of four months after the fiscal year end, considering the lag between the announcement date and fiscal year end. Time series are based on firms' fiscal years.

All variables are truncated at the 1st and 99th percentiles in each year to mitigate the impact of outlying values. Truncation is used, instead of winsorization, to avoid having heavy tails, which can still affect statistical inferences in regressions. However, prices are truncated at $1 and the 99th percentile, and the number of shares outstanding is truncated at one million shares and the 99th percentile in each year. These are to remove firm-years that have small prices and the number of shares outstanding, which can distort biases and accuracies. A cut-off point of $2 for price was also used, but the results were qualitatively the same (not reported).

< Table 1 here>

The descriptive statistics show that the sample covers a wide range of firms and different economic conditions. Market value and total asset show that the sample covers small firms (i.e. a market value of $1.5 million at the 1st percentile) as well as large firms (i.e. a market value of $12.9 billion at the 99th percentile). On the other hand, EBITDA, earnings and the book value of equity show that the sample includes periods of economic contraction (i.e. negative earnings and equity) as well as economic expansion (i.e. positive earnings and equity). A binary variable of negative earnings (NegE) indicates that 28% of sample observations have negative earnings. A binary variable of dividend payment (DD) indicates that 39% of observations pay dividends. Overall, the descriptive statistics show that the sample represents a wide range of firms in both good and bad economic conditions.

5.4. Results

5.4.1. Coefficients

5.4.1.1. Unscaled Earnings Estimation

The first earnings measure, unscaled earnings, is estimated based on reported unscaled accounting values. Specifically, cross-sectional and conditional cross-sectional models use future unscaled earnings for the dependent variable and current unscaled accounting values (except binary variables) for the independent variables. Table 2 reports the averages of coefficients across years, their time-series *t* statistics, and the averages of adjusted R^2s across years.

<Table 2 here>

Panel A of Table 2 reports the coefficients of the HVZ model. Consistent with the coefficients in Hou, van Dijk and Zhang (2012), earnings have coefficients less than one and accruals have negative coefficients. Earnings coefficients less than one indicate that earnings have a tendency of mean convergence. Surprising but consistent with Hou, van Dijk and Zhang (2012), a binary variable of loss firms has positive coefficients in the HVZ model. Panel B of Table 2 reports the coefficients of the RI model. Again, consistent with the results in Li and Mohanram (2014), a binary variable of loss firms, an interaction term between earnings and loss firms, and accruals have negative coefficients. Negative coefficients of a binary variable of loss firms indicate that loss firms have lower future earnings than profit firms. The adjusted R^2s of the RI models are higher than those of the HVZ model, implying that the RI model explains future earnings better than the HVZ model. Panel C of Table 2 reports the coefficients of the CHVZ model. The CHVZ model has higher adjusted R^2s than the HVZ model and the coefficients of a binary variable of loss firms now become negative. Interaction terms between earnings and total assets, earnings and dividends, and earnings and accruals are not significant especially for the short forecast horizons. However, they are remained in the model because their coefficients become significant when the model estimates scaled earnings later. Panel D of Table 2 reports the coefficients of the CRI model. Interaction terms between earnings and book value are not significant, and those between earnings and accruals are significant only for the long forecast horizons. The adjusted R^2s are slightly higher than those of the RI model.

5.4.1.2. Reported Earnings Per Share Estimation

The second earnings measure, reported earnings per share, is a scaled earnings measure. Future reported earnings per share are estimated by using future reported earnings per share as the dependent variable and current per share accounting values as the independent variables. Table 3 shows that cross-sectional and conditional cross-sectional models have different coefficients from those for unscaled earnings in Table 2.

<Table 3 here>

Panel A of Table 3 reports the coefficients of the HVZ model. A binary variable of loss firms now correctly has negative coefficients. The coefficients on earnings and adjusted R^2s are lower than those of the HVZ model for unscaled earnings in Panel A of Table 2 because per share values are less prone to extreme earnings due to scaling effects. Panel B of Table 3 shows that the RI model also has lower earnings coefficients and adjusted R^2s compared to those of the RI model for unscaled earnings in Panel B of Table 2. When conditional cross-sectional models are estimated based on per share values, Panels C and D of Table 3 show that all the interaction terms become significant and the adjusted R^2s increase noticeably compared to their corresponding cross-sectional models in Panels A and B of Table 3. A binary variable of loss firms, accruals and the interaction term between earnings and loss firms all have correct negative coefficients.

5.4.1.3. Street Earnings Per Share Estimation

The third earnings measure, street earnings per share, is estimated in order to compare model performance with analyst forecasts on a level field. This is because IBES reports analyst forecasts based on street earnings per share.[12] Future street earnings per share are estimated by using future street earnings per share as the dependent variable and current per share accounting values as the independent variables.

[12] IBES reports earnings per share based on continuing operations, excluding the impact of extraordinary items and discontinued operations.

<Table 4 here>

Table 4 reports the coefficients of the models for street earnings per share estimation. In Panel A of Table 4, the HVZ model has negative coefficients on accruals and a binary variable of loss firms. However, the coefficients on earnings per share are lower than those for reported earnings per share in Panel A of Table 3, indicating that future street earnings per share are less related to current reported earnings per share. A similar picture is observed for the RI model in Panel B of Table 4. The RI model has lower coefficients on earnings per share compared to their counterparts when the model estimates reported earnings per share in Panel B of Table 3. Panels C and D of Table 4 show that conditional cross-sectional models have negative coefficients on accruals, a binary variable of loss firms and the interaction term between earnings and loss firms. Their adjusted R^2s are relatively higher than their counterpart cross-sectional models in Panels A and B of Table 4, implying that conditional cross-sectional models explain future street earnings per share better than cross-sectional models.

5.4.2. Bias, Accuracy and ERC

5.4.2.1. Unscaled Earnings Estimation

Table 5 reports the averages of biases, accuracies and ERCs across years and their time-series *t* statistics of the RW, HVZ, RI, CHVZ and CRI models, and the differences between them. The results are based on the unscaled earnings estimations and cover 7,434 firms with 66,817 firm-year observations. The current unscaled earnings are used for the RW model. For bias, positive values mean forecasted future earnings are higher than actual future earnings. Biases close to zero indicate that models are less biased. An accuracy is the absolute value of the difference between forecasted earnings and actual earnings, divided by the market value. Therefore, smaller accuracies mean that forecasts are more accurate. On the other hand, an ERC is a measure of the relation between abnormal return and earnings surprise. Therefore, a higher ERC means that earnings forecasts reflect the market expected earnings better. The numbers in bold indicate the values significantly different from zero at the 5% level.

<Table 5 here>

Columns 1 through 5 report the biases, accuracies and ERCs of the RW, HVZ, RI, CHVZ and CRI models, respectively. On the other hand, Columns 6 through 13 report the differences (i.e. improvements) between the models. For instance, Column 9 reports how much the CHVZ model improves the performance of the HVZ model. The negative accuracies mean that the CHVZ model reduces (i.e. improves) the accuracies of the HVZ model. The positive ERCs mean that the CHVZ model increases (i.e. improves) the ERCs of the HVZ model.

However, the differences in bias require a caution. Because the purpose of this project is to measure the improvement of the conditional cross-sectional model over the cross-sectional model, Columns 6 through 13 focus on the magnitude of improvement. While measuring the improvement in accuracy and ERC is straightforward because accuracies and ERCs only have positive values, biases do not. Biases can have either positive or negative values, and neither values are better than the others. If the difference between biases is simply measured, statistical tests tend to conclude that biases in different signs are significantly different from zero although they may be equally biased in magnitude. For instance, biases of -0.3 and +0.3 are likely to be significantly different, although neither is closer to zero than the other. Therefore, this project measures the magnitude of bias approaching zero as the measure of improvement in bias. Specifically, the magnitude of bias approaching zero is calculated as the difference in absolute bias between models in each year. Therefore, the biases in Columns 6 through 13 are different from the simple differences between biases in Columns 1 through 5. The negative biases in Column 9, for example, indicate that the CHVZ model produces biases closer to zero (i.e. improves) than the HVZ model.

Consistent with the results of Gerakos and Gramacy (2013), Column 6 shows that the HVZ model performs worse than the RW model in bias, accuracy and ERC. When the RI model is estimated based on unscaled accounting values, Column 7 shows that the RI model also underperforms the RW model although in a lesser degree. The result indicates that the outperformance of the RI model over the RW model observed in Li and Mohanram (2014) is largely due to the scaling effects (the results of reported earnings per share are reported later in Table 6). However, Column 8 shows that the RI model still outperforms the HVZ model in bias, accuracy and ERC.

The improvements conditional cross-sectional models make on the performance of cross-sectional models are reported in Columns 9 and 10. Column 9 shows that the CHVZ model improves the performance of the HVZ model in bias, accuracy and ERC for almost all forecast horizons: Biases decrease significantly, accuracies also decrease significantly for the long forecast horizons, and ERCs increase for all forecast horizons. Similar results are observed between the CRI and RI models in Column 10: biases, accuracies and ERCs improve for most forecast horizons.

As a result, in Column 11, the CHVZ model performs as well as the RW model. In bias and accuracy, the CHVZ model underperforms the RW model for the one-year ahead forecast horizon. However, the CHVZ model outperforms the RW model in ERC for the two- and three-year ahead forecast horizons. Column 12 shows that the CRI model also underperforms the RW model in bias and accuracy for the one-year ahead forecast horizon. However, the CRI model outperforms the RW model in ERC for the two-year ahead forecast horizon. Between the CHVZ and CRI models, Column 13 shows that both models perform equally well in bias, accuracy and ERC.

5.4.2.2. Reported Earnings Per Share Estimation

Table 6 reports the results for reported earnings per share estimation. The results cover 7,381 firms with 64,380 firm-year observations. Current reported earnings per share are used for the RW model. The results of the RW model in Column 1 of Table 6 are different from those in Column 1 of Table 5 when unscaled current earnings are used for the RW model. This is because future earnings per share (at time $t+s$) are estimated based on the contemporary number of shares outstanding (at time $t+s$) in Table 6, while the current number of shares outstanding (at time t) is used to scale future earnings in Table 5. When future earnings per share are calculated based on the current number of shares outstanding (at time t), Table 6 reports the same biases, accuracies and ERCs as those in Column 1 of Table 5.

<Table 6 here>

The results in Columns 1 through 5 of Table 6 show that the performance of the models improves in bias, accuracy and ERC when the models are estimated based on per share values. Therefore, the comparison between models estimated based on unscaled values and based on scaled values leads to biased results in favour of the scaled model. Li and Mohanram (2014) estimate the RI model based on scaled values and compare its results with the HVZ and RW models, which are estimated based on unscaled values. Therefore, their results are largely driven by scaling effects. As Table 5 shows, when the RI model is estimated on a level field with the HVZ and RW models based on unscaled values, the RI model underperforms the RW model.

Columns 1 through 5 show that, when earnings are estimated on per share level, cross-sectional and conditional cross-sectional models generate biases that are not different from zero. Only the RW model has biases different from zero.

Column 6 reports the performance of the HVZ model compared to the RW model. The HVZ model now performs better than the RW model in accuracy and ERC, while their biases are not statistically different. This result is contrary to that of Gerakos and Gramacy (2013), indicating that the HVZ model improves its performance and has an advantage over the RW model when it is estimated based on per share values. Similar results are observed for the RI model in Column 7: the RI model performs better than the RW model in accuracy and ERC while their biases are not statistically different. Column 8 shows that the RI model generally performs better than the HVZ model. However, the difference is much smaller than those in Li and Mohanram (2014) when the models are estimated on a level field. In fact, for the long forecast horizons, the HVZ model performs better than the RI model in ERC.

Columns 9 and 10 reports the improvements on the performance of cross-sectional models when conditional cross-sectional models are used. Column 9 demonstrates that the CHVZ model improves the performance of the HVZ model in accuracy and ERC for all forecast horizons. The biases of the HVZ model only improve for the three-year ahead forecast horizon. The improvements are more evident when the CRI model is used in Column 10. The CRI model improves the performance of the RI model in almost all forecast horizons in bias, accuracy and ERC. In general, the conditional cross-sectional models improve, or at least perform as well as, the performance of the cross-sectional models in bias, accuracy and ERC.

Columns 11 and 12 report the performances of the conditional cross-sectional models compared to the RW model. In bias, both conditional cross-sectional models perform as well as the RW model. However, they perform significantly better than the RW model in accuracy and ERC for all forecast horizons. Compared to the results in Table 5, Table 6 shows that the conditional cross-sectional models improve their performance when they are estimated on per share level. Column 13 compares the CRI model with the CHVZ model. While the CRI model outperforms the CHVZ model in bias and accuracy, the CHVZ model outperforms the CRI model in ERC for the three- through five-year forecast horizons.

5.4.2.3. Street Earnings Per Share Estimation

Table 7 reports the averages of biases, accuracies and ERCs across years and their time-series *t* statistics of the RW, HVZ, RI, CHVZ, CRI models and analyst forecasts, and the differences between them. Because the estimations of street earnings per share require street earnings per share and analyst forecasts, the results in Table 7 cover less firm-year observations than those in Tables 5 and 6. Table 7 reports the results of 2,620 firms and 17,126 firm-year observations. The current street earnings per share are used for the RW model, and ANA indicates analyst forecasts. Consistent with the previous literature, analyst forecasts show an optimistic bias (i.e. their biases are positive) and the bias increases as a forecast horizon lengthens (Barefield and Comiskey, 1975; Crichfield, Dyckman and Lakonishok, 1978; Stickel, 1990; Abarbanell, 1991; Ali, Klein and Rosenfeld, 1992; Richardson, Teoh and Wysocki, 1999; Easterwood and Nutt, 1999). On the other hand, the RW model has negative biases as the current street earnings per share do not reflect the growth of earnings over time.

<Table 7 here>

Column 7 compares the performance of the HVZ model with the RW model. Although the HVZ model performs better than the RW model for the four- and five-year forecast horizons, the RW model performs better than the HVZ model in accuracy and ERC for the short forecast horizons. The same results are observed for the RI model in Column 8. When the HVZ model is compared with analyst forecasts in Column 9, the HVZ model outperforms analyst forecasts in bias. However, analyst forecasts outperform the HVZ model in accuracy and ERC for the short forecast horizons. Similar results are observed for the RI model in Column 10: the RI model performs better than analyst forecasts in bias, but analyst forecasts outperform the RI model in accuracy and ERC for the short forecast horizons. Between the HVZ and RI models, Column 11 shows that the RI model generally has an edge over the HVZ model especially in accuracy.

Column 12 reports the improvements the CHVZ model makes on the performance of the HVZ model. Although the CHVZ model does not improve the biases of the HVZ model, it improves accuracies and ERCs for all forecast horizons. Similar results are observed for the CRI model. Column 13 indicates that the CRI model improves the accuracies and ERCs of the RI model.

When the conditional cross-sectional models are compared with the RW model, Columns 14 and 15 show that the CHVZ and CRI models have an advantage over the RW model for most biases, accuracies and ERCs. Only in accuracy for the one-year ahead forecast horizon, the RW model performs better than the conditional cross-sectional models. Against analyst forecasts, Columns 16 and 17 show that the conditional cross-sectionals perform better than analyst forecasts in bias, accuracy and ERC for the long forecast horizons (i.e. four- and five-year ahead forecast horizons). Although analyst forecasts still have an advantage in accuracy and ERC for the short forecast horizons (i.e. one- and two-year ahead forecast horizons), the advantage diminishes as a forecast horizon lengthens. In fact, for the three-year ahead forecast horizon, analyst forecasts lose all their advantages over the conditional cross-sectional models and, for the four- and five-year ahead forecast horizons, the conditional cross-sectional models statistically outperform analyst forecasts. The outperformance of analyst forecasts for the short forecast horizons is probably due to an information advantage that analysts can use non-accounting information for their earnings forecasts (Fried and Givoly, 1982; O'Brien, 1988). However, the results show that the information advantage diminishes monotonically as a forecast horizon lengthens and the conditional cross-sectional models start outperforming analyst forecasts from the four-year ahead forecast horizon. Between the CHVZ and CRI models, Column 18 shows that the CRI model has an edge over the CHVZ model in bias and accuracy, while the CHVZ model has an advantage over the CRI model in ERC.

5.5. Robustness Tests

The project conducts various robustness tests to examine whether the improvements conditional cross-sectional models make on the performance of cross-sectional models are genuine. The first three robustness tests divide the sample into three subsamples according to a) a book-to-market ratio; b) past returns; and c) size. The cross-sectional and conditional cross-sectional models are estimated in each subsample and the improvements on the performance of the cross-sectional models are reported. The fourth robustness test estimates the models based on the past five years' data, instead of the past ten years' data. The fifth robustness test divides the sample into two time periods: a) from 1970 to 1987; and b) from 1988 to 2007. The sixth robustness test estimates the models by industry, and reports the average performance across industries.

For the first three robustness tests, the sample is divided into three categories (i.e. high or big, medium, and low or small) according to the values of a book-to-market ratio, past returns and size, respectively. Past returns are the past one year's stock returns. Size is estimated based on the market value of equity, calculated as the product of stock price and the number of shares outstanding. For the sixth robustness test, industry is classified based on the first digit of the SIC codes. The first one digit is used, instead of the first two digits, considering the fact that the models are cross-sectional and conditional cross-sectional models and hence require a sufficient amount of cross-sectional data. Therefore, the averages of seven industries (i.e. excluding the SIC codes starting with 6 for financial firms and 9 for public administration) are reported.

Tables 8, 9 and 10 report the results of the improvements on the HVZ model when the CHVZ model is used across the six different robustness tests for unscaled earnings, reported earnings per share and street earnings per share estimations, respectively. To conserve space, only the results of the improvements on the HVZ model are reported. The results of the improvements on the RI model when the CRI model is used are almost identical and hence reported in Appendices 1, 2 and 3.

Table 8 reports the averages of the improvements across years and their time-series *t* statistics for unscaled earnings estimation. Therefore, the results in each column are comparable to those in Column 9 of Table 5. The last three columns report the number of subsamples when the performance of the CHVZ model is a) better; b) equal; or c) worse statistically than the HVZ model. The values in bold indicate significance at the 5% level.

<Table 8 here>

The last three columns indicate that the CHVZ model improves the performance of the HVZ model in most subsamples in bias, accuracy and ERC. Only in a few subsamples, the CHVZ model underperforms the HVZ model. The improvements are most evident in ERC: in more than two-thirds of the total subsamples, the CHVZ model improves the performance of the HVZ model in ERC across all forecast horizons. The improvements are most evident for high or medium growth firms. This implies that by allowing the coefficients on earnings to vary (i.e. different earnings persistence is used for different firms), the CHVZ model reflects individual firms' earnings prospects better than the HVZ model.

<Table 9 here>

Table 9 reports the improvements on the HVZ model for reported earnings per share. The values are comparable with those in Column 9 of Table 6. Similarly, the last three columns show that the CHVZ model performs better than, or at least as well as, the HVZ model in almost all cases. The improvements are not widely observed in bias. However, in accuracy and ERC, the CHVZ model performs significantly better than the HVZ model in most subsamples.

<Table 10 here>

Table 10 reports the improvements when future street earnings per share are estimated. Because street earnings per share and analyst forecasts are not widely available in the early years of the sample, the sample is not divided over time. The results show a consistent finding: the improvements are minimal in bias, but widely observed in accuracy and ERC for all forecast horizons.

The results of the robustness tests indicate that the improvements are observed in most subsamples and, therefore, not driven by a few subsamples. The value of using the CHVZ model over the HVZ model is most evident for firms with high past returns (i.e. growth firms), as their high earnings persistence is reflected in the CHVZ model.

5.6. Conclusion

The main purpose of this project is to address the fundamental problem of cross-sectional models in earnings estimation. While cross-sectional models reduce survivorship bias that is prone to time-series models, they sacrifice the firm-specific information in earnings estimation (Kothari, 2001). This means that cross-sectional models apply the same coefficients (i.e. the same earnings persistence and future prospects) to all firms in their earnings forecasts.

The project proposes a new model, a conditional cross-sectional model, which allows the coefficient on earnings to vary based on firm-specific information. By allowing earnings persistence to vary across firms, the model applies different future prospects to different firms.

The results indicate that the conditional cross-sectional models improve the performance of the cross-sectional models in almost all dimensions: a) bias, accuracy and ERC; b) for unscaled earnings, reported earnings per share, and street earnings per share estimations; and c) for all forecast horizons. The results of the robustness tests suggest that the improvements are observed across various subsamples and hence not driven by a few subsamples.

Although analyst forecasts still outperform the conditional cross-sectional models in accuracy and ERC for the short forecast horizons, their advantage diminishes monotonically as a forecast horizon lengthens. In fact, for the three-year ahead forecast horizon, the advantage of analyst forecasts disappears and, for the four- and five-year ahead forecast horizons, the conditional cross-sectional models statistically outperform analyst forecasts in bias, accuracy and ERC. Therefore, the project recommends the conditional cross-sectional models over analyst forecasts especially for the long forecast horizons.

This project contributes to the literature by proposing a new model, a conditional cross-sectional model, which addresses the main problem of a cross-sectional model in earnings estimation. By improving model specification, a conditional cross-sectional model uses the same amount of information as a cross-sectional model does but addresses its problem and improves its performance. As far as the author is aware, this is the first paper that applies the conditional mechanism to cross-sectional models. The project presents a new model to valuation model users to improve their earnings forecasts.

Table 1

Descriptive Statistics

Panel A: Firm level									(in $ mil, except SHOUT, NIB and DD)
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
MV	723.5	67.0	2,925.5	1.5	3.5	17.0	323.2	2,933.1	12,914.0
SALE	710.1	88.6	2,560.6	0.0	2.2	22.8	380.2	3,117.1	11,128.4
EBITDA	92.9	7.9	370.4	-32.6	-7.7	1.1	42.3	417.7	1,582.8
E	30.9	2.1	169.6	-99.1	-23.5	-0.3	13.4	149.7	625.0
TA	672.0	77.9	2,490.1	1.9	4.7	22.4	328.3	2,858.1	11,150.0
LT	387.7	31.4	1,533.3	0.5	1.4	8.2	154.9	1,684.0	7,043.5
B	275.3	37.5	971.1	-5.9	1.2	9.6	156.2	1,193.0	4,115.2
AC	-38.2	-2.3	158.1	-687.0	-187.0	-16.8	0.3	11.6	43.4
DIV	8.7	0.0	48.9	0.0	0.0	0.0	1.3	35.2	181.4
SHOUT	46.8	11.3	118.8	1.1	1.5	4.2	35.1	208.2	647.6
NegE	0.28	0.00	0.45	0.00	0.00	0.00	1.00	1.00	1.00
DD	0.39	0.00	0.49	0.00	0.00	0.00	1.00	1.00	1.00

Panel B: Per share									(in $)
	Mean	Median	SD	1%	5%	25%	75%	95%	99%
EPS (reported)	0.33	0.30	1.68	-5.75	-1.71	-0.06	0.92	2.54	4.50
EPS0 (street)	0.67	0.54	1.21	-2.56	-1.06	0.12	1.17	2.73	4.45
TA	15.89	8.75	20.41	0.28	0.77	3.48	20.16	54.97	100.83
B	6.76	4.20	7.94	-0.55	0.19	1.63	8.94	22.28	38.89
AC	-0.73	-0.26	1.93	-8.67	-4.03	-1.04	0.04	1.13	2.90
DIV	0.14	0.00	0.30	0.00	0.00	0.00	0.14	0.80	1.40

The sample includes non-financial US firms listed on NYSE, AMEX or NASDAQ from 1956 to 2012. The sample uses 13,541 firms with 154,653 firm-year observations to estimate earnings forecasts. Three earnings measures are estimated: a) unscaled earnings; b) reported earnings per share; and c) street earnings per share. For unscaled earnings, models use unscaled accounting values in regressions (Panel A). For scaled earnings (i.e. reported earnings per share and street earnings per share), per share accounting values are used (Panel B).

MV is market value, calculated as the product of stock price and the number of shares outstanding; SALE is sales; EBITDA is earnings before interest, taxes, depreciation and amortisation; E is earnings before extraordinary items; TA is total asset; LT is total liabilities; B is the book value of equity; AC is accruals, calculated as the change in current assets excluding cash, minus the change in current liabilities excluding short-term debt and tax payable, minus depreciation and amortization expenses. From 1988, accruals are calculated as earnings minus cash flow from operations; DIV is dividend; SHOUT is the number of shares outstanding; NegE is a binary variable that is one for firms with negative earnings, and zero otherwise; DD is a binary variable that is one for firms paying dividends, and zero for non-payers.

Table 2

Coefficients for Unscaled Earnings Estimations

Panel A: HVZ

		CONS	TA	DIV	DD	E	NegE	AC	Adj. R^2
E_{t+1}	Coefficient	-0.178	0.004	0.200	0.837	0.853	0.417	-0.093	0.826
	t-stat	*-1.24*	*6.76*	*12.59*	*8.22*	*68.72*	*1.68*	*-8.44*	
E_{t+2}	Coefficient	-0.141	0.009	0.351	0.882	0.786	1.013	-0.107	0.749
	t-stat	*-0.63*	*9.29*	*14.03*	*6.84*	*44.24*	*3.80*	*-6.08*	
E_{t+3}	Coefficient	0.468	0.012	0.345	0.767	0.827	0.943	-0.110	0.705
	t-stat	*2.73*	*10.23*	*8.69*	*4.54*	*33.44*	*5.10*	*-5.22*	
E_{t+4}	Coefficient	0.976	0.013	0.395	0.509	0.881	1.236	-0.107	0.673
	t-stat	*5.72*	*10.45*	*8.41*	*2.27*	*35.12*	*6.49*	*-4.00*	
E_{t+5}	Coefficient	1.992	0.014	0.529	0.077	0.890	0.428	-0.091	0.639
	t-stat	*9.08*	*13.10*	*7.27*	*0.22*	*24.51*	*2.26*	*-2.90*	

Panel B: RI

		CONS	NegE	E	NegE*E	B	AC	Adj. R^2
E_{t+1}	Coefficient	-0.382	-1.880	0.894	-0.700	0.015	-0.076	0.831
	t-stat	*-1.68*	*-6.73*	*74.29*	*-12.79*	*9.63*	*-8.03*	
E_{t+2}	Coefficient	-0.621	-1.814	0.860	-0.926	0.031	-0.087	0.759
	t-stat	*-1.78*	*-7.92*	*48.50*	*-14.66*	*12.26*	*-6.61*	
E_{t+3}	Coefficient	-0.380	-1.649	0.883	-0.974	0.042	-0.091	0.717
	t-stat	*-1.05*	*-7.32*	*32.51*	*-12.09*	*11.61*	*-5.93*	
E_{t+4}	Coefficient	-0.119	-1.432	0.976	-1.057	0.045	-0.089	0.695
	t-stat	*-0.37*	*-5.92*	*32.74*	*-19.36*	*11.51*	*-4.81*	
E_{t+5}	Coefficient	0.947	-2.112	1.029	-0.881	0.047	-0.080	0.662
	t-stat	*3.04*	*-6.93*	*34.11*	*-3.33*	*11.68*	*-3.67*	

Panel C: CHVZ

		CONS	E	TA*E	DIV*E	AC*E	DD*E	NegE*E	TA	DIV	AC	DD	NegE	Adj. R^2
E_{t+1}	Coefficient	-0.865	0.993	0.000	0.000	0.000	-0.052	-0.563	0.005	0.125	-0.096	0.117	-0.994	0.829
	t-stat	*-7.51*	*80.40*	*0.00*	*1.29*	*-0.90*	*-4.03*	*-13.72*	*7.93*	*6.63*	*-8.98*	*1.23*	*-3.25*	
E_{t+2}	Coefficient	-1.224	1.042	0.000	0.000	0.000	-0.160	-0.810	0.011	0.307	-0.106	0.463	-0.583	0.760
	t-stat	*-7.19*	*54.65*	*-1.00*	*0.07*	*-0.66*	*-7.33*	*-14.87*	*8.45*	*8.39*	*-6.10*	*5.10*	*-2.15*	
E_{t+3}	Coefficient	-1.181	1.109	0.000	0.000	0.000	-0.170	-0.904	0.017	0.301	-0.108	-0.041	-0.294	0.715
	t-stat	*-7.16*	*38.46*	*-1.43*	*0.68*	*-0.83*	*-3.99*	*-16.87*	*12.25*	*6.06*	*-5.15*	*-0.27*	*-1.07*	
E_{t+4}	Coefficient	-1.299	1.267	0.000	0.002	0.000	-0.285	-1.066	0.022	0.281	-0.101	0.188	-0.085	0.682
	t-stat	*-7.54*	*29.16*	*-1.78*	*2.77*	*-0.24*	*-5.81*	*-21.05*	*15.79*	*6.44*	*-4.66*	*0.68*	*-0.29*	
E_{t+5}	Coefficient	-0.889	1.371	0.000	0.004	0.001	-0.354	-1.187	0.027	0.289	-0.137	-0.204	-0.355	0.650
	t-stat	*-7.08*	*20.33*	*-2.63*	*2.96*	*1.63*	*-6.73*	*-17.50*	*18.25*	*5.08*	*-5.60*	*-0.50*	*-1.17*	

Panel D: CRI										
		CONS	E	B*E	AC*E	NegE*E	B	AC	NegE	Adj. R^2
E_{t+1}	Coefficient	-0.963	0.964	0.000	0.000	-0.570	0.014	-0.105	-0.969	0.833
	t-stat	*-6.80*	*100.75*	*0.00*	*1.14*	*-13.32*	*10.97*	*-10.93*	*-3.09*	
E_{t+2}	Coefficient	-1.291	0.953	0.000	0.000	-0.761	0.031	-0.118	-0.548	0.760
	t-stat	*-6.87*	*59.80*	*0.00*	*-0.64*	*-11.32*	*12.88*	*-7.38*	*-2.12*	
E_{t+3}	Coefficient	-1.330	0.982	0.000	0.000	-0.756	0.045	-0.128	-0.322	0.717
	t-stat	*-6.20*	*39.64*	*-1.43*	*-0.52*	*-9.55*	*16.03*	*-6.88*	*-1.09*	
E_{t+4}	Coefficient	-0.741	1.044	0.000	0.001	-0.846	0.044	-0.153	-0.665	0.694
	t-stat	*-2.63*	*43.73*	*1.00*	*2.90*	*-10.47*	*9.60*	*-8.87*	*-2.54*	
E_{t+5}	Coefficient	-0.401	1.143	0.000	0.001	-0.616	0.048	-0.195	-0.548	0.663
	t-stat	*-1.42*	*29.90*	*-1.00*	*3.31*	*-2.20*	*11.32*	*-9.73*	*-2.14*	

The table reports the averages of coefficients across years, their time-series t statistics (italics) and the averages of adjusted R^2s across years for unscaled earnings estimations. Panel A reports the coefficients of the HVZ model; Panel B reports the coefficients of the RI model; Panel C reports the coefficients of the CHVZ model; and Panel D reports the coefficients of the CRI model. The models use the pooled cross-sectional data for the past 10 years to estimate future unscaled earnings, without look-ahead bias. Unscaled accounting values are used for the independent variables, except for the binary variables. E_{t+s} indicates earnings at time *t+s*. CONS is constant; TA is total asset; DIV is dividend; DD is a binary variable that is one for firms paying dividends, and zero for non-payers; E is earnings before extraordinary items; NegE is a binary variable that is one for firms with negative earnings, and zero otherwise; AC is accruals; B is the book value of equity.

Table 3

Coefficients for Reported Earnings Per Share Estimations

Panel A: HVZ

		CONS	TA	DIV	DD	E	NegE	AC	Adj. R^2
E_{t+1}	Coefficient	0.060	-0.005	0.427	0.131	0.664	-0.045	-0.095	0.470
	t-stat	*10.96*	*-3.45*	*16.67*	*10.97*	*46.31*	*-1.41*	*-7.51*	
E_{t+2}	Coefficient	0.108	-0.004	0.652	0.177	0.456	-0.056	-0.088	0.308
	t-stat	*14.07*	*-2.24*	*30.75*	*9.07*	*32.47*	*-1.85*	*-6.76*	
E_{t+3}	Coefficient	0.145	-0.001	0.762	0.207	0.321	-0.065	-0.074	0.234
	t-stat	*14.63*	*-0.95*	*40.80*	*9.13*	*24.67*	*-2.18*	*-7.35*	
E_{t+4}	Coefficient	0.170	0.000	0.860	0.212	0.242	-0.069	-0.047	0.198
	t-stat	*12.42*	*0.19*	*26.14*	*8.16*	*10.96*	*-2.79*	*-4.14*	
E_{t+5}	Coefficient	0.195	0.000	0.818	0.228	0.245	-0.073	-0.041	0.179
	t-stat	*15.79*	*0.15*	*27.40*	*9.39*	*8.60*	*-2.71*	*-4.51*	

Panel B: RI

		CONS	NegE	E	NegE*E	B	AC	Adj. R^2
E_{t+1}	Coefficient	0.082	-0.150	0.899	-0.486	-0.022	-0.088	0.478
	t-stat	*10.83*	*-10.55*	*86.02*	*-24.41*	*-4.34*	*-7.43*	
E_{t+2}	Coefficient	0.146	-0.176	0.703	-0.495	-0.013	-0.093	0.308
	t-stat	*31.31*	*-10.89*	*73.24*	*-18.65*	*-2.37*	*-7.36*	
E_{t+3}	Coefficient	0.201	-0.175	0.548	-0.410	-0.002	-0.082	0.223
	t-stat	*61.51*	*-8.82*	*57.85*	*-15.17*	*-0.34*	*-7.68*	
E_{t+4}	Coefficient	0.235	-0.149	0.461	-0.270	0.006	-0.066	0.181
	t-stat	*61.48*	*-6.35*	*24.58*	*-5.34*	*1.23*	*-5.41*	
E_{t+5}	Coefficient	0.281	-0.167	0.447	-0.264	0.007	-0.064	0.159
	t-stat	*83.33*	*-6.95*	*18.23*	*-6.68*	*1.82*	*-7.06*	

Panel C: CHVZ

		CONS	E	TA*E	DIV*E	AC*E	DD*E	NegE*E	TA	DIV	AC	DD	NegE	Adj. R^2
E_{t+1}	Coefficient	0.028	0.795	0.001	-0.085	0.021	0.085	-0.280	-0.008	0.318	-0.092	0.075	-0.085	0.492
	t-stat	*4.44*	*44.47*	*2.09*	*-6.26*	*9.48*	*11.72*	*-6.84*	*-5.39*	*12.34*	*-11.27*	*8.00*	*-7.77*	
E_{t+2}	Coefficient	0.059	0.611	-0.002	-0.042	0.012	0.101	-0.283	-0.005	0.545	-0.086	0.113	-0.086	0.327
	t-stat	*10.82*	*24.62*	*-3.49*	*-3.03*	*5.87*	*6.26*	*-5.71*	*-2.53*	*16.49*	*-8.81*	*7.06*	*-6.70*	
E_{t+3}	Coefficient	0.094	0.467	-0.003	-0.066	0.006	0.122	-0.200	-0.001	0.742	-0.069	0.124	-0.063	0.253
	t-stat	*14.98*	*12.53*	*-5.58*	*-3.17*	*2.31*	*4.83*	*-3.47*	*-0.37*	*15.16*	*-7.91*	*7.70*	*-3.61*	
E_{t+4}	Coefficient	0.105	0.422	-0.004	-0.106	0.012	0.072	-0.060	0.001	0.955	-0.058	0.146	-0.016	0.216
	t-stat	*12.54*	*10.96*	*-3.16*	*-3.89*	*3.75*	*2.38*	*-1.01*	*0.77*	*20.91*	*-5.79*	*8.67*	*-0.76*	
E_{t+5}	Coefficient	0.125	0.407	-0.004	-0.201	0.003	0.107	-0.148	0.003	1.065	-0.044	0.142	-0.033	0.199
	t-stat	*12.21*	*8.65*	*-5.25*	*-12.86*	*0.67*	*3.89*	*-3.08*	*1.69*	*22.42*	*-5.00*	*7.00*	*-1.61*	

Panel D: CRI										
		CONS	E	B*E	AC*E	NegE*E	B	AC	NegE	Adj. R^2
E_{t+1}	Coefficient	0.058	0.885	0.002	0.018	-0.388	-0.016	-0.090	-0.116	0.485
	t-stat	*4.27*	*52.34*	*1.13*	*9.71*	*-12.09*	*-3.41*	*-10.87*	*-6.85*	
E_{t+2}	Coefficient	0.086	0.781	-0.004	0.012	-0.456	-0.005	-0.095	-0.107	0.312
	t-stat	*10.75*	*77.15*	*-4.17*	*6.47*	*-13.66*	*-0.91*	*-8.90*	*-7.81*	
E_{t+3}	Coefficient	0.127	0.668	-0.007	0.009	-0.408	0.006	-0.086	-0.098	0.230
	t-stat	*23.40*	*53.28*	*-9.10*	*4.44*	*-12.57*	*1.12*	*-9.23*	*-5.61*	
E_{t+4}	Coefficient	0.161	0.586	-0.007	0.021	-0.254	0.014	-0.084	-0.079	0.187
	t-stat	*36.83*	*31.69*	*-9.70*	*6.10*	*-3.90*	*2.45*	*-9.31*	*-3.92*	
E_{t+5}	Coefficient	0.191	0.586	-0.008	0.020	-0.277	0.017	-0.086	-0.093	0.170
	t-stat	*32.75*	*22.33*	*-9.58*	*3.68*	*-7.55*	*3.60*	*-10.73*	*-4.38*	

The table reports the averages of coefficients across years, their time-series t statistics (italics) and the averages of adjusted R^2s across years for reported earnings per share estimations. Panel A reports the coefficients of the HVZ model; Panel B reports the coefficients of the RI model; Panel C reports the coefficients of the CHVZ model; and Panel D reports the coefficients of the CRI model. The models use the pooled cross-sectional data for the past 10 years to estimate future reported earnings per share, without look-ahead bias. Per share accounting values are used for the independent variables, except for the binary variables. E_{t+s} indicates reported earnings per share at time *t+s*. CONS is constant; TA is total asset; DIV is dividend; DD is a binary variable that is one for firms paying dividends, and zero for non-payers; E is earnings before extraordinary items; NegE is a binary variable that is one for firms with negative earnings, and zero otherwise; AC is accruals; B is the book value of equity.

Table 4

Coefficients for Street Earnings Per Share Estimations

Panel A: HVZ

		CONS	TA	DIV	DD	E	NegE	AC	Adj. R^2
E_{t+1}	Coefficient	0.241	0.003	0.483	0.089	0.400	-0.293	-0.088	0.454
	t-stat	*17.22*	*5.16*	*40.28*	*13.36*	*32.69*	*-7.86*	*-8.92*	
E_{t+2}	Coefficient	0.286	0.004	0.573	0.142	0.255	-0.251	-0.075	0.296
	t-stat	*22.57*	*6.54*	*34.58*	*15.27*	*41.91*	*-6.75*	*-7.44*	
E_{t+3}	Coefficient	0.339	0.005	0.604	0.156	0.179	-0.268	-0.054	0.240
	t-stat	*31.01*	*7.65*	*21.88*	*12.28*	*25.55*	*-8.88*	*-5.17*	
E_{t+4}	Coefficient	0.376	0.005	0.673	0.159	0.127	-0.240	-0.048	0.209
	t-stat	*31.12*	*8.85*	*22.83*	*13.40*	*14.06*	*-7.24*	*-5.24*	
E_{t+5}	Coefficient	0.416	0.005	0.718	0.160	0.096	-0.234	-0.042	0.193
	t-stat	*37.56*	*8.41*	*18.11*	*10.36*	*9.73*	*-7.95*	*-4.51*	

Panel B: RI

		CONS	NegE	E	NegE*E	B	AC	Adj. R^2
E_{t+1}	Coefficient	0.178	-0.339	0.690	-0.504	0.000	-0.078	0.477
	t-stat	*23.85*	*-16.74*	*76.34*	*-30.74*	*-0.52*	*-8.98*	
E_{t+2}	Coefficient	0.264	-0.296	0.534	-0.437	0.003	-0.084	0.296
	t-stat	*41.06*	*-13.53*	*52.26*	*-41.48*	*4.99*	*-8.73*	
E_{t+3}	Coefficient	0.341	-0.311	0.417	-0.342	0.010	-0.075	0.226
	t-stat	*59.74*	*-19.71*	*27.89*	*-45.44*	*8.81*	*-6.36*	
E_{t+4}	Coefficient	0.398	-0.289	0.351	-0.301	0.014	-0.077	0.187
	t-stat	*57.88*	*-13.69*	*17.82*	*-25.13*	*10.13*	*-7.36*	
E_{t+5}	Coefficient	0.451	-0.277	0.290	-0.229	0.019	-0.073	0.166
	t-stat	*49.09*	*-12.26*	*11.44*	*-11.25*	*9.87*	*-6.31*	

Panel C: CHVZ

		CONS	E	TA*E	DIV*E	AC*E	DD*E	NegE*E	TA	DIV	AC	DD	NegE	Adj. R^2
E_{t+1}	Coefficient	0.088	0.769	-0.002	-0.003	0.021	0.000	-0.354	0.000	0.294	-0.086	0.060	-0.182	0.510
	t-stat	*10.74*	*72.73*	*-41.00*	*-0.17*	*6.82*	*0.04*	*-15.31*	*-0.07*	*10.33*	*-13.86*	*9.54*	*-11.38*	
E_{t+2}	Coefficient	0.140	0.610	-0.003	0.003	0.010	-0.006	-0.329	0.002	0.409	-0.073	0.114	-0.156	0.334
	t-stat	*14.95*	*76.45*	*-13.88*	*0.27*	*4.08*	*-1.18*	*-22.83*	*5.07*	*10.10*	*-9.55*	*11.40*	*-7.46*	
E_{t+3}	Coefficient	0.222	0.441	-0.003	-0.055	0.010	0.029	-0.209	0.005	0.577	-0.058	0.109	-0.177	0.267
	t-stat	*32.97*	*33.46*	*-14.24*	*-2.60*	*4.70*	*1.69*	*-14.42*	*17.59*	*9.61*	*-6.48*	*5.00*	*-8.46*	
E_{t+4}	Coefficient	0.272	0.396	-0.003	-0.129	0.007	0.021	-0.199	0.005	0.786	-0.050	0.102	-0.151	0.233
	t-stat	*55.07*	*20.10*	*-18.90*	*-10.16*	*4.92*	*1.08*	*-12.72*	*11.69*	*14.78*	*-6.13*	*4.36*	*-6.63*	
E_{t+5}	Coefficient	0.312	0.374	-0.003	-0.164	0.013	-0.017	-0.155	0.006	0.944	-0.051	0.103	-0.131	0.214
	t-stat	*36.67*	*28.12*	*-15.02*	*-9.41*	*6.05*	*-1.47*	*-6.31*	*9.74*	*12.48*	*-7.70*	*4.31*	*-4.49*	

Panel D: CRI										
		CONS	E	B*E	AC*E	NegE*E	B	AC	NegE	Adj. R^2
E_{t+1}	Coefficient	0.098	0.831	-0.007	0.018	-0.426	0.004	-0.096	-0.192	0.498
	t-stat	*7.63*	*52.40*	*-9.45*	*5.24*	*-14.65*	*6.28*	*-9.26*	*-12.42*	
E_{t+2}	Coefficient	0.169	0.705	-0.009	0.011	-0.415	0.010	-0.098	-0.161	0.317
	t-stat	*12.57*	*69.11*	*-9.81*	*3.95*	*-27.42*	*6.42*	*-8.35*	*-7.88*	
E_{t+3}	Coefficient	0.246	0.582	-0.010	0.005	-0.370	0.018	-0.083	-0.214	0.243
	t-stat	*19.96*	*67.49*	*-9.57*	*2.05*	*-27.89*	*8.87*	*-5.61*	*-14.19*	
E_{t+4}	Coefficient	0.299	0.536	-0.011	0.008	-0.313	0.021	-0.088	-0.177	0.204
	t-stat	*25.23*	*44.96*	*-12.24*	*4.88*	*-26.94*	*10.62*	*-7.26*	*-8.78*	
E_{t+5}	Coefficient	0.338	0.500	-0.012	0.010	-0.245	0.028	-0.085	-0.163	0.186
	t-stat	*19.81*	*42.11*	*-12.16*	*5.27*	*-10.59*	*9.30*	*-6.96*	*-6.16*	

The table reports the averages of coefficients across years, their time-series t statistics (italics) and the averages of adjusted R^2s across years for street earnings per share estimations. Panel A reports the coefficients of the HVZ model; Panel B reports the coefficients of the RI model; Panel C reports the coefficients of the CHVZ model; and Panel D reports the coefficients of the CRI model. The models use the pooled cross-sectional data for the past 10 years to estimate future street earnings per share, without look-ahead bias. Per share accounting values are used for the independent variables, except for the binary variables. E_{t+s} indicates street earnings per share at time *t+s*. CONS is constant; TA is total asset; DIV is dividend; DD is a binary variable that is one for firms paying dividends, and zero for non-payers; E is earnings before extraordinary items; NegE is a binary variable that is one for firms with negative earnings, and zero otherwise; AC is accruals; B is the book value of equity.

Table 5
Bias, Accuracy and ERC: Unscaled Earnings Estimations

Panel A: Bias

	(1) RW	(2) HVZ	(3) RI	(4) CHVZ	(5) CRI	(6) HVZ-RW	(7) RI-RW	(8) RI-HVZ	(9) CHVZ-HVZ	(10) CRI-RI	(11) CHVZ-RW	(12) CRI-RW	(13) CRI-CHVZ
E_{t+1}	-0.004	**0.019**	**0.010**	-0.005	-0.005	**0.008**	**0.005**	**-0.003**	-0.004	0.000	**0.005**	**0.005**	0.000
	-1.44	5.87	2.58	-1.40	-1.48	2.83	1.92	-1.98	-1.25	0.00	2.54	2.90	0.86
E_{t+2}	**-0.018**	**0.030**	**0.019**	-0.002	-0.004	**0.011**	0.007	**-0.005**	**-0.010**	-0.005	0.001	0.002	0.000
	-4.12	5.77	3.38	-0.37	-0.73	2.18	1.34	-2.38	-2.33	-1.31	0.35	0.38	0.06
E_{t+3}	**-0.030**	**0.042**	**0.031**	0.003	0.002	0.010	0.006	-0.004	**-0.017**	**-0.013**	-0.007	-0.007	0.000
	-5.20	6.56	4.46	0.52	0.41	1.39	0.93	-1.50	-3.50	-2.93	-1.19	-1.15	-0.02
E_{t+4}	**-0.039**	**0.056**	**0.043**	**0.012**	**0.024**	0.015	0.009	**-0.006**	**-0.026**	**-0.013**	-0.011	-0.005	**0.007**
	-5.36	7.05	4.74	1.81	3.32	1.26	0.78	-1.93	-4.55	-2.20	-1.32	-0.53	1.80
E_{t+5}	**-0.046**	**0.080**	**0.076**	**0.027**	**0.040**	**0.030**	**0.031**	0.001	**-0.042**	**-0.036**	-0.012	-0.004	0.007
	-5.37	8.17	6.42	4.00	5.58	2.13	2.26	0.28	-6.24	-4.46	-1.08	-0.45	1.62

Panel B: Accuracy

	RW	HVZ	RI	CHVZ	CRI	HVZ-RW	RI-RW	RI-HVZ	CHVZ-HVZ	CRI-RI	CHVZ-RW	CRI-RW	CRI-CHVZ
E_{t+1}	**0.062**	**0.065**	**0.066**	**0.066**	**0.066**	**0.002**	**0.004**	0.001	0.001	0.001	**0.004**	**0.004**	0.000
	21.39	20.95	20.54	20.24	20.23	3.28	4.39	1.56	1.15	0.60	3.92	4.32	0.62
E_{t+2}	**0.086**	**0.090**	**0.091**	**0.087**	**0.086**	**0.004**	**0.005**	0.001	-0.003	**-0.004**	0.001	0.001	-0.001
	25.53	23.04	25.23	25.44	26.28	2.13	3.08	0.89	-1.19	-2.44	0.77	0.51	-0.92
E_{t+3}	**0.104**	**0.111**	**0.109**	**0.103**	**0.103**	**0.007**	**0.005**	-0.002	**-0.008**	**-0.006**	-0.001	-0.001	0.000
	24.30	22.76	25.07	25.73	27.68	2.41	1.98	-1.49	-2.76	-2.72	-0.42	-0.61	-0.53
E_{t+4}	**0.122**	**0.136**	**0.130**	**0.121**	**0.124**	**0.014**	**0.008**	**-0.006**	**-0.015**	-0.007	-0.001	0.001	0.002
	21.27	21.69	20.23	24.28	24.05	3.23	1.89	-3.90	-4.82	-1.65	-0.30	0.37	0.74
E_{t+5}	**0.142**	**0.171**	**0.168**	**0.143**	**0.147**	**0.030**	**0.027**	-0.003	**-0.028**	**-0.022**	0.001	0.005	0.004
	19.61	19.08	16.47	22.48	19.63	5.40	4.09	-1.49	-6.98	-3.90	0.51	1.15	1.13

Panel C: ERC

	RW	HVZ	RI	CHVZ	CRI	HVZ-RW	RI-RW	RI-HVZ	CHVZ-HVZ	CRI-RI	CHVZ-RW	CRI-RW	CRI-CHVZ
E_{t+1}	**0.026**	**0.025**	**0.026**	**0.028**	**0.027**	-0.001	0.000	0.001	**0.002**	**0.001**	0.001	0.001	0.000
	21.57	21.05	19.27	19.88	19.65	-1.14	-0.31	0.79	2.47	4.10	1.64	1.47	-0.85
E_{t+2}	**0.041**	**0.039**	**0.042**	**0.045**	**0.045**	-0.002	0.001	**0.003**	**0.006**	**0.003**	**0.004**	**0.004**	0.000
	18.89	14.97	15.61	18.04	17.74	-1.51	0.27	2.09	4.08	3.75	2.35	2.42	0.74
E_{t+3}	**0.054**	**0.046**	**0.052**	**0.058**	**0.057**	**-0.007**	-0.001	**0.006**	**0.011**	**0.005**	**0.004**	0.004	0.000
	19.18	13.78	13.64	17.14	17.22	-3.36	-0.42	2.41	6.69	4.57	1.93	1.55	-0.68
E_{t+4}	**0.062**	**0.051**	**0.061**	**0.065**	**0.063**	**-0.011**	-0.001	**0.010**	**0.014**	0.002	0.002	0.001	-0.002
	21.05	13.10	13.60	15.72	14.02	-4.51	-0.41	3.53	5.13	1.52	0.77	0.18	-1.36
E_{t+5}	**0.070**	**0.052**	**0.064**	**0.068**	**0.068**	**-0.018**	-0.006	**0.012**	**0.016**	**0.004**	-0.002	-0.002	0.000
	19.19	10.86	11.37	13.82	12.49	-5.84	-1.62	3.77	5.50	3.05	-0.54	-0.41	0.10

The averages of biases, accuracies and ERCs across years and their time-series *t* statistics (italics) are reported for unscaled earnings estimations. A bias is calculated as forecasted earnings minus actual earnings, divided by the current market value. An accuracy is calculated as the absolute difference between forecasted earnings and actual earnings, divided by the current market value. An ERC is calculated as the slope coefficient of a regression of future abnormal stock return on earnings surprise. For future abnormal stock return, the sum of quarterly earnings announcement returns from -1 day to +1 day of earnings announcements are used, adjusted to S&P 500 index returns. Earnings surprise is calculated as the difference between actual earnings minus forecasted earnings divided by the current market value. Earnings surprises are standardised to have a unit variance in each year. For the RW model, unscaled earnings at time *t* are used. For the differences between models in bias, the differences in absolute biases in each year are calculated to estimate the improvements in bias (i.e. the magnitude of bias approaching zero), instead of the differences in bias. For Columns 6 through 13, the negative values in bias and accuracy mean the first model (e.g. HVZ model in Column 6) improves the performance of the second model (RW model in Column 6). In ERC, the positive values mean the first model improves the performance of the second model. Bold numbers indicate significance at the 5% level.

Table 6
Bias, Accuracy and ERC: Reported Earnings Per Share Estimations

Panel A: Bias

	(1) RW	(2) HVZ	(3) RI	(4) CHVZ	(5) CRI	(6) HVZ-RW	(7) RI-RW	(8) RI-HVZ	(9) CHVZ-HVZ	(10) CRI-RI	(11) CHVZ-RW	(12) CRI-RW	(13) CRI-CHVZ
E_{t+1}	-0.002	0.005	0.003	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.001	0.000	**-0.001**
	-0.78	*1.55*	*0.98*	*0.23*	*0.38*	*0.55*	*0.35*	*-0.91*	*-0.23*	*-0.79*	*0.57*	*0.15*	*-1.74*
E_{t+2}	**-0.013**	0.003	0.003	-0.001	0.001	-0.001	-0.003	**-0.001**	0.000	0.000	-0.001	-0.003	**-0.002**
	-3.30	*0.69*	*0.85*	*-0.37*	*0.16*	*-0.33*	*-0.76*	*-2.03*	*-0.20*	*-0.65*	*-0.46*	*-1.04*	*-2.51*
E_{t+3}	**-0.022**	0.001	0.004	-0.003	0.001	-0.001	-0.004	**-0.003**	**-0.002**	**-0.001**	-0.003	-0.006	**-0.002**
	-4.58	*0.21*	*0.85*	*-0.64*	*0.23*	*-0.30*	*-0.93*	*-3.18*	*-1.93*	*-2.03*	*-0.79*	*-1.35*	*-2.63*
E_{t+4}	**-0.029**	-0.001	0.005	-0.005	0.002	0.000	-0.004	**-0.004**	-0.001	**-0.001**	-0.002	-0.006	**-0.004**
	-5.09	*-0.11*	*0.83*	*-0.70*	*0.29*	*-0.09*	*-0.76*	*-2.85*	*-1.36*	*-1.93*	*-0.35*	*-1.11*	*-3.22*
E_{t+5}	**-0.035**	0.000	0.007	-0.005	0.003	0.002	-0.002	**-0.004**	-0.001	**-0.002**	0.001	-0.004	**-0.005**
	-5.53	*-0.05*	*1.02*	*-0.58*	*0.50*	*0.35*	*-0.33*	*-2.91*	*-1.07*	*-2.10*	*0.20*	*-0.65*	*-3.51*

Panel B: Accuracy

	RW	HVZ	RI	CHVZ	CRI	HVZ-RW	RI-RW	RI-HVZ	CHVZ-HVZ	CRI-RI	CHVZ-RW	CRI-RW	CRI-CHVZ
E_{t+1}	**0.056**	**0.056**	**0.055**	**0.054**	**0.054**	0.000	**-0.002**	**-0.001**	**-0.002**	**-0.001**	**-0.002**	**-0.002**	0.000
	22.84	*25.44*	*25.97*	*24.56*	*25.37*	*-0.77*	*-3.04*	*-6.14*	*-6.77*	*-4.01*	*-3.40*	*-4.02*	*-1.64*
E_{t+2}	**0.075**	**0.071**	**0.069**	**0.068**	**0.067**	**-0.004**	**-0.006**	**-0.002**	**-0.002**	**-0.001**	**-0.007**	**-0.008**	**-0.001**
	28.17	*33.43*	*33.51*	*32.40*	*32.53*	*-3.36*	*-5.10*	*-8.07*	*-6.88*	*-6.83*	*-5.75*	*-6.66*	*-3.44*
E_{t+3}	**0.087**	**0.081**	**0.079**	**0.078**	**0.077**	**-0.007**	**-0.009**	**-0.002**	**-0.003**	**-0.002**	**-0.010**	**-0.011**	**-0.001**
	26.34	*29.40*	*29.64*	*29.15*	*29.26*	*-3.94*	*-5.21*	*-7.62*	*-6.47*	*-6.98*	*-6.33*	*-6.94*	*-3.44*
E_{t+4}	**0.099**	**0.090**	**0.088**	**0.088**	**0.086**	**-0.008**	**-0.010**	**-0.002**	**-0.003**	**-0.002**	**-0.011**	**-0.012**	**-0.001**
	23.55	*24.36*	*24.62*	*23.84*	*24.24*	*-4.40*	*-5.47*	*-5.56*	*-5.97*	*-6.10*	*-6.58*	*-6.98*	*-3.44*
E_{t+5}	**0.109**	**0.101**	**0.099**	**0.098**	**0.097**	**-0.009**	**-0.010**	**-0.001**	**-0.003**	**-0.002**	**-0.011**	**-0.013**	**-0.001**
	22.00	*20.66*	*21.31*	*20.61*	*21.16*	*-4.79*	*-5.33*	*-3.21*	*-6.10*	*-7.09*	*-6.96*	*-7.04*	*-2.26*

Panel C: ERC

	RW	HVZ	RI	CHVZ	CRI	HVZ-RW	RI-RW	RI-HVZ	CHVZ-HVZ	CRI-RI	CHVZ-RW	CRI-RW	CRI-CHVZ
E_{t+1}	**0.025**	**0.026**	**0.027**	**0.027**	**0.027**	0.001	**0.002**	**0.001**	**0.001**	0.000	**0.002**	**0.002**	0.000
	21.25	*19.63*	*19.43*	*19.78*	*19.98*	*1.58*	*3.09*	*3.66*	*4.82*	*-0.14*	*3.67*	*3.38*	*-1.60*
E_{t+2}	**0.038**	**0.043**	**0.044**	**0.045**	**0.045**	**0.005**	**0.006**	**0.001**	**0.002**	**0.001**	**0.007**	**0.007**	0.000
	17.84	*16.02*	*15.85*	*16.53*	*16.40*	*2.93*	*3.39*	*1.96*	*5.47*	*5.09*	*4.32*	*4.22*	*0.13*
E_{t+3}	**0.047**	**0.055**	**0.054**	**0.057**	**0.056**	**0.008**	**0.007**	-0.001	**0.002**	**0.002**	**0.010**	**0.009**	**-0.001**
	16.94	*14.59*	*14.39*	*15.13*	*14.76*	*2.70*	*2.58*	*-1.04*	*5.02*	*5.52*	*3.55*	*3.12*	*-1.97*
E_{t+4}	**0.054**	**0.064**	**0.062**	**0.066**	**0.064**	**0.010**	**0.008**	**-0.002**	**0.002**	**0.001**	**0.012**	**0.009**	**-0.003**
	18.63	*14.04*	*13.95*	*14.73*	*14.30*	*2.64*	*2.21*	*-2.84*	*4.23*	*3.39*	*3.49*	*2.67*	*-5.31*
E_{t+5}	**0.060**	**0.071**	**0.069**	**0.073**	**0.070**	**0.011**	**0.009**	**-0.002**	**0.002**	**0.001**	**0.013**	**0.010**	**-0.003**
	19.25	*12.01*	*11.97*	*12.85*	*12.32*	*2.43*	*2.06*	*-2.50*	*5.00*	*1.74*	*3.09*	*2.33*	*-3.90*

The averages of biases, accuracies and ERCs across years and their time-series *t* statistics (italics) are reported for reported earnings per share estimations. A bias is calculated as forecasted reported earnings per share minus actual reported earnings per share, divided by the stock price. An accuracy is calculated as the absolute difference between forecasted reported earnings per share and actual reported earnings per share, divided by the stock price. An ERC is calculated as the slope coefficient of a regression of future abnormal stock return on earnings surprise. For future abnormal stock return, the sum of quarterly earnings announcement returns from -1 day to +1 day of earnings announcements are used, adjusted to S&P 500 index returns. Earnings surprise is calculated as the difference between actual reported earnings per share minus forecasted reported earnings per share divided by the stock price. Earnings surprises are standardised to have a unit variance in each year. For the RW model, reported earnings per share at time *t* are used. For the differences between models in bias, the differences in absolute biases in each year are calculated to estimate the improvements in bias (i.e. the magnitude of bias approaching zero), instead of the differences in bias. For Columns 6 through 13, the negative values in bias and accuracy mean the first model (e.g. HVZ model in Column 6) improves the performance of the second model (RW model in Column 6). In ERC, the positive values mean the first model improves the performance of the second model. Bold numbers indicate significance at the 5% level.

Table 7
Bias, Accuracy and ERC: Street Earnings Per Share Estimations

Panel A: Bias

	(1) RW	(2) ANA	(3) HVZ	(4) RI	(5) CHVZ	(6) CRI	(7) HVZ-RW	(8) RI-RW	(9) HVZ-ANA	(10) RI-ANA	(11) RI-HVZ	(12) CHVZ-HVZ	(13) CRI-RI	(14) CHVZ-RW	(15) CRI-RW	(16) CHVZ-ANA	(17) CRI-ANA	(18) CRI-CHVZ
E_{t+1}	**-0.004**	**0.007**	-0.001	-0.002	**-0.004**	**-0.003**	-0.001	0.000	-0.002	-0.001	0.001	0.001	0.000	0.000	0.000	-0.001	-0.002	**-0.001**
	-2.82	*6.01*	*-0.52*	*-1.50*	*-2.91*	*-2.49*	*-0.57*	*-0.09*	*-1.49*	*-1.02*	*0.97*	*0.75*	*-0.47*	*0.57*	*-0.80*	*-0.63*	*-1.02*	*-1.81*
E_{t+2}	**-0.010**	**0.017**	**-0.005**	-0.004	**-0.007**	**-0.005**	-0.001	-0.002	**-0.006**	**-0.006**	0.000	0.001	0.000	-0.001	-0.002	-0.006	**-0.006**	**-0.001**
	-3.92	*7.20*	*-1.83*	*-1.62*	*-2.89*	*-2.22*	*-0.80*	*-1.09*	*-2.00*	*-2.22*	*-0.82*	*0.59*	*0.00*	*-0.91*	*-1.49*	*-1.63*	*-2.10*	*-1.83*
E_{t+3}	**-0.017**	**0.023**	**-0.009**	**-0.007**	**-0.010**	**-0.008**	**-0.004**	**-0.005**	**-0.009**	**-0.010**	**-0.001**	0.000	0.000	**-0.004**	**-0.005**	**-0.009**	**-0.010**	**-0.001**
	-5.08	*7.48*	*-2.74*	*-2.06*	*-3.20*	*-2.57*	*-1.95*	*-2.23*	*-1.95*	*-2.35*	*-1.76*	*0.31*	*0.08*	*-2.45*	*-2.65*	*-1.80*	*-2.25*	*-1.80*
E_{t+4}	**-0.025**	**0.030**	**-0.014**	**-0.011**	**-0.015**	**-0.012**	**-0.007**	**-0.010**	**-0.012**	**-0.014**	**-0.003**	0.000	0.000	**-0.007**	**-0.009**	**-0.012**	**-0.014**	**-0.002**
	-6.87	*8.47*	*-4.10*	*-3.21*	*-4.32*	*-3.57*	*-3.81*	*-4.30*	*-2.05*	*-2.69*	*-3.47*	*0.27*	*0.49*	*-4.85*	*-5.06*	*-1.95*	*-2.53*	*-3.35*
E_{t+5}	**-0.033**	**0.040**	**-0.019**	**-0.014**	**-0.019**	**-0.016**	**-0.012**	**-0.016**	**-0.019**	**-0.022**	**-0.004**	0.000	0.001	**-0.012**	**-0.015**	**-0.019**	**-0.022**	**-0.003**
	-8.39	*10.15*	*-5.27*	*-4.24*	*-5.34*	*-4.60*	*-6.20*	*-7.32*	*-2.76*	*-3.55*	*-4.76*	*-0.11*	*1.14*	*-7.76*	*-8.82*	*-2.72*	*-3.39*	*-3.29*

Panel B: Accuracy

	RW	ANA	HVZ	RI	CHVZ	CRI	HVZ-RW	RI-RW	HVZ-ANA	RI-ANA	RI-HVZ	CHVZ-HVZ	CRI-RI	CHVZ-RW	CRI-RW	CHVZ-ANA	CRI-ANA	CRI-CHVZ
E_{t+1}	**0.021**	**0.015**	**0.027**	**0.026**	**0.024**	**0.024**	**0.007**	**0.005**	**0.012**	**0.011**	**-0.002**	**-0.003**	**-0.001**	**0.004**	**0.004**	**0.009**	**0.009**	0.000
	25.16	*16.46*	*29.92*	*29.06*	*30.79*	*32.16*	*13.43*	*14.69*	*20.36*	*23.03*	*-6.10*	*-6.61*	*-3.56*	*12.87*	*12.65*	*14.94*	*14.69*	*-0.37*
E_{t+2}	**0.032**	**0.029**	**0.034**	**0.033**	**0.032**	**0.032**	**0.003**	**0.002**	**0.005**	**0.004**	**-0.001**	**-0.002**	**-0.002**	0.000	0.000	**0.003**	**0.002**	**0.000**
	30.27	*21.29*	*33.80*	*35.40*	*36.50*	*37.85*	*4.96*	*3.42*	*4.05*	*3.68*	*-4.70*	*-4.87*	*-3.70*	*1.34*	*0.13*	*2.17*	*1.93*	*-2.63*
E_{t+3}	**0.040**	**0.040**	**0.040**	**0.039**	**0.038**	**0.038**	-0.001	-0.001	-0.001	-0.001	**0.000**	**-0.002**	**-0.002**	**-0.002**	**-0.002**	-0.002	-0.002	0.000
	28.01	*24.93*	*29.00*	*30.71*	*29.85*	*33.36*	*-0.86*	*-1.36*	*-0.28*	*-0.50*	*-1.79*	*-4.15*	*-3.87*	*-5.27*	*-4.45*	*-1.25*	*-1.38*	*-0.22*
E_{t+4}	**0.048**	**0.051**	**0.045**	**0.044**	**0.043**	**0.043**	**-0.003**	**-0.004**	**-0.006**	**-0.007**	**-0.001**	**-0.002**	**-0.001**	**-0.005**	**-0.005**	**-0.008**	**-0.008**	0.000
	22.43	*27.92*	*25.66*	*26.57*	*24.71*	*27.94*	*-4.02*	*-4.26*	*-2.75*	*-3.25*	*-2.94*	*-4.44*	*-3.01*	*-6.38*	*-5.94*	*-3.35*	*-3.77*	*-1.32*
E_{t+5}	**0.056**	**0.065**	**0.051**	**0.050**	**0.049**	**0.049**	**-0.006**	**-0.006**	**-0.014**	**-0.014**	**-0.001**	**-0.001**	**-0.001**	**-0.007**	**-0.008**	**-0.015**	**-0.016**	**-0.001**
	20.86	*28.58*	*25.57*	*25.97*	*24.30*	*25.57*	*-5.67*	*-6.02*	*-5.44*	*-5.95*	*-2.56*	*-4.17*	*-2.98*	*-7.03*	*-6.96*	*-5.82*	*-6.27*	*-2.60*

Panel C: ERC

	RW	ANA	HVZ	RI	CHVZ	CRI	HVZ-RW	RI-RW	HVZ-ANA	RI-ANA	RI-HVZ	CHVZ-HVZ	CRI-RI	CHVZ-RW	CRI-RW	CHVZ-ANA	CRI-ANA	CRI-CHVZ
E_{t+1}	**0.025**	**0.029**	**0.021**	**0.023**	**0.025**	**0.025**	**-0.004**	**-0.002**	**-0.008**	**-0.006**	**0.002**	**0.003**	**0.002**	-0.001	-0.001	**-0.004**	**-0.004**	0.000
	18.63	*13.55*	*13.18*	*15.42*	*19.21*	*19.66*	*-3.94*	*-2.25*	*-5.65*	*-4.07*	*3.99*	*5.92*	*3.49*	*-0.78*	*-0.67*	*-2.86*	*-2.83*	*0.31*
E_{t+2}	**0.044**	**0.051**	**0.045**	**0.047**	**0.050**	**0.049**	0.001	0.003	**-0.006**	**-0.004**	**0.002**	**0.006**	**0.002**	**0.007**	**0.005**	-0.001	-0.002	**-0.002**
	16.46	*13.81*	*14.72*	*14.77*	*18.87*	*18.09*	*0.51*	*1.50*	*-3.67*	*-2.69*	*4.27*	*6.67*	*2.12*	*4.41*	*3.50*	*-0.30*	*-1.37*	*-3.68*
E_{t+3}	**0.058**	**0.064**	**0.060**	**0.061**	**0.065**	**0.063**	0.002	0.003	**-0.004**	-0.002	0.001	**0.005**	0.001	**0.007**	**0.005**	0.001	-0.001	**-0.002**
	17.06	*11.75*	*11.83*	*11.67*	*13.92*	*13.31*	*0.74*	*0.99*	*-1.91*	*-1.20*	*1.46*	*5.90*	*1.17*	*2.84*	*1.86*	*0.47*	*-0.57*	*-2.89*
E_{t+4}	**0.067**	**0.074**	**0.077**	**0.077**	**0.081**	**0.079**	**0.010**	**0.011**	0.003	0.003	0.001	**0.004**	0.002	**0.014**	**0.013**	**0.007**	**0.005**	**-0.002**
	17.87	*12.28*	*11.77*	*11.10*	*13.39*	*12.71*	*2.48*	*2.29*	*1.37*	*1.37*	*0.64*	*6.34*	*1.47*	*4.03*	*3.48*	*3.88*	*2.58*	*-2.13*
E_{t+5}	**0.075**	**0.082**	**0.090**	**0.089**	**0.094**	**0.092**	**0.015**	**0.014**	**0.008**	**0.007**	-0.001	**0.004**	0.002	**0.019**	**0.017**	**0.012**	**0.010**	**-0.003**
	15.91	*13.61*	*11.42*	*10.98*	*12.80*	*12.61*	*2.39*	*2.20*	*2.11*	*1.80*	*-0.85*	*4.23*	*1.34*	*3.35*	*3.12*	*3.83*	*3.18*	*-2.95*

The averages of biases, accuracies and ERCs across years and their time-series *t* statistics (italics) are reported for street earnings per share estimations. A bias is calculated as forecasted street earnings per share minus actual street earnings per share, divided by the stock price. An accuracy is calculated as the absolute difference between forecasted street earnings per share and actual street earnings per share, divided by the stock price. An ERC is calculated as the slope coefficient of a regression of future abnormal stock return on earnings surprise. For future abnormal stock return, the sum of quarterly earnings announcement returns from -1 day to +1 day of earnings announcements are used, adjusted to S&P 500 index returns. Earnings surprise is calculated as the difference between actual street earnings per share minus forecasted street earnings per share divided by the stock price. Earnings surprises are standardised to have a unit variance in each year. For the RW model, street earnings per share at time *t* are used, and ANA indicates analyst forecasts. For the differences between models in bias, the differences in absolute biases in each year are calculated to estimate the improvements in bias (i.e. the magnitude of bias approaching zero), instead of the differences in bias. For Columns 7 through 17, the negative values in bias and accuracy mean the first model (e.g. HVZ model in Column 7) improves the performance of the second model (RW model in Column 7). In ERC, the positive values mean the first model improves the performance of the second model. Bold numbers indicate significance at the 5% level.

Table 8
Difference between CHVZ and HVZ: Unscaled Earnings

Panel A: Bias

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	0.003	**0.005**	**-0.007**	**-0.016**	**-0.005**	0.004	-0.001	0.000	0.001	-0.001	**-0.011**	0.003	-0.001	4	8	1
	1.68	*3.24*	*-4.38*	*-5.87*	*-2.46*	*1.43*	*-1.62*	*0.64*	*0.75*	*-0.19*	*-2.54*	*0.90*	*-0.53*			
E_{t+2}	-0.002	**0.005**	**-0.007**	**-0.020**	**-0.012**	**0.012**	-0.001	0.001	-0.002	-0.007	**-0.022**	0.001	-0.002	4	7	2
	-0.63	*2.03*	*-3.51*	*-3.70*	*-3.22*	*3.29*	*-1.21*	*1.45*	*-0.94*	*-1.56*	*-3.51*	*0.13*	*-0.46*			
E_{t+3}	0.002	0.005	**-0.008**	**-0.022**	**-0.019**	**0.011**	-0.001	**0.001**	0.003	**-0.014**	**-0.030**	-0.005	-0.002	5	6	2
	0.48	*0.94*	*-3.16*	*-3.72*	*-3.55*	*2.09*	*-0.89*	*1.88*	*1.55*	*-2.76*	*-5.11*	*-0.72*	*-0.47*			
E_{t+4}	0.009	-0.004	**-0.013**	**-0.026**	**-0.023**	**-0.011**	-0.001	0.001	**0.005**	**-0.022**	**-0.048**	-0.006	-0.005	6	6	1
	1.15	*-0.77*	*-3.32*	*-4.23*	*-3.16*	*-2.34*	*-0.53*	*1.02*	*2.62*	*-3.58*	*-8.45*	*-0.88*	*-0.68*			
E_{t+5}	-0.006	**-0.022**	**-0.017**	**-0.045**	**-0.033**	-0.010	-0.002	-0.001	**0.010**	**-0.040**	**-0.069**	**-0.018**	-0.005	7	5	1
	-0.64	*-3.94*	*-3.90*	*-5.85*	*-4.80*	*-1.09*	*-1.08*	*-0.52*	*3.10*	*-5.22*	*-7.42*	*-3.08*	*-0.37*			

Panel B: Accuracy

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	-0.001	0.000	**-0.003**	**-0.008**	**-0.004**	0.003	**-0.001**	**-0.001**	**-0.002**	**0.005**	**-0.005**	**0.007**	0.000	7	4	2
	-0.67	*0.27*	*-4.46*	*-4.34*	*-4.01*	*1.45*	*-3.91*	*-2.61*	*-4.25*	*3.04*	*-3.46*	*6.36*	*-0.09*			
E_{t+2}	-0.003	-0.001	-0.001	**-0.013**	**-0.008**	0.003	**-0.001**	-0.001	-0.001	0.000	**-0.015**	**0.008**	-0.004	4	8	1
	-1.45	*-0.37*	*-1.14*	*-3.73*	*-3.80*	*1.22*	*-3.53*	*-1.33*	*-1.29*	*0.05*	*-5.01*	*4.89*	*-1.07*			
E_{t+3}	0.003	0.001	-0.002	**-0.011**	**-0.009**	**0.006**	**-0.001**	**0.001**	0.000	**-0.005**	**-0.022**	**0.005**	0.008	5	5	3
	1.26	*0.34*	*-1.24*	*-3.67*	*-3.21*	*2.57*	*-3.35*	*2.04*	*0.29*	*-1.86*	*-7.77*	*2.89*	*0.69*			
E_{t+4}	**0.010**	**-0.006**	**-0.007**	**-0.015**	**-0.014**	**-0.008**	**-0.001**	0.000	**0.004**	**-0.013**	**-0.031**	0.000	0.039	8	3	2
	1.89	*-2.02*	*-3.45*	*-4.93*	*-4.47*	*-3.23*	*-2.22*	*0.74*	*1.85*	*-4.02*	*-10.03*	*-0.06*	*1.23*			
E_{t+5}	0.001	**-0.014**	**-0.011**	**-0.027**	**-0.023**	**-0.012**	**-0.001**	**0.002**	**0.006**	**-0.026**	**-0.049**	**-0.009**	0.037	9	2	2
	0.27	*-3.64*	*-5.13*	*-5.82*	*-5.68*	*-2.19*	*-2.44*	*3.05*	*2.61*	*-5.83*	*-10.77*	*-4.56*	*1.45*			

Panel C: ERC

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	**0.002**	0.001	-0.001	**0.004**	0.001	0.001	0.000	0.000	**0.002**	**0.002**	**0.003**	0.001	**0.002**	6	7	0
	2.76	*0.88*	*-0.54*	*3.34*	*1.34*	*1.44*	*-0.49*	*0.36*	*3.45*	*2.00*	*2.11*	*1.31*	*2.50*			
E_{t+2}	**0.003**	**0.002**	-0.001	**0.006**	**0.008**	**0.002**	0.000	0.000	0.000	**0.006**	**0.008**	**0.004**	0.003	8	5	0
	3.13	*2.24*	*-0.31*	*2.86*	*5.56*	*1.88*	*0.70*	*0.11*	*0.31*	*4.16*	*4.33*	*1.94*	*1.66*			
E_{t+3}	0.001	**0.005**	0.000	**0.009**	**0.013**	**0.006**	0.001	-0.001	0.001	**0.012**	**0.009**	**0.014**	**0.008**	8	5	0
	0.64	*2.92*	*0.21*	*4.13*	*6.92*	*4.04*	*0.66*	*-0.83*	*0.97*	*6.03*	*4.49*	*5.26*	*4.55*			
E_{t+4}	**0.005**	**0.009**	0.003	**0.010**	**0.016**	**0.012**	-0.001	-0.001	**0.003**	**0.015**	**0.008**	**0.019**	**0.009**	10	3	0
	2.50	*3.24*	*1.09*	*3.65*	*5.90*	*4.87*	*-0.44*	*-1.08*	*2.57*	*4.63*	*3.50*	*4.36*	*3.44*			
E_{t+5}	**0.009**	**0.008**	0.002	**0.017**	**0.015**	**0.014**	**-0.003**	-0.002	0.000	**0.015**	**0.010**	**0.022**	**0.006**	9	3	1
	4.45	*2.58*	*0.84*	*4.94*	*5.11*	*3.78*	*-3.98*	*-1.26*	*0.08*	*4.76*	*4.10*	*4.48*	*2.20*			

The averages of differences between the CHVZ and HVZ models in bias, accuracy and ERC across years and their time-series *t* statistics (italics) are reported for unscaled earnings estimations. A bias is calculated as forecasted earnings minus actual earnings, divided by the current market value. An accuracy is calculated as the absolute difference between forecasted earnings and actual earnings, divided by the current market value. An ERC is calculated as the slope coefficient of a regression of future abnormal stock return on earnings surprise. For future abnormal stock return, the sum of quarterly earnings announcement returns from -1 day to +1 day of earnings announcements are used, adjusted to S&P 500 index returns. Earnings surprise is calculated as the difference between actual earnings minus forecasted earnings divided by the current market value. Earnings surprises are standardised to have a unit variance in each year. For the differences between models in bias, the differences in absolute biases in each year are calculated to estimate the improvements in bias (i.e. the magnitude of bias approaching zero), instead of the differences in bias. Negative values in bias and accuracy mean the CHVZ model improves the performance of the HVZ model. In ERC, the positive values mean the CHVZ model improves the performance of the HVZ model. B/M is a book-to-market ratio; past returns are based on the past one-year stock returns; size is calculated as the market value of equity; 5YR indicates the models are estimated based on the past five years' data, instead of the past ten years' data; industry indicates the models are estimated in each industry based on the first digit of the SIC codes and the averages across industries are reported; (B) indicates the number of subsamples that the CHVZ model performs significantly better than the HVZ model; (E) indicates the number of subsamples that the CHVZ model performs equally well as the HVZ model; and (W) indicates the number of subsamples that the CHVZ model performs significantly worse than the HVZ model. Bold numbers indicate significance at the 5% level.

Table 9
Difference between CHVZ and HVZ: Reported Earnings Per Share

Panel A: Bias

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	-0.001	0.000	**-0.001**	**-0.002**	-0.001	0.000	**-0.002**	-0.001	0.000	0.000	-0.001	0.001	**0.002**	3	9	1
	-1.39	*0.27*	*-2.25*	*-2.74*	*-0.88*	*0.18*	*-2.03*	*-1.08*	*0.72*	*-0.23*	*-0.69*	*0.70*	*2.22*			
E_{t+2}	-0.001	0.000	**-0.002**	-0.002	-0.001	0.000	**-0.002**	0.000	0.001	0.000	-0.001	0.000	0.001	2	11	0
	-0.61	*-0.43*	*-2.56*	*-1.68*	*-0.70*	*0.46*	*-1.76*	*0.07*	*1.02*	*0.32*	*-0.31*	*0.19*	*1.18*			
E_{t+3}	**-0.002**	-0.001	-0.001	-0.002	-0.002	-0.001	-0.002	-0.001	0.000	0.000	**-0.004**	0.000	-0.001	2	11	0
	-1.80	*-1.08*	*-0.71*	*-1.42*	*-1.36*	*-1.51*	*-1.41*	*-0.67*	*-0.13*	*-0.12*	*-2.24*	*0.08*	*-0.86*			
E_{t+4}	0.000	**-0.002**	-0.001	-0.001	-0.001	-0.001	-0.002	0.000	0.001	0.000	-0.003	0.000	0.001	1	12	0
	0.00	*-2.08*	*-1.25*	*-1.20*	*-1.22*	*-0.85*	*-1.54*	*-0.16*	*1.07*	*0.03*	*-1.60*	*0.38*	*0.32*			
E_{t+5}	0.000	-0.001	0.000	0.000	-0.001	**-0.002**	-0.002	-0.001	0.001	0.000	-0.003	0.000	0.004	1	12	0
	0.00	*-1.51*	*-0.83*	*0.17*	*-1.08*	*-2.72*	*-1.49*	*-0.92*	*0.92*	*-0.55*	*-1.36*	*0.94*	*0.76*			

Panel B: Accuracy

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	**-0.001**	**-0.001**	**-0.002**	**-0.003**	**-0.001**	**-0.001**	**-0.003**	**-0.002**	**-0.001**	**-0.002**	**-0.002**	**-0.001**	0.000	12	1	0
	-4.25	*-4.93*	*-10.86*	*-9.05*	*-5.99*	*-3.22*	*-6.36*	*-5.47*	*-5.70*	*-7.05*	*-5.68*	*-4.40*	*-0.65*			
E_{t+2}	**-0.001**	**-0.001**	**-0.002**	**-0.004**	**-0.002**	**-0.001**	**-0.004**	**-0.003**	**-0.001**	**-0.002**	**-0.004**	**-0.001**	0.000	12	1	0
	-3.53	*-4.82*	*-5.44*	*-6.65*	*-5.57*	*-2.76*	*-6.55*	*-4.43*	*-3.98*	*-7.14*	*-10.13*	*-4.34*	*0.05*			
E_{t+3}	**-0.002**	**-0.001**	**-0.002**	**-0.004**	**-0.003**	**-0.001**	**-0.005**	**-0.003**	**-0.001**	**-0.003**	**-0.005**	**-0.001**	0.001	12	1	0
	-3.87	*-3.00*	*-4.22*	*-7.11*	*-5.99*	*-1.88*	*-6.13*	*-4.50*	*-2.89*	*-6.89*	*-10.75*	*-3.56*	*0.74*			
E_{t+4}	-0.001	**-0.001**	**-0.001**	**-0.003**	**-0.003**	0.000	**-0.005**	**-0.002**	-0.001	**-0.002**	**-0.005**	**-0.001**	0.004	9	4	0
	-1.26	*-2.91*	*-2.74*	*-5.05*	*-5.92*	*-0.78*	*-6.07*	*-3.45*	*-1.47*	*-6.27*	*-8.60*	*-3.32*	*1.51*			
E_{t+5}	0.000	**-0.002**	-0.001	**-0.001**	**-0.002**	**-0.002**	**-0.004**	**-0.003**	0.000	**-0.002**	**-0.005**	**-0.001**	0.018	9	4	0
	0.17	*-3.61*	*-1.57*	*-2.95*	*-1.69*	*-3.23*	*-3.90*	*-4.17*	*0.71*	*-5.72*	*-11.89*	*-2.36*	*1.38*			

Panel C: ERC

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	**0.001**	**0.001**	**0.001**	**0.002**	**0.002**	**0.002**	**0.001**	**0.001**	**0.001**	**0.002**	**0.001**	**0.002**	**0.001**	13	0	0
	2.05	*4.07*	*2.22*	*5.16*	*3.98*	*2.89*	*1.72*	*2.11*	*2.11*	*4.79*	*2.22*	*5.16*	*3.49*			
E_{t+2}	**0.003**	**0.002**	**0.002**	**0.002**	**0.002**	0.001	**0.002**	**0.001**	**0.003**	**0.002**	**0.002**	**0.002**	**0.002**	12	1	0
	5.21	*4.19*	*2.41*	*3.66*	*2.93*	*1.10*	*4.65*	*1.70*	*2.80*	*5.07*	*4.49*	*3.44*	*4.36*			
E_{t+3}	**0.002**	**0.002**	**0.002**	**0.003**	**0.001**	0.000	**0.003**	0.001	0.001	**0.003**	**0.002**	**0.002**	**0.002**	10	3	0
	3.21	*3.21*	*2.38*	*2.89*	*1.71*	*0.12*	*3.33*	*1.21*	*1.18*	*5.55*	*6.02*	*2.40*	*2.42*			
E_{t+4}	0.001	**0.002**	0.001	0.001	**0.003**	0.001	**0.005**	0.001	0.000	**0.003**	**0.003**	**0.002**	0.001	6	7	0
	1.11	*2.07*	*0.85*	*0.90*	*4.51*	*0.39*	*6.01*	*0.76*	*0.45*	*4.87*	*4.12*	*2.08*	*1.29*			
E_{t+5}	**0.002**	**0.004**	0.000	**0.003**	0.002	**0.003**	**0.005**	0.001	-0.001	**0.002**	**0.004**	**0.001**	0.001	8	5	0
	2.54	*4.01*	*0.43*	*2.67*	*1.01*	*2.49*	*4.68*	*0.71*	*-1.04*	*4.18*	*5.11*	*2.43*	*0.62*			

The averages of differences between the CHVZ and HVZ models in bias, accuracy and ERC across years and their time-series *t* statistics (italics) are reported for reported earnings per share estimations. A bias is calculated as forecasted reported earnings per share minus actual reported earnings per share, divided by the stock price. An accuracy is calculated as the absolute difference between forecasted reported earnings per share and actual reported earnings per share, divided by the stock price. An ERC is calculated as the slope coefficient of a regression of future abnormal stock return on earnings surprise. For future abnormal stock return, the sum of quarterly earnings announcement returns from -1 day to +1 day of earnings announcements are used, adjusted to S&P 500 index returns. Earnings surprise is calculated as the difference between actual reported earnings per share minus forecasted reported earnings per share divided by the stock price. Earnings surprises are standardised to have a unit variance in each year. For the differences between models in bias, the differences in absolute biases in each year are calculated to estimate the improvements in bias (i.e. the magnitude of bias approaching zero), instead of the differences in bias. Negative values in bias and accuracy mean the CHVZ model improves the performance of the HVZ model. In ERC, the positive values mean the CHVZ model improves the performance of the HVZ model. B/M is a book-to-market ratio; past returns are based on the past one-year stock returns; size is calculated as the market value of equity; 5YR indicates the models are estimated based on the past five years' data, instead of the past ten years' data; industry indicates the models are estimated in each industry based on the first digit of the SIC codes and the averages across industries are reported; (B) indicates the number of subsamples that the CHVZ model performs significantly better than the HVZ model; (E) indicates the number of subsamples that the CHVZ model performs equally well as the HVZ model; and (W) indicates the number of subsamples that the CHVZ model performs significantly worse than the HVZ model. Bold numbers indicate significance at the 5% level.

Table 10
Difference between CHVZ and HVZ: Street Earnings Per Share

Panel A: Bias

	B/M			Past Returns			Size							
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	Industry	(B)	(E)	(W)
E_{t+1}	0.000	0.000	-0.001	-0.001	0.001	**0.003**	0.000	0.001	-0.001	0.000	0.000	0	10	1
	0.00	*0.59*	*-1.50*	*-1.36*	*1.03*	*3.42*	*-0.40*	*0.68*	*-0.25*	*0.34*	*0.25*			
E_{t+2}	0.000	0.000	0.000	0.000	0.001	0.002	0.001	0.001	0.003	0.001	0.000	0	11	0
	-0.30	*0.80*	*0.55*	*0.26*	*0.95*	*1.38*	*0.64*	*1.66*	*1.11*	*0.75*	*0.25*			
E_{t+3}	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.003	0.001	0.001	0	11	0
	0.26	*1.37*	*0.26*	*-0.29*	*0.48*	*1.63*	*0.30*	*1.45*	*1.42*	*1.65*	*0.61*			
E_{t+4}	0.001	0.000	0.000	0.000	0.000	**0.001**	0.001	0.000	**0.004**	0.001	0.001	0	9	2
	1.08	*0.00*	*-0.23*	*0.28*	*-0.32*	*2.03*	*0.74*	*-0.21*	*1.94*	*1.44*	*0.57*			
E_{t+5}	-0.001	0.000	0.000	0.001	**-0.001**	0.000	0.000	**-0.001**	**0.003**	0.001	-0.001	2	8	1
	-0.64	*-1.10*	*0.76*	*0.88*	*-2.05*	*0.10*	*0.26*	*-2.37*	*1.91*	*1.43*	*-0.55*			

Panel B: Accuracy

	B/M			Past Returns			Size							
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	Industry	(B)	(E)	(W)
E_{t+1}	0.000	**-0.001**	**-0.003**	**-0.004**	**-0.002**	0.000	**-0.003**	**-0.002**	-0.005	**-0.003**	**-0.002**	8	3	0
	-0.22	*-2.98*	*-6.67*	*-5.69*	*-5.41*	*0.58*	*-5.51*	*-4.95*	*-1.48*	*-7.74*	*-6.84*			
E_{t+2}	0.000	**-0.001**	**-0.002**	**-0.003**	**-0.002**	0.001	**-0.002**	**-0.001**	0.002	**-0.002**	**-0.003**	8	3	0
	-1.05	*-2.05*	*-4.35*	*-3.87*	*-6.16*	*1.06*	*-3.86*	*-1.87*	*0.81*	*-4.70*	*-3.94*			
E_{t+3}	**-0.002**	**-0.001**	**-0.002**	**-0.002**	**-0.002**	0.000	**-0.002**	-0.001	0.001	**-0.002**	**-0.003**	8	3	0
	-4.91	*-2.99*	*-3.64*	*-4.15*	*-7.06*	*0.52*	*-3.42*	*-1.67*	*0.39*	*-5.10*	*-3.67*			
E_{t+4}	**-0.001**	**-0.001**	**-0.001**	**-0.002**	**-0.002**	-0.001	**-0.002**	**-0.001**	0.001	**-0.001**	**-0.002**	9	2	0
	-3.28	*-3.49*	*-3.21*	*-3.81*	*-5.18*	*-1.22*	*-3.50*	*-2.82*	*0.30*	*-4.19*	*-3.06*			
E_{t+5}	-0.001	**-0.001**	**-0.001**	**-0.001**	**-0.001**	0.000	**-0.002**	**-0.001**	0.002	**-0.001**	**-0.002**	8	3	0
	-1.66	*-3.57*	*-3.76*	*-3.32*	*-4.21*	*-0.91*	*-2.79*	*-2.70*	*0.89*	*-3.64*	*-2.06*			

Panel C: ERC

	B/M			Past Returns			Size							
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	Industry	(B)	(E)	(W)
E_{t+1}	**0.003**	**0.002**	**0.003**	**0.004**	**0.004**	**0.002**	**0.004**	**0.002**	-0.001	**0.003**	**0.003**	10	1	0
	2.53	*3.60*	*3.63*	*3.62*	*4.51*	*2.92*	*4.74*	*4.29*	*-0.37*	*5.20*	*3.92*			
E_{t+2}	**0.005**	**0.004**	**0.005**	**0.005**	**0.006**	0.002	**0.004**	**0.004**	-0.001	**0.005**	**0.006**	9	2	0
	5.37	*5.45*	*3.05*	*3.85*	*5.56*	*0.83*	*3.94*	*3.87*	*-0.27*	*5.11*	*6.95*			
E_{t+3}	0.003	**0.006**	**0.006**	**0.004**	**0.006**	0.001	**0.005**	0.001	0.000	**0.004**	**0.005**	7	4	0
	1.42	*5.67*	*4.91*	*3.52*	*6.56*	*0.69*	*6.27*	*0.63*	*0.22*	*5.23*	*3.52*			
E_{t+4}	0.002	**0.005**	**0.003**	0.002	**0.003**	0.001	**0.006**	0.000	0.000	**0.005**	**0.005**	6	5	0
	1.41	*4.03*	*2.01*	*1.02*	*2.12*	*0.81*	*7.16*	*0.15*	*0.16*	*6.83*	*2.40*			
E_{t+5}	**0.006**	**0.005**	0.000	**0.005**	**0.003**	-0.001	**0.009**	-0.001	0.000	**0.003**	**0.007**	7	4	0
	2.96	*3.56*	*0.00*	*2.66*	*2.54*	*-0.44*	*5.44*	*-1.19*	*0.10*	*2.63*	*3.70*			

The averages of differences between the CHVZ and HVZ models in bias, accuracy and ERC across years and their time-series *t* statistics (italics) are reported for street earnings per share estimations. A bias is calculated as forecasted street earnings per share minus actual street earnings per share, divided by the stock price. An accuracy is calculated as the absolute difference between forecasted street earnings per share and actual street earnings per share, divided by the stock price. An ERC is calculated as the slope coefficient of a regression of future abnormal stock return on earnings surprise. For future abnormal stock return, the sum of quarterly earnings announcement returns from -1 day to +1 day of earnings announcements are used, adjusted to S&P 500 index returns. Earnings surprise is calculated as the difference between actual street earnings per share minus forecasted street earnings per share divided by the stock price. Earnings surprises are standardised to have a unit variance in each year. For the differences between models in bias, the differences in absolute biases in each year are calculated to estimate the improvements in bias (i.e. the magnitude of bias approaching zero), instead of the differences in bias. Negative values in bias and accuracy mean the CHVZ model improves the performance of the HVZ model. In ERC, the positive values mean the CHVZ model improves the performance of the HVZ model. B/M is a book-to-market ratio; past returns are based on the past one-year stock returns; size is calculated as the market value of equity; 5YR indicates the models are estimated based on the past five years' data, instead of the past ten years' data; industry indicates the models are estimated in each industry based on the first digit of the SIC codes and the averages across industries are reported; (B) indicates the number of subsamples that the CHVZ model performs significantly better than the HVZ model; (E) indicates the number of subsamples that the CHVZ model performs equally well as the HVZ model; and (W) indicates the number of subsamples that the CHVZ model performs significantly worse than the HVZ model. Bold numbers indicate significance at the 5% level.

6. Conclusion

The thesis aims to improve the practices of price and earnings estimations. For price estimation, the thesis first addresses the decade-old puzzle in Liu, Nissim and Thomas (2002): the outperformance of multiples using earnings forecasts over multiples using the residual income model in pricing error. Their finding is peculiar given the fact that the residual income model is developed from valuation theory and in fact contains earnings forecasts as its elements. The puzzle undermines the validity of theory-based valuation models and still has remained unresolved (Cooper and Lambertides, 2014). The second issue that the thesis addresses is the problem of cross-sectional models in earnings estimation. Although cross-sectional models have wider coverage, higher statistical power and suffer less from survivorship bias than time-series models, they suffer from one fundamental problem: the loss of firm-specific information in earnings forecasts (Kothari, 2001). This occurs because earnings forecasts from cross-sectional models are estimated based on the same coefficients across firms and, hence, the same earnings persistence and future prospects are applied to all firms.

The first two projects of the thesis address the puzzle in Liu, Nissim and Thomas (2002). The first project examines the results of Liu, Nissim and Thomas (2002) and finds that the puzzling result is a dominant finding in price estimation: multiples using earnings forecasts outperform multiples using the residual income model across four dimensions (i.e. time, countries, calculation methods and performance criteria). An investigation into how it happens improves our understanding in price estimation. Therefore, the first project lays the groundwork for the second project.

The second project explains mathematically how the pricing error of a multiple is determined by the correlation coefficient between price and a value driver. The project demonstrates that the reason why Liu, Nissim and Thomas (2002) find the puzzling result is that they accidentally select the worst-performing residual income models and compare them with the best-performing value drivers in multiples. The project shows that, in fact, the majority of residual income models (i.e. well-chosen residual income models) have higher correlation coefficients with price than earnings forecasts and perform better than earnings forecasts in multiples in pricing error. When future stock returns are estimated, the majority of residual income models again outperform multiples using earnings forecasts, suggesting the superiority of theory-based valuation models to rule-of-thumb based multiples in price and intrinsic value estimations.

The third project addresses the problem of cross-sectional models in earnings estimation by introducing a conditional cross-sectional model. A conditional cross-sectional model allows the coefficient on earnings to vary across firms based on their accounting factors. Therefore, different earnings persistence and future prospects are applied to firms to estimate their earnings forecasts. By improving model specification, a conditional cross-sectional model uses the same amount of information as a cross-sectional model does but overcomes the main weakness of a cross-sectional model. The results show that a conditional cross-sectional model improves the performance of a cross-sectional model: a) across bias, accuracy and ERC; b) for unscaled and scaled earnings estimations; and c) for all forecast horizons. Earnings forecasts from a conditional cross-sectional model still underperforms analyst forecasts in accuracy for the one- and two-year ahead forecast horizons, and in ERC for the one-year ahead forecast horizon. This is partly due to an information advantage analysts have that they can use non-accounting information for their earnings forecasts (Fried and Givoly, 1982; O'Brien, 1988). However, the advantage diminishes monotonically as a forecast horizon lengthens and it disappears when three-year ahead earnings forecasts are estimated. From the four-year ahead earnings forecasts (i.e. the long-term earnings forecasts), a conditional cross-sectional model actually outperforms analyst forecasts statistically in bias, accuracy and ERC. Therefore, the use of a conditional cross-sectional model is recommended over analyst forecasts especially when the long-term earnings forecasts are estimated.

The thesis contributes to the price and earnings estimations literature. First, by addressing the decade-old puzzle in price estimation, the thesis explains how the puzzling result occurs and rectifies the previous misunderstanding that rule-of-thumb based models outperform theory-based valuation models in pricing error. The thesis provides evidence supporting the superiority of theory-based valuation models over rule-of-thumb based multiples, and encourages future researchers to further develop theory-based valuation models. Second, the thesis provides a new model, a conditional cross-sectional model, which overcomes the fundamental problem of a cross-sectional model in earnings estimation. According to a conditional cross-sectional model, firms apply different earnings coefficients and future prospects to estimate their earnings forecasts. By improving model specification, a conditional cross-sectional model keeps the advantages of a cross-sectional model but addresses its main weakness and improves its performance.

References

Abarbanell, Jeffery S., 1991, Do analysts' earnings forecasts incorporate information in prior stock price changes?, *Journal of Accounting and Economics* 14, 147–165.

Abarbanell, Jeffery S., and Victor L. Bernard, 1992, Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior, *The Journal of Finance* 47, 1181–1207.

Affleck-Graves, John, Larry R. Davis, and Richard R. Mendenhall, 1990, Forecasts of earnings per share: possible sources of analyst superiority and bias, *Contemporary Accounting Research* 6, 501–517.

Agarwal, Vineet, and Richard Taffler, 2008, Comparing the performance of market-based and accounting-based bankruptcy prediction models, *Journal of Banking & Finance* 32, 1541–1551.

Akbar, Saeed, and Andrew W. Stark, 2003, Deflators, net shareholder cash flows, dividends, capital contributions and estimated models of corporate valuation, *Journal of Business Finance & Accounting* 30, 1211–1233.

Albrecht, W. Steve, Larry L. Lookabill, and James C. McKeown, 1977, The time-series properties of annual earnings, *Journal of Accounting Research* 15, 226–244.

Ali, Ashiq, April Klein, and James Rosenfeld, 1992, Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS, *The Accounting Review*, 183–198.

Ali, Ashiq, and Peter F. Pope, 1995, The incremental information content of earnings, funds flow and cash flow: the UK evidence, *Journal of Business Finance & Accounting* 22, 19–34.

Arnold, John, and Peter Moizer, 1984, A survey of the methods used by UK investment analysts to appraise investments in ordinary shares, *Accounting and Business Research* 14, 195–207.

Asquith, Paul, Michael B. Mikhail, and Andrea S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245–282.

Baker, Malcolm, and Richard S. Ruback, 1999, Estimating industry multiples, *Working Paper, Harvard University*.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research*, 159–178.

Ball, Ray, and Ross Watts, 1972, Some time series properties of accounting income, *The Journal of Finance* 27, 663–681.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.

Barefield, Russell M., and Eugene E. Comiskey, 1975, The accuracy of analysts' forecasts of earnings per share, *Journal of Business Research* 3, 241–252.

Barker, Richard, 2001, *Determining Value: Valuation Models and Financial Statements* (Pearson Education).

Barker, Richard G., 1999a, Survey and market-based evidence of industry-dependence in analysts' preferences between the dividend yield and price-earnings ratio valuation models, *Journal of Business Finance & Accounting* 26, 393–418.

Barker, Richard G., 1999b, The role of dividends in valuation models used by analysts and fund managers, *European Accounting Review* 8, 195–218.

Barth, Mary E., William H. Beaver, and Wayne R. Landsman, 1998, Relative valuation roles of equity book value and net income as a function of financial health, *Journal of Accounting and Economics* 25, 1–34.

Barth, Mary E., William H. Beaver, and Wayne R. Landsman, 2001, The relevance of the value relevance literature for financial accounting standard setting: another view, *Journal of Accounting and Economics* 31, 77–104.

Barth, Mary E., and Greg Clinch, 1996, International accounting differences and their relation to share prices: Evidence from UK, Australian, and Canadian firms, *Contemporary Accounting Research* 13, 135–170.

Barth, Mary E., and Greg Clinch, 2009, Scale effects in capital markets-based accounting research, *Journal of Business Finance & Accounting* 36, 253–288.

Barth, Mary E., Donald P. Cram, and Karen K. Nelson, 2001, Accruals and the prediction of future cash flows, *The Accounting Review* 76, 27–58.

Basu, Sanjoy, 1977, Investment performance of common stocks in relation to their price-earnings ratios: a test of the efficient market hypothesis, *The Journal of Finance* 32, 663–682.

Basu, Sudipta, 1997, The conservatism principle and the asymmetric timeliness of earnings, *Journal of Accounting and Economics* 24, 3–37.

Beaver, William H., 1968, The information content of annual earnings announcements, *Journal of Accounting Research*, 67–92.

Beaver, William, Richard Lambert, and Dale Morse, 1980, The information content of security prices, *Journal of Accounting and Economics* 2, 3–28.

Berkman, Henk, Michael E. Bradbury, and Jason Ferguson, 2000, The accuracy of price-earnings and discounted cash flow methods of IPO equity valuation, *Journal of International Financial Management and Accounting* 11, 71–83.

Bernard, Victor L., 1995, The Feltham-Ohlson framework: implications for empiricists, *Contemporary Accounting Research* 11, 733–747.

Bhattacharya, Sudipto, 1979, Imperfect information, dividend policy, and “the bird in the hand” fallacy, *The Bell Journal of Economics*, 259–270.

Biddle, Gary C., Robert M. Bowen, and James S. Wallace, 1997, Does EVA beat earnings? Evidence on associations with stock returns and firm values, *Journal of Accounting and Economics* 24, 301–336.

Biddle, Gary C., Gim S. Seow, and Andrew F. Siegel, 1995, Relative versus incremental information content, *Contemporary Accounting Research* 12, 1–23.

Block, Stanley B., 1999, A study of financial analysts: practice and theory, *Financial Analysts Journal* 55, 86–95.

Bradshaw, Mark T., 2002, The use of target prices to justify sell-side analysts' stock recommendations, *Accounting Horizons* 16, 27–41.

Bradshaw, Mark T., 2004, How do analysts use their earnings forecasts in generating stock recommendations?, *The Accounting Review* 79, 25–50.

Bradshaw, Mark T., 2011, Analysts' forecasts: what do we know after decades of work?, *Working Paper, Boston College*.

Bradshaw, Mark T., Michael S. Drake, James N. Myers, and Linda A. Myers, 2012, A re-examination of analysts' superiority over time-series forecasts of annual earnings, *Review of Accounting Studies* 17, 944–968.

Branson, Bruce C., Kenneth S. Lorek, and Donald P. Pagach, 1995, Evidence on the superiority of analysts quarterly earnings forecasts for small capitalization firms, *Decision Sciences* 26, 243–263.

Brav, Alon, John R. Graham, Campbell R. Harvey, and Roni Michaely, 2005, Payout policy in the 21st century, *Journal of Financial Economics* 77, 483–527.

Brooks, LeRoy D., and Dale A. Buckmaster, 1976, Further evidence of the time series properties of accounting income, *The Journal of Finance* 31, 1359–1373.

Brown, Lawrence D., 1993, Earnings forecasting research: Its implications for capital markets research, *International Journal of Forecasting* 9, 295–320.

Brown, Lawrence D., Robert L. Hagerman, Paul A. Griffin, and Mark E. Zmijewski, 1987, Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings, *Journal of Accounting and Economics* 9, 61–87.

Brown, Lawrence D., and Michael S. Rozeff, 1978, The superiority of analyst forecasts as measures of expectations: Evidence from earnings, *The Journal of Finance* 33, 1–16.

Brown, Lawrence D., and Michael S. Rozeff, 1979, Univariate time-series models of quarterly accounting earnings per share: A proposed model, *Journal of Accounting Research* 17, 179–189.

Chang, Woo-Jin, Wayne R. Landsman, and Steven J. Monahan, 2012, Selecting an Accounting-based Valuation Model, *Working*.

Chan, K. C., and Nai-Fu Chen, 1988, An unconditional asset-pricing test and the role of firm size as an instrumental variable for risk, *The Journal of Finance* 43, 309–325.

Cheng, C.S. Agnes, and Ray McNamara, 2000, The valuation accuracy of the price-earnings and price-book benchmark valuation methods, *Review of Quantitative Finance and Accounting* 15, 349–370.

Collins, Daniel W., Morton Pincus, and Hong Xie, 1999, Equity valuation and negative earnings: The role of book value of equity, *The Accounting Review* 74, 29–61.

Collins, William A., and William S. Hopwood, 1980, A multivariate analysis of annual earnings forecasts generated from quarterly forecasts of financial analysts and univariate time-series models, *Journal of Accounting Research* 18, 390–406.

Cooper, Ian A., and Neophytos Lambertides, 2014, Is there a limit to the accuracy of equity valuation using multiples?, *Working Paper, Rochester*.

Courteau, Lucie, Jennifer L. Kao, Terry O'Keefe, and Gordon D. Richardson, 2006, Relative accuracy and predictive abiliy of direct valuation methods, price to aggregate earnings method and a hybrid approach, *Accounting and Finance* 46, 553–575.

Courteau, Lucie, Jennifer L. Kao, and Gordon D. Richardson, 2001, Equity valuation employing the ideal versus ad hoc terminal value expressions, *Contemporary Accounting Research* 18, 625–661.

Cowen, Amanda, Boris Groysberg, and Paul Healy, 2006, Which types of analyst firms are more optimistic?, *Journal of Accounting and Economics* 41, 119–146.

Crichfield, Timothy, Thomas Dyckman, and Josef Lakonishok, 1978, An evaluation of security analysts' forecasts, *The Accounting Review*, 651–668.

DeAngelo, Linda Elizabeth, 1990, Equity valuation and corporate control, *The Accounting Review* 65, 93–112.

De Bondt, Werner FM, and Richard H. Thaler, 1990, Do security analysts overreact?, *The American Economic Review*, 52–57.

Dechow, Patricia M., 1994, Accounting earnings and cash flows as measures of firm performance: The role of accounting accruals, *Journal of Accounting and Economics* 18, 3–42.

Dechow, Patricia M., Amy P. Hutton, and Richard G. Sloan, 1999, An empirical assessment of the residual income valuation model, *Journal of Accounting and Economics* 26, 1–34.

Dechow, Patricia M., and Richard G. Sloan, 1997, Returns to contrarian investment strategies: Tests of naive expectations hypotheses, *Journal of Financial Economics* 43, 3–27.

Deloof, Marc, Wouter De Maeseneire, and Koen Inghelbrecht, 2009, How do investment banks value initial public offerings (IPOs)?, *Journal of Business Finance & Accounting* 36, 130–160.

Demirakos, Efthimios G., Norman C. Strong, and Martin Walker, 2004, What valuation models do analysts use?, *Accounting Horizons* 18, 221–240.

Dimson, Elroy, Paul Marsh, and Mike Staunton, 2003, Global evidence on the equity risk premium, *Journal of Applied Corporate Finance* 15, 27–38.

Easterwood, John C., and Stacey R. Nutt, 1999, Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism?, *The Journal of Finance* 54, 1777–1797.

Edwards, E., and P. Bell, 1961, *The Theory and Management of Business Income* (University of California Press, Berkeley).

Elton, Edwin J., Martin J. Gruber, and Mustafa N. Gultekin, 1984, Professional expectations: Accurary and diagonosis of errors, *Journal of Financial and Quantitative Analysis* 19, 351–363.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *The Journal of Finance* 51, 55–84.

Fama, Eugene F., and Kenneth R. French, 2000, Forecasting profitability and earnings, *The Journal of Business* 73, 161–175.

Fama, Eugene F., and Kenneth R. French, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491–518.

Feltham, Gerald A., and James A. Ohlson, 1995, Valuation and clean surplus accounting for operating and financial activities, *Contemporary Accounting Research* 11, 689–731.

Feltham, Gerald A., and James A. Ohlson, 1996, Uncertainty resolution and the theory of depreciation measurement, *Journal of Accounting Research*, 209–234.

Ferson, Wayne E., and Rudi W. Schadt, 1996, Measuring fund strategy and performance in changing economic conditions, *The Journal of Finance* 51, 425–461.

Forker, John, and Ronan Powell, 2008, A comparison of error rates for EVA, residual income, GAAP-earnings and other metrics using a long-window valuation approach, *European Accounting Review* 17, 471–502.

Foster, George, 1977, Quarterly accounting data: Time-series properties and predictive-ability results, *The Accounting Review*, 1–21.

Francis, Jennifer, Per Olsson, and Dennis R. Oswald, 2000, Comparing the accuracy and explainability of dividend, free cash flow, and abnormal earnings equity value estimates, *Journal of Accounting Research* 38, 45–70.

Francis, Jennifer, and Donna Philbrick, 1993, Analysts' decisions as products of a multi-task environment, *Journal of Accounting Research* 31, 216–230.

Francis, Jennifer, Donna Philbrick, and Katherine Schipper, 1994, Shareholder litigation and corporate disclosures, *Journal of Accounting Research* 32, 137–164.

Francis, Jennifer, Katherine Schipper, and Linda Vincent, 2003, The relative and incremental explanatory power of earnings and alternative (to earnings) performance measures for returns, *Contemporary Accounting Research* 20, 121–164.

Frankel, R., and C. Lee, 1998, Accounting valuation, market expectation, and cross-sectional stock returns, *Journal of Accounting and Economics* 25, 283–319.

Fried, Dov, and Dan Givoly, 1982, Financial analysts' forecasts of earnings: a better surrogate for market expectations, *Journal of Accounting and Economics* 4, 85–107.

Gerakos, Joseph, and Robert B. Gramacy, 2013, Regression-based earnings forecasts, *Working Paper, University of Chicago*.

Goncharov, Igor, and David Veenman, 2013, Stale and scale effects in markets-based accounting research: Evidence from the valuation of dividends, *European Accounting Review* 23, 25–55.

Green, J. Peter, Andrew W. Stark, and Hardy M. Thomas, 1996, UK evidence on the market valuation of research and development expenditures, *Journal of Business Finance & Accounting* 23, 191–216.

Gregory, Alan, Richard DF Harris, and Maria Michou, 2003, Contrarian investment and macroeconomic risk, *Journal of Business Finance & Accounting* 30, 213–256.

Griffin, Paul A., 1977, The time-series behavior of quarterly earnings: Preliminary evidence, *Journal of Accounting Research* 15, 71–83.

Hopwood, William S., and James C. McKeown, 1990, Evidence on surrogates for earnings expectations within a capital market context, *Journal of Accounting, Auditing & Finance* 5, 339–363.

Hou, Kewei, and David T. Robinson, 2006, Industry concentration and average stock returns, *The Journal of Finance* 61, 1927–1956.

Hou, Kewei, and Mathijs A. van Dijk, 2011, Profitability shocks and the size effect in the cross-section of expected stock returns, *Working Paper, Fisher College of Business*, 03–001.

Hou, Kewei, Mathijs A. van Dijk, and Yinglei Zhang, 2012, The implied cost of capital: A new approach, *Journal of Accounting and Economics* 53, 504–526.

Imam, Shahed, Richard Barker, and Colin Clubb, 2008, The use of valuation models by UK investment analysts, *European Accounting Review* 17, 503–535.

Jacob, John, Steve Rock, and David P. Weber, 2008, Do non-investment bank analysts make better earnings forecasts?, *Journal of Accounting, Auditing & Finance* 23, 23–61.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional CAPM and the cross-section of expected returns, *The Journal of Finance* 51, 3–53.

John, Kose, and Joseph Williams, 1985, Dividends, dilution, and taxes: A signalling equilibrium, *The Journal of Finance* 40, 1053–1070.

Jones, Christopher S., and Selale Tuzel, 2013, Inventory investment and the cost of capital, *Journal of Financial Economics* 107, 557–579.

Kaplan, Steven N., and Richard S. Ruback, 1995, The valuation of cash flow forecasts: An empirical analysis, *The Journal of Finance* 50, 1059–1093.

Kasznik, Ron, and Baruch Lev, 1995, To warn or not to warn: Management disclosures in the face of an earnings surprise, *The Accounting Review* 70, 113–134.

Kim, Moonchul, and Jay R. Ritter, 1999, Valuing IPOs, *Journal of Financial Economics* 53, 409–437.

Kim, Oliver, Steve C. Lim, and Taewoo Park, 2009, Measuring the impact of sales on earnings and equity price, *Review of Quantitative Finance and Accounting* 32, 145–168.

Koller, Tim, Marc H Goedhart, and David Wessels, 2005, *Valuation: Measuring and Managing the Value of Companies* (John Wiley & Sons, Hoboken, N.J.).

Kothari, S. P., 2001, Capital markets research in accounting, *Journal of Accounting and Economics* 31, 105–231.

Kothari, Sriprakask P., and Jerold L. Zimmerman, 1995, Price and return models, *Journal of Accounting and Economics* 20, 155–192.

Kross, William, Byung Ro, and Douglas Schroeder, 1990, Earnings expectations: The analysts' information advantage, *The Accounting Review* 65, 461–476.

Landsman, Wayne R., and Joseph Magliolo, 1988, Cross-sectional capital market research and model specification, *The Accounting Review* 63, 586–604.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, *The Journal of Finance* 51, 1715–1742.

Lee, Charles M. C., James Myers, and Bhaskaran Swaminathan, 1999, What is the intrinsic value of the Dow?, *The Journal of Finance* 54, 1693–1741.

Lee, Charles M. C., Eric C. So, and Charles C. Y. Wang, 2014, Evaluating Firm-Level Expected-Return Proxies, *Working Paper, Stanford University*.

Lev, Baruch, and Doron Nissim, 2006, The persistence of the accruals anomaly, *Contemporary Accounting Research* 23, 193–226.

Li, Kevin K., and Partha S. Mohanram, 2014, Evaluating cross-sectional forecasting models for implied cost of capital, *Review of Accounting Studies* 19, 1152–1185.

Lin, Hsiou-wei, and Maureen F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101–127.

Lintner, John, 1956, Distribution of incomes of corporations among dividends, retained earnings, and taxes, *American Economic Review* 46, 97–113.

Lipe, Robert, and Roger Kormendi, 1994, Mean reversion in annual earnings and its implications for security valuation, *Review of Quantitative Finance and Accounting* 4, 27–46.

Little, Ian MD, 1962, Higgledy piggledy growth, *Bulletin of the Oxford University Institute of Economics & Statistics* 24, 387–412.

Little, Ian MD, and Arthur C. Rayner, 1966, *Higgledy Piggledy Growth Again* (Basil Blackwell, Oxford).

Litzenberger, Robert H., and Krishna Ramaswamy, 1979, The effect of personal taxes and dividends on capital asset prices: theory and empirical evidence, *Journal of Financial Economics* 7, 163–195.

Liu, Jing, Doron Nissim, and Jacob Thomas, 2002, Equity valuation using multiples, *Journal of Accounting Research* 40, 135–172.

Liu, Jing, Doron Nissim, and Jacob Thomas, 2007, Is cash flow king in valuations?, *Financial Analysts Journal* 63, 56–68.

Lundholm, Russell, and Terry O'Keefe, 2001, Reconciling value estimates from the discounted cash flow model and the residual income model, *Contemporary Accounting Research* 18, 311–335.

Lys, Thomas, and Sungkyu Sohn, 1990, The association between revisions of financial analysts' earnings forecasts and security-price changes, *Journal of Accounting and Economics* 13, 341–363.

Lys, Thomas, and Lisa Gilbert Soo, 1995, Analysts' forecast precision as a response to competition, *Journal of Accounting, Auditing & Finance* 10, 751–765.

Markowitz, Harry, 1952, Portfolio selection, *The Journal of Finance* 7, 77–91.

McNichols, Maureen, and Patricia C. O'Brien, 1997, Self-selection and analyst coverage, *Journal of Accounting Research* 35, 167–199.

Mendenhall, Richard R., 1991, Evidence on the possible underweighting of earnings-related information, *Journal of Accounting Research* 29, 170–179.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.

Miller, Merton H., and Franco Modigliani, 1961, Dividend policy, growth, and the valuation of shares, *The Journal of Business* 34, 411–433.

Miller, Merton H., and Kevin Rock, 1985, Dividend policy under asymmetric information, *The Journal of Finance* 40, 1031–1051.

Nichols, Donald R., and Jeffrey J. Tsay, 1979, Security price reactions to long-range executive earnings forecasts, *Journal of Accounting Research* 17, 140–155.

O'Brien, Patricia C., 1988, Analysts' forecasts as earnings expectations, *Journal of Accounting and Economics* 10, 53–83.

Ohlson, James A., 1995, Earnings, book values, and dividends in equity valuation, *Contemporary Accounting Research* 11, 661–687.

Ohlson, James A., 2005, On accounting-based valuation formulae, *Review of Accounting Studies* 10, 323–347.

Ohlson, James A., and Beate E. Juettner-Nauroth, 2005, Expected EPS and EPS growth as determinants of value, *Review of Accounting Studies* 10, 349–365.

O'Sullivan, Noel, 2000, The impact of board composition and ownership on audit quality: Evidence from large UK companies, *The British Accounting Review* 32, 397–414.

Palepu, Krishna G., Paul M. Healy, and Erik Peek, 2013, *Business Analysis and Valuation* (Cengage Learning).

Patatoukas, Panos N., 2011, Customer-base concentration: implications for firm performance and capital markets, *The Accounting Review* 87, 363–392.

Patell, James M., 1976, Corporate forecasts of earnings per share and stock price behavior: Empirical test, *Journal of Accounting Research* 14, 246–276.

Peasnell, Kenneth V., 1982, Some formal connections between economic values and yields and accounting numbers, *Journal of Business Finance & Accounting* 9, 361–381.

Penman, Stephen B., 1980, An empirical investigation of the voluntary disclosure of corporate earnings forecasts, *Journal of Accounting Research* 18, 132–160.

Penman, Stephen H., 1998a, Combining earnings and book value in equity valuation, *Contemporary Accounting Research* 15, 291–324.

Penman, Stephen H., 1998b, A synthesis of equity valuation techniques and the terminal value calculation for the dividend discount model, *Review of Accounting Studies* 2, 303–323.

Penman, Stephen H., 2005, Discussion of "On Accounting-Based Valuation Formulae" and "Expected EPS and EPS Growth as Determinants of Value," *Review of Accounting Studies* 10, 367–378.

Penman, Stephen H., 2013, *Financial Statement Analysis and Security Valuation* (McGraw-Hill/Irwin, New York).

Penman, Stephen H., and Theodore Sougiannis, 1998, A comparison of dividend, cash flow, and earnings approaches to equity valuation, *Contemporary Accounting Research* 15, 343–383.

Pownall, Grace, Charles Wasley, and Gregory Waymire, 1993, The stock price effects of alternative types of management earnings forecasts, *The Accounting Review*, 896–912.

Rajan, Raghuram, and Henri Servaes, 1997, Analyst following of initial public offerings, *The Journal of Finance* 52, 507–529.

Ramakrishnan, Ram TS, and Jacob K. Thomas, 1992, What matters from the past: Market value, book value, or earnings? Earnings valuation and sufficient statistics for prior information, *Journal of Accounting, Auditing & Finance* 7, 423–464.

Rayburn, Judy, 1986, The association of operating cash flow and accruals with security returns, *Journal of Accounting Research* 24, 112–133.

Richardson, Scott, Siew Hong Teoh, and Peter Wysocki, 1999, Tracking analysts' forecasts over the annual earnings horizon: are analysts' forecasts optimistic or pessimistic?, *Working Paper, London Business School*.

Shanken, Jay, 1990, Intertemporal asset pricing: An empirical investigation, *Journal of Econometrics* 45, 99–120.

Skinner, Douglas J., 1994, Why firms voluntarily disclose bad news, *Journal of Accounting Research* 32, 38–60.

Skinner, Douglas J., and Eugene Soltes, 2011, What do dividends tell us about earnings quality?, *Review of Accounting Studies* 16, 1–28.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289–315.

Stickel, Scott E., 1990, Predicting individual analyst earnings forecasts, *Journal of Accounting Research* 28, 409–417.

Sudarsanam, Sudi, and Ashraf A. Mahate, 2003, Glamour acquirers, method of payment and post-acquisition performance: The UK evidence, *Journal of Business Finance & Accounting* 30, 299–342.

Toms, J. S., 2002, Firm resources, quality signals and the determinants of corporate environmental reputation: Some UK evidence, *The British Accounting Review* 34, 257–282.

Watts, Ross L., and Richard W. Leftwich, 1977, The time series of annual accounting earnings, *Journal of Accounting Research* 15, 253–271.

Waymire, Gregory, 1984, Additional evidence on the information content of management earnings forecasts, *Journal of Accounting Research* 22, 703–718.

Wiese, Robert F., 1930, *Investing for True Value* (Barron's).

Williams, John Burr, 1938, *The Theory of Investment Value*. Vol. 36 (Harvard University Press Cambridge, MA).

Yee, Kenton K., 2004, Forward versus trailing earnings in equity valuation, *Review of Accounting Studies* 9, 301–329.

Yoo, Yong Keun, 2006, The valuation accuracy of equity valuation using a combination of multiples, *Review of Accounting and Finance* 5, 108–123.

Appendices to Chapter 3

Appendix 1

Derivation of Residual Income Model from Dividend Discount Model

All variables are measured on a per share basis. A subscript *i* for a firm is omitted for conciseness. Subscripts on variables indicate time period.

The dividend discount model defines stock price as the sum of discounted expected future dividends.

$$P_0 = \frac{DIV_1}{(1+r)} + \frac{DIV_2}{(1+r)^2} + \frac{DIV_3}{(1+r)^3} + \cdots \tag{13}$$

The clean surplus relation assumes that all changes in equity are reflected in the income statement in the period, except transactions between owners. Therefore, the book value in year *t* is estimated as:

$$B_t = B_{t-1} + E_t - DIV_t \tag{14}$$

Rearranging Equation (14) in terms of dividend:

$$DIV_t = E_t + B_{t-1} - B_t \tag{15}$$

Substituting Equation (15) into (13) results in:

$$\begin{aligned} P_0 &= \frac{E_1 + B_0 - B_1}{(1+r)} + \frac{E_2 + B_1 - B_2}{(1+r)^2} + \ldots \\ &= \frac{E_1 - rB_0 + (1+r)B_0 - B_1}{(1+r)} + \frac{E_2 - rB_1 + (1+r)B_1 - B_2}{(1+r)^2} + \ldots \\ &= B_0 + \frac{E_1 - rB_0}{(1+r)} + \frac{E_2 - rB_1}{(1+r)^2} + \frac{E_3 - rB_2}{(1+r)^3} + \ldots \qquad (16) \end{aligned}$$

Equation (16) is the residual income model.

Appendix 2

Rank Correlation Coefficients of Seven Key Multiples across Calculation Methods, Performance Criteria and Countries

Panel A: Within the US

		Bias				Accuracy			
		H.Mean	Mean	Median	VW.Mean	H.Mean	Mean	Median	VW.Mean
Bias	H. Mean								
	Mean	1.00***							
	Median	1.00***	1.00***						
	VW. Mean	1.00***	1.00***	1.00***					
Accuracy	H. Mean	1.00***	1.00***	1.00***	1.00***				
	Mean	1.00***	1.00***	1.00***	1.00***	1.00***			
	Median	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***		
	VW. Mean	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	1.00***	

Panel B: Within the UK

		Bias				Accuracy			
		H.Mean	Mean	Median	VW.Mean	H.Mean	Mean	Median	VW.Mean
Bias	H. Mean								
	Mean	1.00***							
	Median	0.96***	0.96***						
	VW. Mean	0.99***	0.99***	0.95***					
Accuracy	H. Mean	1.00***	1.00***	0.96***	0.99***				
	Mean	0.96***	0.96***	0.89***	0.95***	0.96***			
	Median	0.96***	0.96***	0.89***	0.95***	0.96***	1.00***		
	VW. Mean	0.96***	0.96***	0.89***	0.98***	0.96***	0.96***	0.96***	

Panel C: Between the US and UK

			Bias				Accuracy			
			H.Mean	Mean	Median	VW.Mean	H.Mean	Mean	Median	VW.Mean
UK	Bias	H. Mean	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***
		Mean	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***
		Median	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***
		VW. Mean	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***
	Accuracy	H. Mean	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***	0.96***
		Mean	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***
		Median	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***	0.93***
		VW. Mean	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***

Appendix 3

Pricing Errors of Multiples by Median (US)

Panel A: 1987 – 2010	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.161	0.001	0.711	0.769	11	0.500	0.363	0.530	0.457	11
CFO/P	0.184	0.003	0.842	0.804	12	0.550	0.385	0.664	0.486	12
EPS/P	0.109	0.002	0.638	0.636	8	0.436	0.312	0.479	0.423	10
EBITDA/P	0.138	0.001	0.671	0.665	9	0.451	0.323	0.515	0.409	8
SALE/P	0.383	0.002	1.445	1.016	14	0.777	0.459	1.277	0.538	13
EPS0/P	0.075	0.001	0.506	0.537	6	0.359	0.265	0.365	0.356	6
EPS1/P	0.053	0.001	0.413	0.451	3	0.297	0.224	0.292	0.297	3
EPS2/P	0.055	0.001	0.373	0.408	2	0.268	0.200	0.266	0.268	2
EPS3/P	0.058	0.000	0.363	0.396	1	0.261	0.195	0.259	0.260	1
EG/P	0.110	0.001	0.517	0.513	4	0.350	0.245	0.396	0.321	5
EBITDA/FV	0.136	-0.003	0.671	0.667	10	0.452	0.325	0.514	0.410	9
SALE/FV	0.380	-0.005	1.451	1.014	13	0.778	0.459	1.282	0.538	13
RIM1/P	0.121	0.001	0.560	0.580	7	0.389	0.278	0.420	0.365	7
RIM2/P	0.076	0.001	0.437	0.513	4	0.324	0.250	0.303	0.319	4

Panel B: 1987 – 1999	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.164	0.003	0.715	0.753	11	0.498	0.356	0.539	0.452	11
CFO/P	0.224	0.002	0.951	0.887	12	0.613	0.423	0.761	0.522	12
EPS/P	0.108	0.001	0.620	0.627	8	0.427	0.308	0.461	0.411	8
EBITDA/P	0.149	0.000	0.675	0.681	9	0.459	0.327	0.517	0.416	10
SALE/P	0.408	0.003	1.518	1.037	13	0.808	0.465	1.348	0.549	13
EPS0/P	0.079	0.001	0.507	0.540	6	0.361	0.266	0.365	0.360	7
EPS1/P	0.059	0.000	0.415	0.457	3	0.299	0.226	0.294	0.300	3
EPS2/P	0.059	0.001	0.378	0.423	2	0.275	0.207	0.266	0.278	2
EPS3/P	0.061	0.000	0.367	0.413	1	0.268	0.202	0.258	0.271	1
EG/P	0.106	0.001	0.502	0.520	4	0.347	0.248	0.378	0.317	4
EBITDA/FV	0.148	-0.002	0.675	0.684	10	0.460	0.329	0.516	0.415	9
SALE/FV	0.407	0.000	1.524	1.040	14	0.809	0.468	1.354	0.549	13
RIM1/P	0.126	0.001	0.567	0.552	7	0.385	0.267	0.435	0.354	6
RIM2/P	0.078	0.002	0.449	0.524	5	0.332	0.255	0.312	0.327	5

Panel C: 2000 – 2010	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.159	0.000	0.707	0.784	12	0.502	0.372	0.523	0.461	12
CFO/P	0.148	0.003	0.727	0.728	11	0.492	0.354	0.555	0.446	11
EPS/P	0.111	0.002	0.654	0.645	8	0.443	0.315	0.494	0.430	10
EBITDA/P	0.128	0.002	0.667	0.652	9	0.444	0.318	0.514	0.401	8
SALE/P	0.360	0.000	1.375	0.989	14	0.750	0.451	1.208	0.530	13
EPS0/P	0.071	0.001	0.506	0.533	6	0.358	0.265	0.365	0.352	6
EPS1/P	0.048	0.001	0.411	0.447	3	0.295	0.222	0.291	0.293	3
EPS2/P	0.052	0.001	0.369	0.393	2	0.262	0.194	0.265	0.260	2
EPS3/P	0.056	0.000	0.360	0.381	1	0.255	0.188	0.260	0.251	1
EG/P	0.114	0.001	0.531	0.509	5	0.353	0.243	0.412	0.324	5
EBITDA/FV	0.125	-0.003	0.667	0.655	10	0.445	0.320	0.513	0.403	9
SALE/FV	0.355	-0.009	1.380	0.988	13	0.750	0.449	1.212	0.530	13
RIM1/P	0.117	0.001	0.554	0.606	7	0.393	0.288	0.407	0.371	7
RIM2/P	0.074	0.000	0.426	0.504	4	0.317	0.247	0.295	0.310	4

Appendix 4

Pricing Errors of Multiples by Value-Weighted Mean (US)

Panel A: 1987 – 2010										
	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.677	0.367	1.143	1.161	12	0.849	0.492	1.022	0.877	12
CFO/P	0.519	0.219	1.198	1.054	11	0.771	0.457	1.054	0.675	11
EPS/P	0.427	0.206	0.979	0.854	10	0.647	0.398	0.850	0.585	10
EBITDA/P	0.379	0.175	0.885	0.830	9	0.596	0.370	0.756	0.522	9
SALE/P	1.029	0.413	2.234	1.496	14	1.253	0.571	2.117	1.091	14
EPS0/P	0.256	0.124	0.662	0.654	6	0.462	0.307	0.538	0.442	7
EPS1/P	0.198	0.103	0.527	0.529	3	0.373	0.252	0.422	0.358	3
EPS2/P	0.186	0.095	0.455	0.472	2	0.331	0.223	0.364	0.326	2
EPS3/P	0.187	0.096	0.441	0.462	1	0.323	0.215	0.354	0.314	1
EG/P	0.306	0.158	0.632	0.630	4	0.453	0.280	0.537	0.430	4
EBITDA/FV	0.335	0.133	0.872	0.825	8	0.580	0.369	0.732	0.502	8
SALE/FV	0.962	0.361	2.166	1.475	13	1.209	0.559	2.039	1.029	13
RIM1/P	0.295	0.129	0.679	0.682	7	0.479	0.301	0.565	0.437	5
RIM2/P	0.306	0.183	0.569	0.650	5	0.445	0.294	0.469	0.439	6

Panel B: 1987 – 1999										
	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.659	0.348	1.134	1.128	11	0.829	0.475	1.016	0.851	12
CFO/P	0.636	0.268	1.406	1.229	12	0.899	0.515	1.254	0.797	11
EPS/P	0.440	0.217	0.982	0.866	10	0.651	0.397	0.857	0.589	10
EBITDA/P	0.398	0.173	0.905	0.854	9	0.613	0.373	0.776	0.536	9
SALE/P	1.053	0.405	2.334	1.526	14	1.284	0.572	2.215	1.106	14
EPS0/P	0.286	0.142	0.690	0.674	5	0.481	0.309	0.571	0.460	5
EPS1/P	0.236	0.127	0.550	0.554	3	0.393	0.257	0.451	0.380	3
EPS2/P	0.225	0.125	0.481	0.511	2	0.359	0.238	0.391	0.349	2
EPS3/P	0.224	0.125	0.466	0.498	1	0.350	0.228	0.381	0.342	1
EG/P	0.354	0.196	0.650	0.671	4	0.481	0.292	0.562	0.481	7
EBITDA/FV	0.367	0.147	0.897	0.848	8	0.601	0.373	0.760	0.527	8
SALE/FV	1.009	0.365	2.304	1.497	13	1.257	0.565	2.178	1.054	13
RIM1/P	0.337	0.156	0.703	0.684	7	0.495	0.296	0.601	0.453	4
RIM2/P	0.339	0.204	0.600	0.680	6	0.473	0.309	0.501	0.473	6

Panel C: 2000 – 2010										
	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.694	0.382	1.152	1.193	12	0.868	0.509	1.027	0.905	12
CFO/P	0.414	0.178	0.961	0.923	11	0.655	0.410	0.816	0.602	11
EPS/P	0.414	0.196	0.977	0.840	10	0.643	0.398	0.845	0.580	10
EBITDA/P	0.361	0.176	0.866	0.810	9	0.581	0.367	0.737	0.511	9
SALE/P	1.008	0.422	2.140	1.471	14	1.224	0.570	2.024	1.079	14
EPS0/P	0.229	0.110	0.633	0.633	6	0.445	0.304	0.506	0.428	7
EPS1/P	0.165	0.081	0.504	0.511	3	0.354	0.248	0.394	0.344	3
EPS2/P	0.151	0.071	0.428	0.442	2	0.306	0.210	0.335	0.304	2
EPS3/P	0.153	0.073	0.414	0.429	1	0.298	0.203	0.326	0.291	1
EG/P	0.263	0.127	0.613	0.596	4	0.427	0.269	0.512	0.394	4
EBITDA/FV	0.306	0.122	0.846	0.802	8	0.561	0.366	0.704	0.479	8
SALE/FV	0.918	0.358	2.032	1.454	13	1.164	0.554	1.902	1.005	13
RIM1/P	0.257	0.104	0.655	0.675	7	0.464	0.305	0.529	0.425	6
RIM2/P	0.277	0.166	0.539	0.620	5	0.420	0.281	0.436	0.411	5

Appendix 5

Pricing Errors of Multiples by Median (UK)

Panel A: 1987 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.316	0.014	1.116	1.141	13	0.743	0.510	0.891	0.542	13
CFO/P	0.189	0.004	0.745	0.801	11	0.519	0.379	0.567	0.418	10
EPS/P	0.129	0.009	0.802	0.529	6	0.416	0.260	0.698	0.358	8
EBITDA/P	0.125	0.007	0.597	0.622	7	0.407	0.303	0.454	0.345	6
SALE/P	0.405	0.022	1.421	1.119	12	0.795	0.485	1.246	0.523	12
EPS0/P	0.108	-0.002	0.502	0.490	4	0.336	0.231	0.389	0.304	5
EPS1/P	0.081	-0.003	0.427	0.407	2	0.286	0.197	0.328	0.261	3
EPS2/P	0.076	-0.003	0.408	0.409	3	0.276	0.199	0.310	0.239	1
EPS3/P	0.074	-0.003	0.407	0.397	1	0.270	0.195	0.313	0.241	2
EG/P	0.162	0.000	0.790	0.685	9	0.506	0.338	0.629	0.453	11
EBITDA/FV	0.097	-0.015	0.716	0.654	8	0.457	0.315	0.559	0.415	9
SALE/FV	0.411	-0.015	1.570	1.277	14	0.953	0.542	1.313	0.800	14
RIM1/P	0.111	0.002	0.497	0.522	5	0.338	0.242	0.381	0.296	4
RIM2/P	0.124	0.017	0.559	0.689	10	0.417	0.315	0.391	0.354	7

Panel B: 1987 – 1999

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.217	0.013	0.948	0.951	13	0.611	0.431	0.756	0.507	14
CFO/P	0.160	0.004	0.664	0.691	11	0.467	0.331	0.497	0.396	10
EPS/P	0.088	0.014	0.438	0.421	2	0.304	0.205	0.327	0.240	2
EBITDA/P	0.081	0.015	0.459	0.573	8	0.350	0.276	0.308	0.298	7
SALE/P	0.294	0.026	0.996	0.962	14	0.655	0.436	0.806	0.487	12
EPS0/P	0.116	0.001	0.502	0.473	5	0.333	0.225	0.392	0.291	6
EPS1/P	0.097	-0.009	0.437	0.432	3	0.301	0.210	0.331	0.262	4
EPS2/P	0.094	-0.010	0.421	0.446	4	0.296	0.219	0.314	0.237	1
EPS3/P	0.101	0.001	0.442	0.417	1	0.292	0.209	0.346	0.255	3
EG/P	0.212	0.030	0.786	0.654	9	0.505	0.302	0.638	0.408	11
EBITDA/FV	0.106	-0.017	0.499	0.537	7	0.362	0.259	0.359	0.331	9
SALE/FV	0.342	0.010	1.138	0.882	12	0.701	0.419	0.959	0.502	13
RIM1/P	0.103	0.006	0.465	0.475	6	0.309	0.229	0.361	0.288	5
RIM2/P	0.120	0.017	0.512	0.676	10	0.386	0.304	0.357	0.330	8

Panel C: 2000 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.346	0.014	1.161	1.194	13	0.783	0.527	0.924	0.569	13
CFO/P	0.197	0.000	0.766	0.838	11	0.533	0.389	0.584	0.423	9
EPS/P	0.149	0.007	0.928	0.606	6	0.470	0.299	0.814	0.400	8
EBITDA/P	0.139	0.004	0.633	0.662	7	0.425	0.316	0.489	0.357	6
SALE/P	0.438	0.021	1.526	1.164	12	0.837	0.509	1.349	0.541	12
EPS0/P	0.106	-0.009	0.503	0.499	4	0.337	0.232	0.388	0.307	4
EPS1/P	0.076	-0.002	0.425	0.395	2	0.281	0.196	0.327	0.259	3
EPS2/P	0.070	-0.002	0.404	0.398	3	0.269	0.190	0.309	0.238	2
EPS3/P	0.065	-0.003	0.396	0.393	1	0.264	0.190	0.302	0.234	1
EG/P	0.147	-0.009	0.792	0.700	9	0.506	0.345	0.626	0.470	11
EBITDA/FV	0.093	-0.013	0.781	0.701	10	0.492	0.331	0.614	0.459	10
SALE/FV	0.436	-0.037	1.702	1.397	14	1.046	0.618	1.411	0.858	14
RIM1/P	0.115	-0.002	0.515	0.544	5	0.353	0.251	0.391	0.323	5
RIM2/P	0.126	0.015	0.582	0.692	8	0.434	0.321	0.408	0.372	7

Appendix 6

Pricing Errors of Multiples by Value-Weighted Mean (UK)

Panel A: 1987 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.630	0.167	1.761	1.354	12	0.974	0.543	1.597	0.769	12
CFO/P	0.049	-0.115	0.679	0.736	10	0.485	0.384	0.477	0.409	6
EPS/P	-0.071	-0.188	0.814	0.576	6	0.464	0.356	0.672	0.432	9
EBITDA/P	0.277	0.119	0.715	0.716	9	0.487	0.330	0.592	0.421	7
SALE/P	0.700	0.244	1.706	1.354	12	0.975	0.498	1.565	0.842	13
EPS0/P	0.190	0.060	0.561	0.566	5	0.384	0.252	0.451	0.333	4
EPS1/P	0.146	0.043	0.470	0.470	3	0.323	0.211	0.371	0.302	3
EPS2/P	0.135	0.042	0.449	0.448	2	0.308	0.206	0.354	0.271	1
EPS3/P	0.136	0.045	0.457	0.424	1	0.303	0.202	0.368	0.271	1
EG/P	0.049	-0.085	0.746	0.701	7	0.495	0.373	0.560	0.430	8
EBITDA/FV	0.175	0.023	0.855	0.778	11	0.544	0.367	0.682	0.488	11
SALE/FV	0.492	0.077	1.568	1.357	14	0.983	0.587	1.317	0.854	14
RIM1/P	-0.105	-0.182	0.551	0.546	4	0.413	0.319	0.379	0.379	5
RIM2/P	-0.093	-0.191	0.563	0.712	8	0.456	0.395	0.343	0.439	10

Panel B: 1987 – 1999

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.477	0.162	1.137	1.173	13	0.791	0.490	0.945	0.677	13
CFO/P	0.102	0.038	0.668	0.828	11	0.518	0.420	0.432	0.452	10
EPS/P	-0.001	-0.093	0.489	0.511	6	0.348	0.240	0.343	0.354	6
EBITDA/P	0.273	0.174	0.590	0.667	9	0.451	0.316	0.468	0.434	9
SALE/P	0.593	0.231	1.255	1.244	14	0.849	0.466	1.098	0.733	14
EPS0/P	0.157	0.027	0.546	0.505	5	0.364	0.246	0.437	0.295	4
EPS1/P	0.131	0.033	0.469	0.478	2	0.326	0.230	0.361	0.281	1
EPS2/P	0.131	0.038	0.455	0.490	3	0.318	0.226	0.350	0.294	2
EPS3/P	0.148	0.023	0.506	0.490	3	0.326	0.221	0.414	0.294	2
EG/P	0.139	-0.034	0.799	0.702	10	0.498	0.339	0.639	0.456	11
EBITDA/FV	0.182	0.045	0.620	0.645	8	0.440	0.311	0.473	0.429	8
SALE/FV	0.495	0.084	1.347	1.082	12	0.821	0.420	1.176	0.665	12
RIM1/P	0.043	-0.017	0.506	0.438	1	0.348	0.239	0.369	0.301	5
RIM2/P	0.032	-0.045	0.504	0.579	7	0.377	0.296	0.335	0.374	7

Panel C: 2000 – 2010

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.677	0.167	1.910	1.430	13	1.030	0.562	1.744	0.805	12
CFO/P	0.034	-0.133	0.682	0.692	7	0.476	0.370	0.489	0.390	6
EPS/P	-0.104	-0.264	0.927	0.559	5	0.519	0.400	0.775	0.436	9
EBITDA/P	0.279	0.109	0.749	0.728	10	0.498	0.334	0.625	0.417	7
SALE/P	0.732	0.249	1.821	1.369	12	1.013	0.514	1.681	0.859	13
EPS0/P	0.200	0.066	0.565	0.578	6	0.390	0.258	0.455	0.344	4
EPS1/P	0.150	0.048	0.471	0.462	3	0.323	0.210	0.374	0.306	3
EPS2/P	0.136	0.050	0.448	0.438	2	0.305	0.200	0.355	0.268	2
EPS3/P	0.132	0.048	0.441	0.410	1	0.296	0.196	0.353	0.260	1
EG/P	0.022	-0.123	0.728	0.711	8	0.493	0.378	0.535	0.423	8
EBITDA/FV	0.173	-0.001	0.927	0.825	11	0.582	0.388	0.741	0.547	11
SALE/FV	0.491	0.070	1.643	1.519	14	1.043	0.654	1.361	0.881	14
RIM1/P	-0.182	-0.278	0.558	0.521	4	0.447	0.370	0.380	0.385	5
RIM2/P	-0.159	-0.299	0.581	0.719	9	0.497	0.463	0.341	0.451	10

Appendices to Chapter 4

Appendix 1

Pricing Error of Multiples

Panel A: Harmonic mean method

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.016	-0.128	0.655	0.727	8	0.476	0.389	0.450	0.429	9
CFO/P	0.022	-0.142	0.766	0.744	9	0.516	0.401	0.566	0.461	10
EBITDA/P	0.014	-0.122	0.634	0.659	7	0.447	0.353	0.450	0.408	8
SALE/P	0.029	-0.241	0.965	0.839	10	0.626	0.488	0.735	0.477	11
EPS/P	0.013	-0.082	0.596	0.629	6	0.423	0.327	0.420	0.415	6
EPS0/P	0.009	-0.061	0.505	0.557	5	0.369	0.287	0.345	0.366	5
EPS1/P	0.006	-0.050	0.428	0.475	4	0.314	0.244	0.290	0.309	4
EPS2/P	0.006	-0.056	0.395	0.431	1	0.288	0.223	0.269	0.280	2
EPS3/P	0.006	-0.062	0.393	0.425	2	0.286	0.223	0.269	0.275	1
EBITDA/FV	0.095	-0.021	0.628	0.653	11	0.438	0.319	0.460	0.416	7
SALE/FV	0.149	-0.154	1.133	0.949	13	0.700	0.493	0.903	0.529	12
RIMG0R11/P	0.006	-0.073	0.413	0.421	3	0.290	0.224	0.295	0.270	3
RIMG4RC/P	0.142	-0.280	3.786	0.704	12	0.783	0.463	3.707	0.481	13

Panel B: Median method

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.182	0.002	0.797	0.840	8	0.546	0.397	0.608	0.478	9
CFO/P	0.216	0.001	0.952	0.870	10	0.601	0.413	0.769	0.518	10
EBITDA/P	0.168	0.002	0.771	0.747	7	0.508	0.357	0.604	0.449	8
SALE/P	0.399	0.001	1.415	1.108	11	0.812	0.492	1.226	0.572	11
EPS/P	0.116	0.001	0.678	0.685	6	0.463	0.335	0.509	0.447	6
EPS0/P	0.088	0.001	0.568	0.594	5	0.397	0.292	0.416	0.390	5
EPS1/P	0.066	0.000	0.469	0.504	1	0.333	0.248	0.337	0.325	4
EPS2/P	0.070	0.001	0.431	0.458	2	0.305	0.224	0.313	0.295	2
EPS3/P	0.076	0.001	0.429	0.452	3	0.302	0.221	0.314	0.291	1
EBITDA/FV	0.183	0.043	0.713	0.696	9	0.480	0.329	0.557	0.454	7
SALE/FV	0.487	0.062	1.546	1.188	12	0.883	0.505	1.359	0.656	12
RIMG0R11/P	0.088	-0.001	0.452	0.454	4	0.307	0.216	0.343	0.288	3
RIMG4RC/P	1.072	0.003	11.493	0.895	13	1.424	0.399	11.454	0.516	13

Panel C: Value-weighted mean method

	Bias					Accuracy				
	Mean	Median	SD	IQR	Rank	Mean	Median	SD	IQR	Rank
B/P	0.940	0.514	1.633	1.394	10	1.104	0.590	1.528	1.109	10
CFO/P	0.753	0.311	1.784	1.237	9	0.999	0.520	1.659	0.829	9
EBITDA/P	0.608	0.257	1.511	1.024	7	0.819	0.440	1.408	0.682	7
SALE/P	1.484	0.572	3.490	1.915	11	1.687	0.670	3.396	1.529	11
EPS/P	0.557	0.269	1.280	0.987	6	0.776	0.452	1.161	0.678	6
EPS0/P	0.374	0.174	0.937	0.774	5	0.583	0.358	0.823	0.527	5
EPS1/P	0.293	0.145	0.745	0.633	4	0.471	0.293	0.647	0.434	4
EPS2/P	0.277	0.143	0.638	0.576	2	0.425	0.263	0.551	0.398	3
EPS3/P	0.281	0.145	0.615	0.570	3	0.419	0.261	0.531	0.398	2
EBITDA/FV	0.641	0.303	1.510	0.975	8	0.822	0.440	1.420	0.713	8
SALE/FV	1.652	0.688	3.689	2.069	13	1.843	0.760	3.597	1.728	13
RIMG0R11/P	0.232	0.102	0.586	0.549	1	0.394	0.246	0.492	0.369	1
RIMG4RC/P	1.495	0.103	17.251	1.059	12	1.802	0.434	17.222	0.614	12

Appendix 2

Relation between Stock Return and Target Price of Residual Income Models

Panel A: 12MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.002
g=0%	-0.001	-0.002	-0.002	-0.002	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004	-0.004	-0.004	0.004
g=1%		-0.002	-0.002	-0.003	-0.003	-0.003	-0.003	-0.004	-0.004	-0.004	-0.004	-0.005	0.004
g=2%			-0.003	-0.003	-0.003	-0.003	-0.004	-0.004	-0.004	-0.005	-0.005	-0.005	0.004
g=3%				-0.002	-0.003	-0.004	-0.004	-0.004	-0.005	-0.005	-0.005	-0.006	0.007
g=4%					-0.003	-0.003	-0.003	-0.004	-0.004	-0.004	-0.005	-0.005	0.001
g=5%						-0.002	-0.002	-0.003	-0.003	-0.004	-0.004	-0.005	0.010

Panel B: 24MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	-0.007	-0.007	-0.008	-0.008	-0.008	-0.008	-0.008	-0.009	-0.009	-0.009	-0.009	-0.009	0.004
g=0%	-0.001	-0.001	-0.002	-0.003	-0.003	-0.004	-0.005	-0.005	-0.005	-0.006	-0.007	-0.007	0.022
g=1%		-0.002	-0.002	-0.003	-0.003	-0.004	-0.005	-0.005	-0.006	-0.006	-0.007	-0.008	0.023
g=2%			-0.002	-0.002	-0.003	-0.004	-0.004	-0.005	-0.006	-0.007	-0.007	-0.008	0.022
g=3%				0.000	-0.002	-0.003	-0.003	-0.004	-0.004	-0.005	-0.006	-0.007	0.023
g=4%					0.000	-0.001	-0.002	-0.003	-0.003	-0.004	-0.005	-0.005	0.004
g=5%						-0.001	-0.002	-0.003	-0.003	-0.004	-0.005	-0.006	0.032

Panel C: 36MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.024	0.024	0.023	0.023	0.023	0.023	0.023	0.022	0.022	0.022	0.022	0.021	0.033
g=0%	0.040	0.039	0.038	0.037	0.036	0.035	0.034	0.033	0.032	0.031	0.030	0.029	0.055
g=1%		0.038	0.037	0.036	0.035	0.034	0.033	0.032	0.031	0.029	0.028	0.027	0.054
g=2%			0.035	0.034	0.033	0.032	0.031	0.030	0.028	0.027	0.026	0.025	0.054
g=3%				0.035	0.034	0.032	0.032	0.031	0.029	0.028	0.027	0.026	0.052
g=4%					0.033	0.032	0.031	0.030	0.029	0.027	0.026	0.025	-0.001
g=5%						0.031	0.029	0.028	0.027	0.026	0.025	0.023	0.076

Panel D: 48MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.034	0.034	0.033	0.033	0.033	0.033	0.032	0.032	0.032	0.031	0.031	0.031	0.034
g=0%	0.053	0.052	0.050	0.049	0.048	0.046	0.045	0.043	0.042	0.040	0.039	0.037	0.042
g=1%		0.051	0.049	0.048	0.047	0.045	0.044	0.042	0.041	0.037	0.035	0.034	0.043
g=2%			0.046	0.045	0.043	0.042	0.040	0.039	0.037	0.035	0.034	0.032	0.042
g=3%				0.044	0.042	0.040	0.039	0.038	0.036	0.035	0.033	0.032	0.045
g=4%					0.043	0.041	0.039	0.038	0.036	0.035	0.032	0.031	0.000
g=5%						0.041	0.038	0.037	0.035	0.033	0.032	0.030	0.028

Appendix 3

Buy-and-Hold Abnormal Return of Residual Income Models

Panel A: 12MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.020	0.019	0.019	0.019	0.019	0.019	0.019	0.018	0.018	0.018	0.018	0.018	0.024
g=0%	0.021	0.022	0.022	0.022	0.021	0.021	0.022	0.021	0.022	0.022	0.022	0.021	0.012
g=1%		0.022	0.023	0.023	0.021	0.020	0.020	0.021	0.020	0.019	0.019	0.020	0.009
g=2%			0.023	0.022	0.022	0.021	0.021	0.021	0.020	0.020	0.019	0.019	0.010
g=3%				0.019	0.019	0.020	0.020	0.020	0.020	0.020	0.018	0.017	0.009
g=4%					0.020	0.019	0.018	0.018	0.017	0.017	0.017	0.018	0.004
g=5%						0.016	0.017	0.017	0.017	0.016	0.015	0.014	0.009

Panel B: 24MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.041	0.040	0.039	0.040	0.041	0.041	0.041	0.040	0.040	0.040	0.039	0.039	0.056
g=0%	0.049	0.050	0.049	0.049	0.049	0.047	0.046	0.046	0.046	0.045	0.045	0.043	0.036
g=1%		0.050	0.049	0.049	0.048	0.046	0.046	0.047	0.046	0.044	0.042	0.041	0.033
g=2%			0.048	0.048	0.045	0.044	0.045	0.045	0.044	0.043	0.041	0.039	0.028
g=3%				0.047	0.046	0.045	0.045	0.045	0.043	0.043	0.043	0.042	0.027
g=4%					0.046	0.045	0.045	0.043	0.042	0.041	0.040	0.037	0.015
g=5%						0.040	0.041	0.040	0.039	0.035	0.034	0.032	0.021

Panel C: 36MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.084	0.082	0.081	0.082	0.082	0.082	0.081	0.080	0.080	0.080	0.079	0.080	0.102
g=0%	0.124	0.124	0.123	0.122	0.120	0.118	0.117	0.117	0.116	0.116	0.114	0.114	0.084
g=1%		0.126	0.124	0.123	0.120	0.118	0.118	0.119	0.116	0.114	0.113	0.111	0.075
g=2%			0.120	0.120	0.118	0.115	0.116	0.115	0.114	0.110	0.107	0.105	0.071
g=3%				0.116	0.116	0.115	0.116	0.115	0.114	0.114	0.112	0.111	0.069
g=4%					0.108	0.107	0.107	0.106	0.103	0.104	0.103	0.080	0.052
g=5%						0.101	0.102	0.101	0.100	0.076	0.075	0.072	0.054

Panel D: 48 MTH

	Discount rate (*r*)												
	1%	2%	3%	4%	5%	6%	7%	8%	9%	10%	11%	12%	CAPM
No TV	0.112	0.109	0.107	0.107	0.107	0.108	0.106	0.106	0.106	0.105	0.104	0.105	0.113
g=0%	0.138	0.138	0.137	0.134	0.134	0.131	0.123	0.123	0.122	0.122	0.119	0.119	0.088
g=1%		0.139	0.138	0.134	0.130	0.125	0.126	0.127	0.125	0.123	0.122	0.121	0.076
g=2%			0.128	0.128	0.126	0.125	0.125	0.125	0.125	0.120	0.117	0.114	0.069
g=3%				0.122	0.122	0.120	0.122	0.122	0.120	0.121	0.119	0.118	0.068
g=4%					0.112	0.113	0.113	0.112	0.109	0.111	0.108	0.108	0.053
g=5%						0.106	0.107	0.107	0.105	0.103	0.101	0.097	0.055

Appendices to Chapter 5

Appendix 1

Difference between CRI and RI: Unscaled Earnings

Panel A: Bias

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	-0.002	0.002	**-0.003**	**-0.010**	0.001	-0.001	**-0.001**	0.000	-0.001	0.003	**-0.008**	**0.007**	-0.002	4	8	1
	-0.52	*0.87*	*-2.57*	*-3.23*	*0.53*	*-0.24*	*-2.09*	*0.49*	*-0.79*	*1.00*	*-2.19*	*2.58*	*-0.70*			
E_{t+2}	-0.007	0.001	**-0.003**	**-0.015**	**-0.007**	0.006	-0.001	**0.002**	-0.003	-0.004	**-0.021**	**0.009**	-0.004	4	7	2
	-1.65	*0.33*	*-1.73*	*-2.47*	*-1.85*	*1.17*	*-1.54*	*2.39*	*-1.06*	*-0.97*	*-3.53*	*3.24*	*-1.01*			
E_{t+3}	-0.004	-0.002	**-0.003**	**-0.015**	**-0.013**	0.006	-0.001	**0.002**	-0.001	-0.007	**-0.034**	0.006	-0.008	4	8	1
	-0.98	*-0.33*	*-2.07*	*-2.83*	*-2.54*	*1.11*	*-1.51*	*2.05*	*-0.52*	*-1.45*	*-7.69*	*1.51*	*-1.61*			
E_{t+4}	**-0.021**	**-0.013**	**-0.008**	**-0.027**	**-0.014**	**-0.011**	**-0.003**	0.000	0.000	**-0.013**	**-0.030**	0.002	**-0.020**	10	3	0
	-3.40	*-1.87*	*-3.17*	*-3.71*	*-1.77*	*-2.36*	*-3.01*	*0.20*	*0.03*	*-2.10*	*-2.67*	*0.55*	*-3.01*			
E_{t+5}	**-0.051**	**-0.032**	**-0.016**	**-0.037**	**-0.028**	**-0.021**	**-0.004**	0.000	0.002	**-0.032**	**-0.065**	**-0.009**	**-0.048**	11	2	0
	-3.64	*-3.65*	*-4.12*	*-4.20*	*-3.49*	*-2.05*	*-2.60*	*-0.05*	*0.54*	*-3.93*	*-4.72*	*-3.36*	*-3.71*			

Panel B: Accuracy

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	-0.002	0.000	**-0.003**	**-0.008**	0.001	0.000	0.000	**-0.001**	**-0.002**	**0.003**	**-0.003**	**0.003**	0.000	5	6	2
	-1.06	*0.19*	*-8.20*	*-3.77*	*1.43*	*0.03*	*-1.21*	*-2.99*	*-4.19*	*2.16*	*-3.07*	*2.60*	*-0.05*			
E_{t+2}	**-0.013**	-0.001	**-0.003**	**-0.013**	**-0.006**	0.001	**-0.001**	0.000	**-0.003**	-0.003	**-0.013**	**0.003**	**-0.007**	8	4	1
	-5.62	*-0.47*	*-3.37*	*-3.26*	*-3.48*	*0.42*	*-2.93*	*0.41*	*-3.95*	*-1.35*	*-6.45*	*1.99*	*-3.62*			
E_{t+3}	**-0.007**	0.001	**-0.001**	**-0.012**	-0.004	0.003	**-0.001**	**0.001**	0.001	-0.004	**-0.019**	**0.005**	**-0.009**	6	5	2
	-3.07	*0.18*	*-1.97*	*-3.46*	*-1.38*	*1.13*	*-2.91*	*2.23*	*1.30*	*-1.44*	*-8.37*	*2.92*	*-3.77*			
E_{t+4}	**-0.013**	**-0.010**	**-0.006**	**-0.021**	0.001	**-0.009**	**-0.001**	**0.001**	0.001	**-0.008**	**-0.015**	0.001	-0.002	8	4	1
	-3.26	*-3.65*	*-4.43*	*-4.19*	*0.26*	*-2.67*	*-2.76*	*2.88*	*1.66*	*-1.99*	*-1.80*	*0.42*	*-0.24*			
E_{t+5}	**-0.041**	**-0.018**	**-0.013**	**-0.028**	**-0.012**	**-0.022**	-0.001	**0.002**	0.000	**-0.019**	**-0.041**	**-0.004**	**-0.016**	10	2	1
	-3.90	*-3.88*	*-5.79*	*-3.85*	*-2.58*	*-4.00*	*-0.62*	*3.12*	*0.15*	*-3.82*	*-4.18*	*-4.25*	*-1.86*			

Panel C: ERC

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	**0.002**	0.000	0.000	**0.003**	**0.002**	0.001	0.000	0.000	0.001	**0.002**	**0.002**	**0.001**	**0.001**	7	6	0
	3.51	*0.57*	*0.00*	*3.85*	*2.30*	*1.21*	*0.92*	*-0.75*	*1.14*	*5.30*	*3.41*	*2.43*	*1.91*			
E_{t+2}	0.002	**0.003**	0.000	**0.003**	**0.004**	**0.003**	0.000	0.000	0.000	**0.003**	**0.006**	0.001	**0.003**	7	6	0
	1.52	*1.84*	*-0.29*	*2.90*	*3.56*	*2.19*	*-0.26*	*-0.14*	*-0.54*	*4.24*	*4.25*	*1.20*	*3.37*			
E_{t+3}	0.002	**0.008**	0.000	**0.006**	**0.006**	0.002	**-0.001**	**-0.001**	-0.001	**0.005**	**0.008**	**0.002**	**0.006**	7	4	2
	1.60	*3.75*	*0.25*	*3.61*	*4.49*	*1.48*	*-1.87*	*-2.21*	*-0.84*	*4.04*	*5.26*	*1.75*	*3.75*			
E_{t+4}	**0.004**	**0.008**	-0.001	**0.004**	0.002	0.001	0.000	-0.001	**-0.002**	0.002	0.002	**0.002**	**0.004**	5	7	1
	2.93	*4.35*	*-1.17*	*1.94*	*1.35*	*0.34*	*0.11*	*-1.49*	*-2.19*	*1.46*	*0.75*	*1.93*	*3.37*			
E_{t+5}	**0.005**	**0.009**	**-0.004**	**0.008**	**0.004**	**0.008**	-0.001	0.000	-0.001	**0.005**	**0.006**	**0.003**	**0.007**	9	3	1
	3.29	*4.69*	*-2.37*	*3.21*	*2.21*	*2.78*	*-1.57*	*0.29*	*-0.40*	*2.98*	*2.52*	*1.74*	*3.34*			

Appendix 2
Difference between CRI and RI: Reported Earnings Per Share

Panel A: Bias

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	0.000	0.000	0.000	**-0.001**	0.000	0.000	**-0.001**	**-0.001**	0.000	0.000	0.000	**-0.001**	0.000	4	9	0
	-0.19	*-0.12*	*-0.36*	*-2.13*	*-0.35*	*-1.13*	*-1.97*	*-1.83*	*-0.16*	*-0.20*	*-0.13*	*-1.76*	*0.81*			
E_{t+2}	-0.001	-0.001	**-0.001**	**-0.002**	-0.001	0.000	**-0.002**	-0.001	0.000	0.000	-0.001	0.000	0.000	3	10	0
	-1.26	*-1.25*	*-1.73*	*-2.07*	*-1.27*	*0.70*	*-2.00*	*-1.29*	*0.94*	*-0.09*	*-0.61*	*-0.23*	*0.43*			
E_{t+3}	-0.001	-0.001	0.000	**-0.002**	-0.001	**-0.001**	-0.002	-0.001	0.001	0.000	**-0.003**	0.000	0.000	3	10	0
	-1.53	*-1.09*	*-0.53*	*-2.30*	*-1.21*	*-1.77*	*-1.45*	*-1.59*	*1.65*	*-0.51*	*-2.27*	*-0.11*	*0.18*			
E_{t+4}	-0.001	**-0.002**	0.000	**-0.002**	**-0.003**	**-0.002**	**-0.003**	**-0.001**	0.001	-0.001	**-0.004**	0.001	0.000	7	6	0
	-1.10	*-2.07*	*-0.05*	*-1.70*	*-2.80*	*-2.37*	*-2.45*	*-1.88*	*1.21*	*-1.49*	*-3.04*	*0.66*	*-0.31*			
E_{t+5}	-0.002	**-0.002**	0.000	0.000	**-0.003**	**-0.002**	**-0.003**	**-0.002**	**0.001**	**-0.001**	**-0.004**	0.001	0.000	7	5	1
	-1.66	*-2.25*	*0.15*	*0.00*	*-2.11*	*-2.11*	*-1.95*	*-2.10*	*1.91*	*-2.09*	*-3.50*	*0.54*	*0.21*			

Panel B: Accuracy

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	0.000	0.000	**-0.001**	**-0.002**	**-0.001**	-0.001	**-0.003**	**-0.001**	**-0.001**	**-0.001**	0.000	**-0.001**	**0.000**	9	4	0
	-0.53	*0.22*	*-6.23*	*-7.64*	*-3.30*	*-1.57*	*-7.21*	*-5.46*	*-2.28*	*-3.97*	*-1.59*	*-4.68*	*-1.99*			
E_{t+2}	**-0.001**	**-0.001**	**-0.001**	**-0.003**	**-0.002**	0.000	**-0.005**	**-0.002**	**0.000**	**-0.001**	**-0.002**	**-0.001**	**-0.001**	12	1	0
	-2.22	*-2.81*	*-5.13*	*-6.19*	*-5.48*	*-0.80*	*-7.30*	*-5.20*	*-2.40*	*-6.71*	*-6.87*	*-4.68*	*-2.30*			
E_{t+3}	**-0.001**	**-0.001**	**-0.002**	**-0.002**	**-0.003**	**-0.001**	**-0.006**	**-0.002**	0.000	**-0.002**	**-0.004**	**-0.001**	-0.001	11	2	0
	-2.83	*-3.24*	*-5.02*	*-5.98*	*-7.18*	*-3.71*	*-7.02*	*-4.40*	*0.00*	*-7.53*	*-10.21*	*-5.48*	*-0.63*			
E_{t+4}	-0.001	**-0.001**	**-0.001**	**-0.002**	**-0.003**	**-0.001**	**-0.006**	**-0.001**	0.000	**-0.002**	**-0.003**	**-0.001**	0.001	10	3	0
	-1.63	*-3.68*	*-6.58*	*-5.67*	*-6.19*	*-2.25*	*-6.55*	*-3.53*	*-0.08*	*-6.05*	*-8.71*	*-2.98*	*0.93*			
E_{t+5}	**-0.002**	**-0.002**	**-0.001**	**-0.001**	**-0.003**	**-0.001**	**-0.006**	**-0.003**	**0.001**	**-0.002**	**-0.004**	**-0.001**	0.006	11	1	1
	-3.29	*-5.22*	*-3.70*	*-3.87*	*-5.94*	*-3.81*	*-6.53*	*-3.60*	*2.86*	*-5.64*	*-12.00*	*-3.56*	*1.25*			

Panel C: ERC

	B/M			Past Returns			Size				Period					
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	1970-1987	1988-2007	Industry	(B)	(E)	(W)
E_{t+1}	0.000	**0.001**	0.000	**0.001**	0.000	0.001	**0.002**	0.000	0.000	0.000	0.000	0.000	0.000	3	10	0
	1.23	*2.22*	*1.09*	*2.37*	*0.23*	*1.65*	*4.57*	*-0.14*	*-0.16*	*1.40*	*1.19*	*-1.51*	*-0.20*			
E_{t+2}	0.001	0.000	**0.002**	**0.002**	0.000	**0.001**	**0.003**	0.000	0.001	**0.001**	**0.002**	**0.001**	**0.001**	8	5	0
	1.32	*0.56*	*3.61*	*3.78*	*0.58*	*2.23*	*6.03*	*0.86*	*1.29*	*4.20*	*5.30*	*2.49*	*1.94*			
E_{t+3}	**0.001**	0.001	**0.003**	**0.002**	**0.002**	0.001	**0.003**	0.001	-0.001	**0.001**	**0.002**	**0.001**	**0.001**	9	4	0
	3.31	*0.80*	*4.16*	*3.50*	*3.49*	*1.12*	*4.45*	*1.19*	*-1.10*	*4.01*	*3.90*	*3.86*	*2.30*			
E_{t+4}	0.001	0.002	**0.003**	**0.002**	0.000	-0.001	**0.005**	0.001	-0.001	**0.002**	**0.002**	**0.001**	-0.001	6	7	0
	1.28	*1.48*	*3.56*	*2.41*	*-0.29*	*-0.43*	*5.67*	*0.58*	*-1.03*	*4.30*	*2.25*	*2.53*	*-1.26*			
E_{t+5}	**0.002**	**0.003**	**0.004**	**0.002**	**0.002**	0.001	**0.005**	0.002	0.000	0.001	0.001	**0.001**	-0.001	7	6	0
	2.48	*2.83*	*3.40*	*2.14*	*2.50*	*0.91*	*3.56*	*1.60*	*-0.38*	*1.68*	*0.82*	*1.93*	*-0.62*			

Appendix 3
Difference between CRI and RI: Street Earnings Per Share

Panel A: Bias

	B/M			Past Returns			Size							
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	Industry	(B)	(E)	(W)
E_{t+1}	0.000	0.000	0.000	**-0.001**	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	1	10	0
	-0.34	*0.31*	*-0.84*	*-1.77*	*-0.31*	*1.07*	*-0.53*	*-0.33*	*-0.83*	*0.48*	*0.10*			
E_{t+2}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0	11	0
	-0.39	*-0.54*	*-0.75*	*-0.27*	*-0.10*	*0.30*	*-0.28*	*0.32*	*-0.20*	*0.53*	*0.52*			
E_{t+3}	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.003**	0.000	0.000	0	10	1
	0.83	*0.84*	*0.19*	*-0.05*	*0.97*	*0.73*	*0.31*	*0.50*	*1.89*	*1.00*	*0.01*			
E_{t+4}	0.000	0.000	0.000	0.000	0.000	**0.001**	0.000	0.000	0.001	0.000	0.000	0	10	1
	0.48	*0.00*	*0.46*	*0.29*	*0.00*	*2.00*	*0.39*	*-0.45*	*0.50*	*0.56*	*0.08*			
E_{t+5}	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0	11	0
	0.36	*0.16*	*-0.47*	*0.59*	*0.38*	*1.49*	*0.67*	*-0.89*	*-0.03*	*0.84*	*0.40*			

Panel B: Accuracy

	B/M			Past Returns			Size							
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	Industry	(B)	(E)	(W)
E_{t+1}	0.000	0.000	**-0.001**	**-0.003**	**-0.001**	0.000	**-0.002**	**-0.002**	-0.002	**-0.001**	**-0.001**	7	4	0
	1.07	*0.72*	*-5.64*	*-5.16*	*-4.31*	*-0.89*	*-3.52*	*-7.34*	*-1.21*	*-6.99*	*-4.80*			
E_{t+2}	**-0.001**	**-0.001**	**-0.001**	**-0.002**	**-0.002**	0.000	**-0.002**	**-0.001**	-0.001	**-0.001**	**-0.001**	9	2	0
	-3.32	*-2.36*	*-3.51*	*-4.04*	*-4.18*	*0.94*	*-3.25*	*-3.45*	*-0.64*	*-3.57*	*-4.07*			
E_{t+3}	**-0.001**	**-0.001**	**-0.002**	**-0.002**	**-0.002**	0.000	**-0.002**	**-0.001**	0.002	**-0.001**	**-0.002**	9	2	0
	-3.75	*-2.70*	*-3.00*	*-3.78*	*-5.73*	*0.92*	*-3.38*	*-3.56*	*1.70*	*-3.64*	*-2.97*			
E_{t+4}	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.002**	0.000	**-0.002**	**0.000**	0.001	**-0.001**	**-0.002**	9	2	0
	-2.75	*-2.82*	*-4.33*	*-3.26*	*-4.29*	*-0.66*	*-3.16*	*-1.76*	*0.58*	*-3.57*	*-3.46*			
E_{t+5}	**-0.002**	**-0.001**	**-0.001**	**-0.001**	**-0.002**	0.000	**-0.002**	**-0.001**	-0.001	**-0.001**	**-0.002**	9	2	0
	-2.35	*-2.90*	*-2.88*	*-3.21*	*-3.73*	*-1.09*	*-2.85*	*-2.38*	*-0.65*	*-2.82*	*-2.41*			

Panel C: ERC

	B/M			Past Returns			Size							
	High	Medium	Low	High	Medium	Low	Big	Medium	Small	5YR	Industry	(B)	(E)	(W)
E_{t+1}	0.001	**0.002**	**0.001**	**0.002**	**0.003**	0.000	**0.002**	0.001	0.001	**0.001**	**0.001**	7	4	0
	1.54	*4.00*	*2.40*	*1.94*	*4.72*	*0.92*	*2.16*	*1.52*	*0.72*	*2.16*	*2.44*			
E_{t+2}	**0.003**	**0.002**	**0.002**	**0.002**	**0.003**	-0.002	**0.003**	0.001	-0.004	**0.002**	**0.003**	8	3	0
	2.35	*3.24*	*2.68*	*2.34*	*3.28*	*-0.92*	*2.31*	*1.21*	*-1.42*	*2.37*	*5.48*			
E_{t+3}	-0.001	**0.003**	**0.003**	**0.006**	**0.005**	-0.002	**0.004**	-0.001	-0.006	0.001	0.000	5	6	0
	-0.40	*3.82*	*2.01*	*3.43*	*3.87*	*-0.68*	*3.02*	*-1.04*	*-1.23*	*0.88*	*0.47*			
E_{t+4}	0.002	0.003	**0.004**	0.002	0.002	0.000	**0.005**	-0.001	-0.001	0.001	**0.004**	3	8	0
	0.82	*1.39*	*2.13*	*1.66*	*0.74*	*-0.03*	*2.92*	*-1.04*	*-0.41*	*0.42*	*1.77*			
E_{t+5}	**0.004**	**0.004**	0.000	**0.003**	0.003	0.000	**0.007**	0.001	0.002	0.001	**0.005**	5	6	0
	1.92	*2.65*	*-0.03*	*1.96*	*1.64*	*0.08*	*3.85*	*0.41*	*0.88*	*0.76*	*2.22*			