A study of the reliability of cross-sectional earnings forecasting models for estimating IPO firms' implied cost of capital

Abstract

Purpose – The study evaluates the earnings forecasting models of Hou et al. (J Account Econ, 53:504-526, 2012) and Li and Mohanram (Rev Account Stud, 19:1152-1185, 2014) in terms of bias and accuracy and validity of the implied cost of capital (ICC) estimates for a sample of IPOs.

Design/methodology/approach – The authors use a sample of 1,657 NYSE, Amex and Nasdaq IPOs from 1972 to 2013.

Findings – The models of Hou et al. and Li and Mohanram produce relatively inaccurate and biased earnings forecasts, leading to unreliable ICC estimates, particularly for small and loss-making IPOs that constitute the bulk of new listings. As a remedy, we propose a new earnings forecasting model, a combination of Hou et al.'s and Li and Mohanram's EP models, and show that it produces more accurate and less biased earnings forecasts and more valid ICC estimates.

Originality/value – The study contributes novel results to the literature on the validity of cross-sectional earnings models in forecasting IPO firm earnings and estimating the ICC. The findings are directly relevant for practitioners, who can improve their earnings forecasting accuracy for IPO firms and related ICC estimates. The insights can be extended to other settings where investors have limited access to financial information, such as acquisitions of private targets.

Key words: Cost of equity; Cross-sectional earnings models; Implied cost of capital; IPOs

Word count: 6159

1. Introduction

Price discovery for in relation to IPO firms is challenging, as there is no stock return information, limited availability of financial information, and no analyst coverage *before* the firm lists. To value the IPO, investors can use the multiples approach and the discounted cash flow method. Kim and Ritter (1999, p. 409) examine the accuracy of multiples valuation for IPOs and conclude that the "approach results in very little precision in the valuations." Paleari et al. (2014) find that underwriters select comparable firms with higher valuations than peers selected by sell-side analysts and matching algorithms, which produces inflated IPO valuations. Purnanandam and Swaminathan (2004) caution against using multiples for IPOs valuation, as these provide inflated valuations for over half of the IPOs in their sample, with overvaluation ranging from 14% to 50% relative to peers. The low reliability of the multiples method can explain why underwriters and investors frequently rely on the discounted cash flow valuation method to value IPOs. Roosenboom (2012) finds that 60% of French underwriters use the discounted cash flow method to price IPO stocks. Deloof et al. (2009) report that the discounted cash flow method was the most popular valuation method used by underwriters for Euronext Brussels IPOs, with lower valuation errors than the multiple method. Kaplan and Ruback (1995) find that valuations based on discounted cash flows are within 10% of the market values of completed management buyouts and leveraged recapitalizations, and have lower valuation errors than a comparable-company EBITDA-multiple valuation. Further, they find that the valuation accuracy of the discounted cash flow method improves with the precision of the implied cost of capital estimates. Thus, to assess IPO pricing, investors are likely to use the discounted cash flow method as either the main or a complementary valuation approach, and a crucial input required to apply the method is the implied cost of capital.

Applying the discounted cash flow method for IPOs requires an estimate of the implied cost of capital (ICC), which is not readily available before the firm lists. The textbook approaches to calculating ICC use either realized returns or analyst forecasts to infer expected returns (e.g., Fama and French, 1997). These methods can work reasonably well for stocks with a long stock return history and active analyst following.[1] However, these conditions do not apply to IPO stocks. A remedy is to use cross-sectional earnings forecasting models to generate inputs necessary to estimate the ICC. However, it is unclear whether the standard cross-sectional forecasting models produce accurate earnings estimates and, consequently, reliable ICC estimates for IPO stocks. This paper sets out to answer this question. This question is important because unreliable ICC estimates can inflate a firm's cost of capital, leading to lower valuation, misallocation of investor funds, and reduced shareholder wealth.[2]

The accounting literature proposes the use of cross-sectional forecasting models to predict future earnings and to use earnings estimates as inputs into ICC models. This approach removes the problem of missing or biased analyst forecasts and unavailable and noisy stock returns. Hou, van Dijk and Zhang (2012, hereafter HVZ) predict earnings from contemporary accounting data and Li and Mohanram (2014, hereafter LM) forecast earnings (1) as a function of past earnings, allowing for a differential persistence of loss firms, the earnings persistence (EP) model, and (2) based on the residual income (RI) model. They find that both models outperform the HVZ model. However, it is unclear if these conclusions apply to IPO firms.

[1] Fama and French (1997, p. 154) argue that the unexpected news component in realised returns tends to corrupt factor loadings and risk premia, which results in "woefully imprecise estimates of the cost of equity." Francis and Philbrick (1993), Dugar and Nathan (1995) and McNichols and O'Brien (1997) highlight that analyst forecasts tend to be overly optimistic, which leads to upwardly-biased ICC estimates. Easton and Monahan (2005, p. 501) investigate seven ICC estimates and conclude that most are compromised by the high bias and inaccuracy of analyst estimates. Li and Mohanram (2012, p.1153) also stress that analyst earnings forecasts are "available only for a subset of firms, with almost half of all firms not having analyst coverage in most years."

[2] ICC can also be used to assess post-IPO performance, which is important considering the lack of consensus on whether post-IPO returns reflect fair pricing or correction of initial mispricing (Ritter, 1991; Brav and Gompers, 1997; Brav et al., 2000; Eckbo et al,. 2000). ICC also helps assess the risk of the IPO stock and factors into portfolio managers' asset allocation decisions, active risk control, and style analysis. Thus, investors are likely to forecast ICC for IPO firms beyond its valuation application.

In this study, we perform two related analyses. First, we test the reliability of the earnings forecasts of the HVZ, EP and RI models in the context of IPO stocks. Specifically, we investigate the extent to which these models can be used to (1) reliably predict post-listing earnings and (2) derive valid ICC estimates for newly-listed firms. No study to date has examined the performance of the HVZ, EP and RI models in the context of IPOs, and such an analysis is important as poor performance of the models means investors would have to rely either on inaccurate ICC estimates or on other methods to infer ICC for IPO stocks.

Second, we propose a new model that combines the HVZ and EP models, i.e., the HVZ/EP model, and test whether it yields incrementally more reliable estimates than the HVZ, EP and RI models. We provide three motivations for the new model. First, the HVZ/EP model captures the differential earnings dynamics of loss firms, which is a common feature of IPO firms. Ritter and Welch (2002) find that 79% of IPOs between 1999 and 2000 were loss-making, and Ritter (2018) reports that 54% of IPOs reported losses over the period 2001–2017. Second, the model controls for the fact that a significant proportion of IPOs either already pay dividends or initiate dividend payments shortly after going public. Martin and Zeckhauser (2010) report that 30% of IPOs between 1990 and 2006 paid out dividends in a three-year period before going public. Kale et al. (2012) report that 65% of dividend initiations in the US are within two years of the IPO. Third, we include the HVZ model because Li and Mohanram (2014) document that the HVZ model explains a larger share of earnings variation than the EP and RI models (their Table 1 shows that the adjusted R2 for the HVZ model is 89.6% vs. 68.1% for the EP and RI models when forecasting next-year earnings). As the variation in IPOs' earnings is expected to be higher than the Compustat population, HVZ seems the preferred model to capture the less predictable earnings of IPO firms. We propose that a model that more closely captures IPO characteristics, such as the differential persistence of loss-making firms and the impact of dividends on future earnings, should be capable of accurately capturing IPO firms' earnings, and we compare the performance of the HVZ/EP model, in terms of accuracy and bias of earnings forecasts and reliability of ICC estimates, with the HVZ, EP and RI models.

We test the performance of the HVZ, EP, RI and the HVZ/EP models using a sample of IPOs from 1972 to 2013. To ensure that earnings and ICC forecasts were available to investors at the time of the IPO, we use only IPOs with prospectus financial information available before the listing. We document that the EP, RI and HVZ earnings forecasts tend to be optimistically biased. Over a one-year horizon, the EP, RI and HVZ mean *signed* forecast errors are -1.63%, -1.27% and -1.32%, respectively. These forecast biases are up to 3.4 times larger than for a broad cross-section of listed firms (Table 3 in Li and Mohanram 2014). The results for the absolute forecast errors are similar: average one-year-ahead earnings forecast errors are 3.64%, 3.72% and 4.08% for the EP, RI and HVZ models, respectively, which are up to 2.5 times higher than for a broad cross-section of stocks reported in Li and Mohanram (2014). Thus, standard cross-sectional earnings forecasting models perform particularly poorly for IPOs.

The HVZ/EP model produces smaller mean bias and forecast errors of -0.045% and 3.41%, respectively, for one-year-ahead earnings forecasts. The average improvement in forecast bias beyond the HVZ, EP and RI earnings forecasts is statistically and economically significant. To illustrate, the HVZ/EP mean bias for one-year-ahead earnings forecasts is 73% smaller than the HVZ forecast bias and 65% smaller than the EP forecast bias. The mean gain in accuracy against the HVZ, EP and RI models is 12%, and is particularly significant compared with the HVZ model (mean difference in accuracy of 19.6%). Our conclusions are similar for longer forecasting horizons when we compare forecasted and actual earnings two and three years ahead. Thus, the

HVZ/EP model outperforms the existing cross-sectional earnings forecasting models, producing smaller bias and higher accuracy of earnings forecasts for a sample of newly-listed firms.[3]

Next, we use the four earnings forecast models to estimate IPO firms' ICC. Specifically, we calculate a composite ICC, rCOMP, as the average of the four ICC measures suggested by Easton (2004). Because we use IPO prospectus information and pro-forma figures to calculate earnings forecasts, ICC uses accounting information available *before* the listing. We then assess the construct validity of the ICC estimates. Specifically, we follow Li and Mohanram (2014) and Guay et al. (2011) and use the Fama-MacBeth approach to regress one-year-ahead buy-and-hold returns on each composite ICC. A statistically significant association with a coefficient value of one indicates a valid ICC estimate. We calculate returns for the first three years after the IPO using the same method as Li and Mohanram (2014).

We document that ICC estimates from the HVZ, EP and RI models tend to be too low when regressed on the 12-month buy-and-hold returns measured after the IPO (coefficients are 1.31; 1.22; 1.12, respectively) and too high when regressed on the annualized 36-month buy-and-hold returns starting two years after the IPO (coefficients of 0.87; 0.74; 0.75, respectively). The ICCs of the HVZ/EP model are the most stable and closest to one in magnitude (coefficient of 0.94 for the 12-month buy-and-hold returns and 0.96 for the 36-month buy-and-hold returns). In robustness tests, we show that the HVZ/EP model produces more reliable ICC estimates for loss-making and

[3] An alternative approach to building a new earnings forecasting model is to combine forecasts from existing earnings models, in the hope that the combined forecasts will have higher accuracy than individual estimates: see Granger and Ramanathan (1984) and Guerard and Beidleman (1986) for a discussion about combining forecasts. The challenge of this approach is that the correlation in IPOs' earnings forecast errors is unknown *ex ante*, and it is unclear if the errors in individual forecasts cancel each other out, improving the accuracy of the composite estimate, or if they augment each other, reducing the accuracy of the composite estimate. We created two composite earnings forecasts based on equal weighted and principal component analysis of earnings estimates from the HVZ, EP and RI models. The HVZ/EP model produces more accurate and less biased estimates than the composite forecasts.

smaller IPOs. Overall, we conclude that researchers and investors should consider using the HVZ/EP model to forecasts IPO firms' earnings and to estimate the ICC.

This paper is of interest to investors, managers and academics, and it bridges topics relevant to accounting and finance. This is the first study to examine cross-sectional earnings forecasting models in terms of their accuracy and bias, and the validity of the models' ICC estimates for newly-listed firms. The challenge of the IPO setting is that before the listing, there is no history of stock returns or analyst coverage to apply ICC estimates based on an asset pricing model or analyst estimates. This means that investors have to rely on cross-sectional earnings forecast models to build ICC estimates. We show that the HVZ, EP and RI models produce more biased and inaccurate forecasts for new listings than a broad cross-section of stocks, and that resultant ICCs tend to be relatively unreliable, particularly for the loss-making and small stocks that constitute the bulk of new listings. As a remedy, we propose the HVZ/EP model, which we show has lower bias, higher accuracy and produces more reliable ICC estimates in the settings we examine. Our findings suggest that investors can improve the reliability of ICC estimates for newly-listed firms by using the HVZ/EP model.

Our study contributes to the literature on the validity of cross-sectional and time-series models in forecasting firm fundamentals, and responds to Williams's (2009, 274) call for "a more problem driven approach to accounting research and practice." Lorek (2014, 147) reviews the literature on statistical cash-flow models and highlights that unavailability of analyst forecasts increases investor interest and reliance on statistical models, and that "identification of best-performing statistically based [cash flow] prediction models is of importance to analysts, investors and researchers." Nielsen, Rimmel and Yosano (2015) emphasize the importance of estimating the cost of capital for Japanese IPOs and link it to the quality of IPO prospectus disclosure.

Our paper also relates to the literature that examines performance of IPO valuation methods (Deloof et al., 2009; Kaplan and Ruback, 1995; Roosenboom, 2012; Berkman et al., 2000). These papers compare prospectus valuations obtained using multiples and discounted cash flow methods to the actual IPO pricing. Our study adds to this literature, as more precise ICC estimates improve the accuracy of the discounted cash flow method. Of note in this literature are studies that try to directly estimate ICC. For example, Berkman et al. (2000) estimate ICC using equity betas obtained from comparable firms in the same industry as the IPO firm. Cogliati et al. (2011) estimate equity betas using 250 days of trading after the IPO. Our study shows how ICC can be estimated directly using IPO firms' accounting information.

2. Related literature

Two main approaches have been proposed to measure cost of capital. The first approach relies on realised returns and asset pricing models. However, asset pricing models are plagued by the fact that their estimates are based on noisy past realised returns, and the unexpected news component in realised returns tends to corrupt the reliability of factor loading and factor premia estimates (Fama and French, 1997). The second approach is the implied cost of capital based on a valuation model (Bhattacharya et al., 2012; Botosan et al., 2004; Francis et al., 2004). The rationale behind the ICC framework is straightforward: use a specific valuation model, accept the current stock price as at least semi-strong market efficient, and "back-out" the internal rate of return, which equates the current stock price of the firm with its expected future payoffs to shareholders. The internal rate of return is then considered to be the market's *ex ante* assessment of the firm's CoE. Lee et al. (2010) examine the predictive power of seven ICC and two RFB proxies and conclude that "all of the ICC estimates tested perform much better than the beta-based measures widely touted in finance textbooks" (Lee et al., 2010, p. 26). Thus, more recent literature relies on valuation-based proxies for estimating firms' ICC.

A caveat in using ICC is that two conditions must be met to yield an unbiased CoE estimate: (1) market prices are assumed to be efficient and (2) forecasted future payoffs are congruent with overall market expectations. Assuming semi-strong market efficiency, which is reasonable for actively-traded stocks, the difficulty in practice reduces to reliably measure future payoffs to shareholders. Researchers typically use analysts' short- and long-term consensus earnings forecasts to proxy for market expectations, but with reliance on analyst forecasts two problems arise. First, a large proportion of stocks is not covered by analysts. Li and Mohanram (2012, p. 1153) report that "analyst forecasts are available only for a subset of firms, with almost half of all firms not having analyst coverage in most years. This problem is not trivial because most of the firms without analyst following are typically small and young." Importantly, non-listed stocks, such as IPOs before listing, do not have analyst coverage. This coverage bias limits the ICC methodology to large and well-established firms. Second, analyst forecasts tend to be overly optimistic (McNichols and O'Brien (1997), which leads to upwardly-biased ICC estimates. Forecast bias can be substantial enough to render an otherwise valid approach unreliable (Easton and Monahan, 2005; Mohanram and Gode, 2013).

2.1 The HVZ model

To overcome the difficulties related to reliance on analyst forecasts, recent literature recommends using earnings forecasts from either longitudinal or cross-sectional models to capture future payoffs to shareholders.[4] Longitudinal models impose strong data requirements, limiting their use. Cross-

[4] For excellent reviews of the earnings forecasting literature see Echterling et al. (2015) and Easton and Monahan (2016). Recent studies in this literature focus on the use of qualitative information, such as narrative disclosures, in

sectional models remain useable even for firms without long time-series of earnings realisations, which explains their comparative popularity. The most common models are by Hou et al. (2012) and Li and Mohanram (2014), which we discuss next.

Hou et al. (2012) forecast earnings from contemporary accounting data and find that their estimates are superior to analyst forecasts in respect of forecast bias and earnings response coefficients. Further, ICC estimates calculated from their model are more reliable proxies for CoE than estimates derived from analyst earnings forecasts. The HVZ model builds on cross-sectional profitability models and is specified as:

$$E_{i,t+\tau} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 D_{i,t} + \alpha_3 DD_{i,t} + \alpha_4 E_{i,t} + \alpha_5 NegE_{i,t} + \alpha_6 AC_{i,t} + \varepsilon, \quad (1)$$

where $E_{i,t+\tau}$ is earnings in year t+τ (τ = 1 to 5) of firm *i*, $A_{i,t}$ is total assets, $D_{i,t}$ is dividends, $DD_{i,t}$ is an indicator variable for dividend paying firms, $E_{i,t}$ is earnings, $NegE_{i,t}$ is an indicator variable for loss firms, and $AC_{i,t}$ is working capital accruals.

2.2 The LM models

Li and Mohanram (2014) propose two parsimonious alternatives to the HVZ model. The earnings persistence (EP) model requires only current earnings data to predict future earnings, and includes an indicator variable for loss firms ($NegE_{i,t}$) to account for different persistence of profits and losses in the form of an interaction term ($NegE_{i,t} * E_{i,t}$),

$$E_{i,t+\tau} = \beta_0 + \beta_1 NegE_{i,t} + \beta_2 E_{i,t} + \beta_3 (NegE * E)_{i,t} + \varepsilon. \quad (2)$$

earnings forecasting (Bochkay and Levine, 2017) and alternative estimation techniques, such as least absolute deviation (Evans et al., 2017) and mixed data sampling (MIDAS) regressions (Ball and Ghysels, 2017) and econometric concerns (Gerakos and Gramacy, 2013). Other studies focus on the term structure of implied costs of equity capital (Callen and Lyle, 2019), correlations between future realised returns and the composite implied cost of capital estimated from cross-sectional earnings forecasting models (Paton et al., 2019) and links between earnings and stock prices that are helpful in earnings forecasting (Harris and Wang, 2019).

The residual income (RI) model predicts earnings based on current earnings, equity book value and total accruals. The RI model derives from the well-known residual income model,

$$E_{i,t+\tau} = \chi_0 + \chi_1 NegE_{i,t} + \chi_2 E_{i,t} + \chi_3 (NegE * E)_{i,t} + \chi_4 B_{i,t} + \chi_5 TACC_{i,t} + \varepsilon, \tag{3}$$

where $B_{i,t}$ is equity book value and $TACC_{i,t}$ are total accruals of firm *i* as described in Richardson et al. (2005). Li and Mohanram (2014) find that both models outperform the HVZ model in terms of forecast accuracy, forecast bias, and greater construct validity of the model-based ICC estimates.

2.3 The HVZ/EP model

The HVZ model does not account for differential earnings persistence between profitable and loss-making firms, though losses are less persistent than profits. However, a significant proportion of IPO firms are loss-making. The EP model accounts for this feature but does not model how current dividends affect future earnings. These considerations motivate us to combine the HVZ and EP models into one comprehensive forecasting solution, the HVZ/EP model:

$$E_{i,t+\tau} = \psi_0 + \psi_1 A_{i,t} + \psi_2 D_{i,t} + \psi_3 DD_{i,t} + \psi_4 E_{i,t} + \psi_5 NegE_{i,t} + \psi_6 AC_{i,t} + \psi_7 (NegE * E)_{i,t} + \varepsilon. \tag{4}$$

The HVZ/EP model captures the differential earnings dynamics of loss firms and the effect of dividends on future earnings, which can improve the accuracy of earnings estimates. We do not consider combining the HVZ and RI models, as the only innovation is addition of the book value, and previous studies find that book values are not associated with IPO offer prices and market values (Bartov et al., 2002; Aggarwal et al., 2009). As standard valuation models show that market prices reflect future earnings, this evidence does not support the expectations that book values will predict future IPO earnings.[5]

3. Testing the accuracy and bias of earnings forecasts and the validity of ICCs

Forecasting earnings from cross-sectional models is a two-step procedure. First, coefficients in each earnings forecasting model are estimated using a broad cross-section of listed firms. Second, estimated coefficients are multiplied by IPOs' accounting information. We estimate the HVZ, EP, RI, HVZ/EP models using the previous ten years of accounting data for the Compustat universe available at the end of each year *t*. This includes all firms with fiscal years ending from June t to May t+1. To mitigate the impact of outliers, all variables are winsorized at the 1st and 99th percentile in each year. Consistent with HVZ (2012), all models are estimated in absolute dollar values.[6] Then, for each IPO between January and December t+1 we multiply accounting information immediately preceding the IPO date by the coefficients from the cross-sectional earnings forecasting models to compute one- to three-year-ahead earnings forecasts.

3.1 Forecast bias and accuracy

After calculating IPOs' earnings forecasts, we measure forecast bias and accuracy to examine the extent to which the models generate accurate predictions of IPOs' future earnings. Forecast bias is defined as the difference between actual earnings, E_{t+1}, and forecasted earnings, $\widehat{E_{t+1}}$. To allow

[5] Book values may not predict IPO stock earnings because a significant proportion of newly-listed firms include negative book values. Aggarwal et al. (2009, p. 258) document that "[F]orty-one percent of the 1997-2001 sample had negative pre-IPO book values of equity" but valuation and earnings forecasting models assume positive book value. Aggarwal et al. (2009) highlight that for this reason, researchers often remove negative book value firms from analysis (Beatty et al., 2000; Hand, 2003).
[6] Li and Mohanram (2014) estimate their models on a per share basis. However, the number of shares outstanding reported on Compustat is frequently significantly different from the IPO prospectus information. Sensitivity tests show the robustness of our conclusions when we estimate the models on a per share basis.

for a meaningful comparison between IPOs, forecast bias is scaled by market value of equity calculated at the end of the first month of trading, MV_{1},

$$EPSbias = \frac{E_{t+1} - \widehat{E_{t+1}}}{MV_1}. \tag{5}$$

A negative bias denotes overpredicted earnings, i.e., optimistic forecasts. We winsorize forecast bias at the 1st and 99th percentile. Forecast accuracy is the absolute value of forecast biases.

3.2 Calculating ICCs and testing their validity

After calculating earnings forecasts, we use them as inputs into ICC estimates. As in Easton (2004), HVZ (2012) and LM (2014), we calculate four ICC estimates: rPE, rPEG, rMPEG, rAEGM.[7] We then create a composite ICC estimate (rCOMP), which is the average of the four ICC measures calculated for each earnings model. To illustrate, $rCOMP_{HVZ}$ is the average of the rPE, rPEG, rMPEG, rAEGM estimates when we use the HVZ model to forecast earnings.

To test the validity of the estimates, we follow Li and Mohanram (2014) and Guay et al. (2011) and run Fama-MacBeth regressions of 12-, 24- and 36-month buy-and-hold returns, with returns reported in annual terms, on the composite ICC. We allow a four-month gap between the earnings estimation date and the start of the return period. We then test whether the regression coefficients are (1) statistically different from zero and (2) indistinguishable from one. A significant and consistent association between rCOMP and buy-and-hold returns with a coefficient value of one indicates a valid estimate. We require at least 15 IPOs in each fiscal year, and set ICC estimates to range between 0 and 0.50, as it is unlikely that investors would expect returns below zero or above 50 percent (Barth et al., 2013).[8]

[7] Appendix A reports how each ICC is calculated.

[8] Sensitivity tests show that the tone of our conclusions is unaffected when we do not impose these filters.

4. Data and sample selection

We use all NYSE, Amex and Nasdaq listed firms on the Compustat annual files up to 2015 to estimate the cross-sectional earnings models. For the HVZ and EP models, we collect 205,484 and 208,070 firm-year observations, respectively, from 1950 to 2015. Data availability for the RI model begins in 1960, yielding 196,303 firm-year observations. Given that each model is estimated over the past ten years, the first factor loadings are available in 1959 for the HVZ, EP and HVZ/EP models, and in 1969 for the RI model.

The sample of newly-listed firms includes all IPOs from the Securities Data Company (SDC) database over the period 1972–2013, excluding unit IPOs, closed-end funds, real estate investment trusts (REITs), American Depositary Receipts and Shares (ADRs & ADSs) and non-U.S. listed firms. We only select IPOs for which we can identify pre-listing earnings numbers to calculate future earnings forecasts. We search Compustat for prospectus earnings information, as Compustat backfills accounting information. We cross-validate Compustat data with SEC S-1 fillings from EDGAR to confirm that investors had access to the accounting information at the time of the IPO that is then back-filled on Compustat. Further, to build confidence that we only use pre-IPO information to construct earnings forecasts, we include IPOs for which the difference between the SDC IPO date and the Compustat fiscal year-end immediately preceding the IPO is at least 90 days and at most 365 days. Thus, we select only IPOs for which investors could reasonably expect to have access to prospectus information. This produces a sample of 2,485 IPOs. We then keep IPOs for which all relevant market (CRSP) and accounting data (Compustat) is available, to predict one- to three-year ahead earnings for all models. These conditions generate a sample of 1,657 IPOs.

Table 1 reports summary statistics for the variables from the HVZ and LM models. The noteworthy results are that a typical IPO firm is relatively small, with an average equity book value of 66.3m USD, and that a significant portion of IPOs pay dividends (20%), a result consistent with Martin and Zeckhauser (2010). Around 29% of IPOs reported losses before going public, consistent with Ritter and Welch (2002) and Ritter (2018).[9] Panel B reports Pearson correlations between variables, and these are comparable with earlier research (e.g., Hou et al., 2012; Li and Mohanram, 2014).

5. Analysis and results

5.1 Forecast bias and accuracy of the models

In the first step, we estimate the coefficients for the HVZ, EP and RI models, which we then use to predict future earnings.[10] Next, we turn to estimating the new HVZ/EP model. Panel A of Table 2 shows the expected signs of coefficients for the HVZ and EP models, which are the basis for the HVZ/EP model. Panel B reports average coefficients for the HVZ/EP model for the broad cross-section of listed firms. The signs and magnitudes of the coefficients are consistent with estimates in HVZ (2012) and LM (2014). To illustrate, the earnings coefficients are positive and highly significant across all forecast horizons, which is consistent with current earnings having a strong predictive power for future earnings. The coefficient for $NegE * E$ is negative and highly significant. Importantly, controlling for the differential persistence of loss firms affects the signs of coefficients on some explanatory variables from the HVZ (2012) model. Specifically, compared with the HVZ model, the dividend indicator is negative. This result is consistent with the residual income model, where higher dividends today reduce retained earnings, leading to lower future earnings. Further, the HVZ/EP model predicts that loss-making IPOs will continue reporting losses

[9] In untabulated results, we find that 26% of IPO firms have negative book values, a result consistent with Aggarwal et al. (2009).

[10] The results are available upon request. Although our estimation period is longer than those of previous studies, the signs and magnitudes of the coefficients are consistent with estimates in HVZ (2012) and LM (2014).

after listing. This contrasts with the HVZ model, which predicts that negative pre-IPO earnings reverse immediately. The prediction of the HVZ/EP model is consistent with the EP model estimates and results in Joos and Plesko (2005, p. 853) who find that "losses can persist for a number of years, i.e., a current loss does not necessarily reverse to profitability in the immediate future." Thus, the HVZ understates persistence of losses, which can lead to inaccurate earnings estimates. Overall, the HVZ/EP model provides estimates more consistent with economic theory and past empirical evidence on the behaviour of earnings.

We use the Table 2 cross-sectional estimates and pre-IPO data to forecast one-, two- and three-year-ahead earnings for newly-listed stocks. We then calculate earnings forecast bias and accuracy. Table 3, Panel A reports mean and median forecast bias for each of the four earnings forecasting models. HVZ, EP, and RI earnings forecasts tend to be significantly optimistically biased. Specifically, over a one-year horizon, the EP, RI and HVZ mean *signed* forecasts errors are -1.63%, -1.27% and -1.32%, respectively. These forecast biases are up to 3.4 times larger than for a broad cross-section of listed firms (Table 3 in Li and Mohanram 2014). As is typical in the literature, forecast precision decreases as the forecast horizon increases to two- and three-year-ahead earnings. Our results suggest that standard earnings forecasting models perform poorly for newly-listed firms.

The HVZ/EP model earnings forecasts have lower bias than the HVZ (2012) and LM (2014) models, a result consistent with the Table 2 evidence that the HVZ/EP model better captures post-IPO earnings dynamics. To illustrate, the HVZ/EP mean bias for one-year-ahead earnings forecasts is -0.45% or 73% smaller than the HVZ forecast bias and 65% smaller than the EP forecast bias. Results for longer forecast periods are qualitatively similar. Panel B confirms that HVZ/EP model produces significantly less biased forecasts than the HVZ, EP and RI forecasts, which suggests that investors should rely on the HVZ/EP model when forecasting post-IPO earnings.[11]

The Table 4 results for absolute forecast errors are similar to the forecast bias results: one-year-ahead forecast errors are 3.64%, 3.72% and 4.08% for the EP, RI and HVZ models, which are up to 2.5 times higher than for a broad cross-section of stocks reported in Li and Mohanram (2014). These results support our conclusion regarding the poor performance of standard earnings forecast models for IPO firms. The HVZ/EP model's mean forecast error is 3.41%, which is statistically lower than the estimates from the other models. The average improvement in error over the HVZ, EP and RI models is 12%, and the gain in accuracy is particularly significant against the HVZ model (mean difference in accuracy of 19.6%). Our conclusions are similar for longer windows when we compare forecasted and actual earnings two and three years ahead. Overall, Tables 3 and 4 suggest that the HVZ/EP model outperforms the existing models in terms of smaller bias and higher accuracy for a sample of newly-listed firms.[12]

In untabulated results, we created two composite earnings forecasts based on the earnings estimates from the HVZ, EP and RI models. First, we create an equally-weighted composite forecast based on a combination of the HVZ, EP and RI models. Second, we use principal component analysis on the HVZ, EP and RI forecasts to extract the factor that explains the common variation in the three earnings forecasts. We then compare the accuracy and bias of the two composite forecasts against the HVZ/EP model estimates. We find that the HVZ/EP model

[11] In untabulated results, we also confirm that the HVZ/EP has lower forecast bias than the random walk model. We perform this test because Bradshaw et al. (2012) report that the random walk time-series forecasts of earnings compete reasonably well with analyst forecasts over varying forecasting horizons. Gerakos and Gramacy (2013) report that the naïve random walk model outperforms the HVZ model and that the HVZ model is particularly inaccurate for firms without analyst coverage.

[12] The Table 4 evidence that the forecast error for the RI model is on average slightly higher than the EP model suggests that including book values does not improve the accuracy of IPO earnings forecasting. Panel B of Table 4 reports that the correlation between book value and total assets is 0.855, and since the HVZ/EP model controls for total assets, the explanatory power of book values for earnings is likely to be subsumed by assets.

produces less biased and more accurate earnings estimates than the two composite forecasts. This test validates our argument fora new earnings forecasting model rather than an approach that combines estimates from existing models.

5.2 Testing the validity of the model-based Implied Cost of Capital estimates

Next, we use the forecasted earnings to estimate IPO firms' ICC. Specifically, the composite ICC, rCOMP, is the average of rPE, rPEG, rMPEG, and rAEGM. As we use IPO prospectus information to calculate earnings forecasts, ICCs can be estimated at the time of listing. To assess the construct validity of the ICC estimates, we follow Li and Mohanram (2014) and Guay et al. (2011) and use the Fama-MacBeth approach to regress annualized buy-and-hold returns on each model's composite ICC. A significant and consistent association with a coefficient value of one indicates a valid ICC estimate.

Panel A of Table 5 reports the descriptive statistics for rCOMP, estimated using the four earnings forecasting models. Over the one-year forecast period, rCOMP ranges from 10.23% for the HVZ/EP model to 11.04 for the EP model. We observe similar trends over longer forecast periods. Panel B reports the Fama-MacBeth regression results. Coefficient estimates are positive and significantly different from zero for all ICCs. We observe that ICC estimates from the HVZ, EP and RI models tend to be too low when regressed on 12-month buy-and-hold returns after the IPO (as implied by coefficients of 1.31; 1.22; 1.12, respectively) and too high when regressed on annualized returns measured over 36 months after the IPO (as illustrated by coefficients of 0.87; 0.74; 0.75, respectively). The HVZ/EP ICCs are the most stable and closest to one in magnitude (coefficient of 0.94 for the 12-month returns, 1.04 for the 24-month returns, and 0.96 for the 36-month returns). We conclude that the HVZ/EP model earnings forecasts seems to produce the most reliable ICC estimates.[13] However, in statistical terms, we cannot reject the null that, in the pooled IPO sample, the coefficients from all models are significant and close to one.

5.3 Robustness tests

In untabulated results, we perform several robustness tests to build confidence in our conclusions. Scale effects can bias coefficients and confound inferences in regression analyses. To corroborate the Table 5 conclusions, we re-run the analysis on share price deflated earnings and use closing prices instead of market values in the ICC calculations. The magnitudes of the Fama-MacBeth coefficient estimates are similar to Table 5. Next, we examine whether our results are robust to other estimation methods. Specifically, we estimate the association between buy-and-hold returns and composite ICC using pooled OLS regressions controlling for time-fixed effects. We find that the coefficient estimates remain unchanged and close to one. Thus, using other estimation methods yields similar conclusions. Further, we run the analysis when we keep only stocks with non-missing information for the entire three-year period, which makes coefficients more comparable across forecast horizons. Conclusions are unchanged when we use a constant sample for the analysis.

To sharpen the analysis, we also compare the performance of the models in subsamples. The first test focuses on ICC estimates for loss-making and profitable IPOs. We find that only the HVZ/EP and EP models produce reliable ICC estimates for loss-making firms. For profitable firms, the HVZ/EP and HVZ models' ICCs have coefficients that are statistically different from zero and close to one in magnitude.

The second test focuses on the reliability of ICC estimates for small rather than large IPO firms. This test is useful, as IPOs are frequently small firms. Only the HVZ/EP model's ICC estimates

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[13] In untabulated tests we confirm that HVZ/EP remains the most stable model when not requiring ICC to range between 0 and 0.5 and not requiring a minimum number of IPOs per year.

are significantly different from zero for large IPO firms, with the coefficient value close to one. The HVZ/EP and HVZ models produce reliable ICC estimates for small IPO stocks. Overall, sensitivity tests suggest that the HVZ/EP model produces the most reliable estimates across the settings we examine.

5.4 Further research

The HVZ/EP model seems to offer an improvement over the HVZ, EP and RI models among IPO firms and produces robust results in subsamples. Further research could focus on the model's applicable boundary, to identify the limits beyond which the model does offer material improvement over the Hou et al. (2012) and Li and Mohanram (2014) models. For example, a researcher could correlate IPO characteristics with the incremental forecast accuracy of the HVZ/EP model to identify cases where the model's application is likely to generate the most and least benefits. Further, research could examine the applicability of the model in other settings with similar characteristics to IPOs. One such promising area is acquisitions of private targets, where financial information is scarce and most private targets are loss-making (Chen, 2019).

6. Summary and conclusions

IPOs are among the most demanding empirical settings in accounting and finance, particularly for ICC estimates, due to lack of (1) financial data, (2) analyst coverage and (3) share price history. However, this is also a setting where ICC estimates are very useful in valuation, to help mitigate against adverse IPO selection, and for efficient capital allocation to newly-listed firms (Rock 1986). This study evaluates the performance and validity of the HVZ (2012) and Li and Mohanram (2014) earnings forecasting models and the resultant ICC estimates for newly-listed firms. We document that the models produce relatively inaccurate and biased earnings forecasts, which results in unreliable ICC estimates. As a remedy, we propose a new earnings forecasting model, the HVZ/EP model, and benchmark it against the HVZ, EP and RI models. We find that the new model produces more accurate and less biased earnings forecasts and more valid ICC estimates. Our results suggest that the HVZ/EP model can be reliably used in the IPO setting.

The paper's findings are directly relevant for practitioners, who can improve earnings forecasting accuracy for IPO firms and related ICC estimates. More reliable ICC estimates should improve IPO valuation, helping investors in evaluating the offering price and guiding their decision to participate in the IPO. Our insights can be extended to other settings where investors have limited access to financial information, such as acquisitions of private targets.

The study also responds to the call by Echterling, Eierle and Ketterer (2015) for more research on the validity of ICC estimates. They highlight that "[P]erhaps most needed is a greater understanding of the underlying reasons for the differing empirical ICC results observed." Our results suggest that earnings forecasting models developed to capture the broad cross-section of listed firms, such as the Hou et al. (2012) and Li and Mohanram (2014) models can perform poorly when applied to subsamples, such as IPO firms, that exhibit significantly different earnings properties. Thus, a researcher has to consider how the distributional properties of the sample may affect the efficacy of earnings forecasting models, and whether model adjustments can improve forecasting accuracy, bias and the association between the ICC and actual returns.

Appendix A.

This section reports the standard calculation of the ICCs. The models differ with respect to assumptions about dividend payments, and short-term and perpetual abnormal earnings growth. rPE is calculated as

$$r_{PE} = \left(\frac{MV}{E_{t+1}}\right)^{-1}, \tag{1}$$

and rPEG as

$$r_{PEG} = \sqrt{\frac{E_{t+2} - E_{t+1}}{MV}}, \tag{2}$$

where E_{t+1} and E_{t+2} equal one- and two-year ahead earnings forecasts (in absolute dollar values) from the earnings forecasting models, MV is the equity market value that can be calculated using the prospectus offer price and the number of outstanding shares. rMPEG is calculated as

$$r_{MPEG} = A + \sqrt{A^2 + \frac{E_{t+2} - E_{t+1}}{MV}}, \tag{3}$$

where $A = D_{t+1}/2MV$. D_{t+1} equals dividends in *t*+1, which are forecasted assuming dividend payout ratio at *t* for firms with positive earnings, or using dividends at *t* divided by six percent of total assets at *t* as a proxy for dividend payout ratio for firms with current negative earnings (Gebhardt et al., 2001). rAEGM model is defined as

$$r_{AEGM} = A + \sqrt{A^2 + \frac{E_{t+1}}{MV}\left(\frac{E_{t+2} - E_{t+1}}{E_{t+1}} - G_{AEG}\right)}, \tag{4}$$

where $A = \frac{1}{2}\left(G_{AEG} + \frac{D_{t+1}}{MV}\right)$. G_{AEG} equals perpetual growth rate in abnormal earnings set to the current risk-free rate minus three percent (Gode and Mohanram, 2003). The current risk-free rate is calculated by taking the average of the one-month Treasury bill rate over the rolling past 12-month windows and then annualising these averages by compounding over 12 months (Barth et al., 2013). Treasury bill rates are from the Kenneth French website.

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Table 1. Summary statistics

Panel A: Summary Statistics

Variable	Mean	1%	25%	Median	75%	99%	STD	Obs.
B(t)	66.31	-173.16	-0.28	4.78	17.97	1,048.30	661.68	1,657
A(t)	402.94	1.25	10.17	28.54	105.94	5,399.50	3,212.43	1,657
E(t)	8.24	-40.83	-0.58	1.39	5.02	165.22	60.48	1,657
NegE(t)	0.29	0.00	0.00	0.00	1.00	1.00	0.45	1,657
NegE*E(t)	-2.53	-40.83	-0.58	0.00	0.00	0.00	9.80	1,657
D(t)	4.06	0.00	0.00	0.00	0.00	95.63	33.99	1,657
DD(t)	0.20	0.00	0.00	0.00	0.00	1.00	0.40	1,657
AC(t)	-4.15	-85.51	0.00	0.00	0.00	19.53	49.14	1,657
TACC(t)	1.68	-61.06	0.00	0.00	0.00	86.78	90.66	1,657

Panel B: Pearson Correlations

	B(t)	A(t)	E(t)	NegE(t)	NegE*E(t)	D(t)	DD(t)	AC(t)
A(t)	0.855***							
E(t)	0.701***	0.578***						
NegE(t)	-0.065***	-0.059**	-0.179***					
NegE*E(t)	0.014	-0.006	0.208***	-0.407***				
D(t)	0.232***	0.191***	0.475***	-0.054**	0.016			
DD(t)	0.059**	0.048**	0.143***	-0.220***	0.101***	0.236***		
AC(t)	-0.371***	-0.197***	-0.627***	0.024	0.053**	-0.432***	-0.051**	
TACC(t)	0.084***	0.103***	0.079***	-0.032	0.024	-0.084***	0.053**	-0.062**

Panel A reports summary statics for the variables used to forecast earnings from the HVZ, EP and RI models. The IPO sample includes 1,657 firms. All values in mUSD, except for NegE, DD and NegE*E. Panel B reports the Pearson correlation coefficients between variables. ***, **, * denotes significance at the one, five, ten percent level or better.

Table 2. Coefficient estimates from the HVZ/EP model

Panel A: Coefficient signs for the HVZ and EP models

	Intercept	A(t)	D(t)	DD(t)	E(t)	NegE(t)	AC(t)	NegE*E(t)	Adj. R^2
HVZ model	+	+	+	+	+	+	−		
EP model	+				+	−		−	

Panel B: HVZ/EP model estimate

	Intercept	A(t)	D(t)	DD(t)	E(t)	NegE(t)	AC(t)	NegE*E(t)	Adj. R^2
E(t+1)	3.116	0.003	0.224	-0.119	0.867	-7.429	-0.028	-0.860	0.89
	(4.48)	*(3.87)*	*(3.58)*	*(-1.73)*	*(29.33)*	*(-4.15)*	*(-2.15)*	*(-5.59)*	
E(t+2)	5.574	0.005	0.310	0.316	0.825	-10.322	-0.040	-1.396	0.83
	(6.73)	*(5.25)*	*(4.20)*	*(2.67)*	*(22.31)*	*(4.87)*	*(-2.41)*	*(-6.18)*	
E(t+3)	8.347	0.007	0.375	-0.182	0.808	-11.823	-0.038	-1.663	0.80
	(8.29)	*(6.30)*	*(4.27)*	*(-2.86)*	*(19.04)*	*(-5.26)*	*(-2.09)*	*(-6.17)*	

The HVZ/EP model is estimated annually using the previous ten years of data, from 1959 to 2015. Similarly to LM(2014), we set working and total accruals to zero if they are missing. Average mean coefficients and time-series average t-statistics based on robust standard errors (in parentheses) are reported.

Table 3. Forecast bias of the forecasting models for the IPO sample

Panel A: Time-series averages						
	E(t+1)		E(t+2)		E(t+3)	
	Mean	Median	Mean	Median	Mean	Median
HVZ	-0.0163	-0.0013	-0.0311	-0.0047	-0.0440	-0.0159
	(-9.98)	*(-5.91)*	*(-11.20)*	*(-7.55)*	*(-12.01)*	*(-10.16)*
EP	-0.0127	-0.0033	-0.0282	-0.0102	-0.0439	-0.0182
	(-9.17)	*(-7.13)*	*(-11.22)*	*(-9.21)*	*(-12.83)*	*(-11.58)*
RI	-0.0132	-0.0041	-0.0287	-0.0104	-0.0435	-0.0199
	(9.21)	*(-7.44)*	*(-11.30)*	*(-9.37)*	*(-12.76)*	*(-11.62)*
HVZ/EP	-0.0045	0.0020	-0.0153	-0.0013	-0.0285	-0.0105
	(-3.54)	*(0.14)*	*(-6.56)*	*(-3.75)*	*(-8.93)*	*(-7.21)*
Panel B: The HVZ/EP *pairwise comparison*						
HVZ-HVZ/EP	-0.0118	-0.0033	-0.0158	-0.0035	-0.0155	-0.0054
	(-10.58)	*(-5.05)*	*(-9.36)*	*(-3.82)*	*(-8.55)*	*(-1.85)*
EP-HVZ/EP	-0.0082	-0.0054	-0.0130	-0.0089	-0.0154	-0.0077
	(-13.96)	*(-21.18)*	*(-14.19)*	*(-22.53)*	*(-15.00)*	*(-22.48)*
RI-HVZ/EP	-0.0087	-0.0062	-0.0134	-0.0092	-0.0150	-0.0094
	(-13.98)	*(-21.58)*	*(-14.37)*	*(-22.9)*	*(-12.69)*	*(-22.45)*

Panel A reports time-series averages of the mean and median forecast biases for the cross-sectional earnings forecasting models. In parentheses time-series t-statistics for mean and median (Wilcoxon signed-rank test) are reported. Panel B reports pairwise comparisons (differences) between the models with t-statistics for mean (paired t-test) and median (Wilcoxon signed rank sum test) differences reported in parentheses. Results are based on 1,657 IPOs.

Table 4. Forecast accuracy of the forecasting models for the IPO sample

Panel A: Time-series averages						
	E(t+1)		E(t+2)		E(t+3)	
	Mean	Median	Mean	Median	Mean	Median
HVZ	0.0408	0.0227	0.0725	0.0418	0.0966	0.0542
	(30.14)	*(35.26)*	*(32.09)*	*(35.26)*	*(32.22)*	*(35.26)*
EP	0.0364	0.0204	0.0681	0.0412	0.0924	0.0547
	(32.95)	*(35.26)*	*(33.97)*	*(35.26)*	*(33.27)*	*(35.26)*
RI	0.0372	0.0212	0.0687	0.0408	0.0927	0.0552
	(32.12)	*(35.26)*	*(33.89)*	*(35.26)*	*(33.60)*	*(35.26)*
HVZ/EP	0.0341	0.0208	0.0633	0.0398	0.0860	0.0514
	(35.49)	*(35.26)*	*(35.69)*	*(35.26)*	*(34.46)*	*(35.26)*
Panel B: Pairwise comparison						
HVZ-HVZ/EP	0.0067	0.0019	0.0091	0.0021	0.0106	0.0028
	(8.11)	*(9.69)*	*(7.54)*	*(8.01)*	*(7.36)*	*(7.04)*
EP-HVZ/EP	0.0023	-0.0005	0.0048	0.0015	0.0065	0.0032
	(4.35)	*(0.94)*	*(5.87)*	*(4.27)*	*(6.73)*	*(6.07)*
RI-HVZ/EP	0.0031	0.0003	0.0054	0.0011	0.0067	0.0038
	(5.50)	*(1.51)*	*(6.40)*	*(4.32)*	*(6.67)*	*(5.80)*

Notes: Panel A reports time-series averages of the mean and median forecast accuracy for the cross-sectional earnings forecasting models. In parentheses time-series t-statistics for mean and median (Wilcoxon signed-rank test) are reported. Panel B reports pairwise comparisons (differences) between the models with t-statistics for mean (paired t-test) and median (Wilcoxon signed rank sum test) differences reported in parentheses. Results are based on 1,657 IPOs.

Table 5. Fama-Macbeth regressions of realized returns on the composite implied cost of capital measures

	12-month returns		24-month returns		36-month returns	
	Mean	STD	Mean	STD	Mean	STD
Panel A. Descriptive statistics for rCOMP						
rCOMP						
HVZ	0.1069	.0832843	0.1094	.0895164	0.1092	.0904919
EP	0.1104	.0842122	0.1216	.0919818	0.1219	.0948777
RI	0.1094	.0862912	0.1214	.0920103	0.1215	.0943968
HVZ/EP	0.1023	.0812156	0.1111	.0868589	0.1111	.088602

	12-month returns		24-month returns		36-month returns	
rCOMP	Coeff. *(t-stat.)*	Adj. R² *(%)*	Coeff. *(t-stat.)*	Adj. R² *(%)*	Coeff. *(t-stat.)*	Adj. R² *(%)*
Panel B. Fama-MacBeth regression coefficients of realised returns on the composite ICC						
HVZ	1.3059	0.61	1.0623	1.86	0.8789	0.92
= 0	*(2.87)****		*(2.59)***		*(2.44)***	
= 1	*(0.67)*		*(0.14)*		*(0.33)*	
EP	1.2236	0.94	0.9960	1.42	0.7437	0.64
= 0	*(1.87)**		*(2.34)***		*(2.00)**	
= 1	*(0.35)*		*(0.00)*		*(0.69)*	
RI	1.1186	0.87	1.0324	1.57	0.7539	0.63
= 0	*(1.80)**		*(2.45)***		*(1.98)**	
= 1	*(0.20)*		*(0.01)*		*(0.65)*	
HVZ/EP	0.9403	0.41	1.0383	1.60	0.9573	0.91
= 0	*(1.81)**		*(2.52)***		*(2.69)****	
= 1	*(0.10)*		*(0.10)*		*(0.10)*	

Notes: Panel A documents descriptive statistics for the composite ICC measure rCOMP estimated separately for the HVZ, EP, RI and HVZ/EP models. Panel B reports Fama and MacBeth (1973) regressions of realized returns on implied cost of capital (ICC) computed for the HVZ, EP, RI and HVZ/EP models. In parentheses are t-statistics for whether the mean coefficient is equal to zero or one. ***, **, * denotes significance at the one, five, ten percent level or better.