

Advanced Corporate Finance

An empirical assessment of the relationship
between the cost of equity and realized equity
returns

Prof. Pierluigi Murro

RELATORE

Prof. Fabrizio Core

CORRELATORE

Ruggero Di Rao Marotta

Matr. n.784361

CANDIDATO

Table of Contents

1. Introduction	3
2. Data and Methodology	5
3. Literature review	7
4. Results	15
4.1. Replication of Hou's study	15
4.2. Applicability to small-sized firms	19
4.3. Predictive power over the years	24
4.4. Discussion of results	27
5. Limitations	28
6. Conclusion and Future Research	28

1. Introduction

Estimation of the cost of capital represents an important and, at the same time, heavily debated topic in finance. It reflects the risk of a firm and, consequently, the investor's expected return. Therefore, it has several implications in many corporate finance settings.

Previous studies show that well-known models, such as the Capital Asset Pricing Model or the Fama-French 3 and 5 factor models, based on realized returns as proxies for expected returns, lead to imprecise estimates (Fama and French, 1997; Elton, 1999). Therefore, a new approach has been proposed: the Implied Cost of Capital (ICC). The ICC is the Internal Rate of Return (IRR) which equates the firm's stock price to the net present value of the expected future cash flows. This model is forward looking and does not rely on past return realizations. It is widely used in corporate finance studies, such as assessing the impact of corporate governance on cost of capital (e.g. Botosan, 1997; Francis et al, 2005), the relation between earnings attributes and cost of capital (Francis et al., 2004) or the relationship between investment and cost of capital (Frank and Shen, 2016). It has also been considered for investment purposes (Simon, 2024).

There are three main ICC methods proposed in the literature, each of which can have different sub approaches. These include the Dividend Discount Model (DDM), the Residual Income Valuation Model (RIM), and the Abnormal Earnings Growth Model (AEGM) (Echterling et al., 2015).

The most common approach to estimate future cash flows is to rely on sell-side analysts' forecasts, which are available on Thomson Reuters Institutional Brokers Estimate System (I/B/E/S) (Echterling et al., 2015). Alternatively, Hou et al. (2012) use a mechanical forecast and show that, overall, their model (HVZ) is a better proxy for future earnings compared to analyst-based earnings forecasts, as suggested by the higher ERC (Earnings Response Coefficient), a parameter which captures the reaction of stock prices to unexpected earnings. The subsequent relationship with the realized returns confirms the high predictive power of such model.

However, their results show that the model is less suited for specific subclasses, such as the size. In fact, SMEs are perceived as riskier, therefore creating higher return expectations, which are only partially met. Additionally, Hou's et al.'s cross-sectional ICC model is less biased, but its accuracy represents a major concern. This resulted in the

development of new and more accurate models, such as the ones proposed by Li and Mohanram, Hess and Wolf (Simon, 2024) and Azevedo et al. (2021).

In this study, I aim to better understand the reasons for the limitations by replicating the framework adopted by Hou et al. (2012) and adapting it for SMEs, consistently with Li's et al. (2014) study which proposed RI and EP models outperform the HVZ in terms of accuracy, bias and ERC relative to small firms. Potential reasons for the lower predictive power of the model could be the higher volatility of the earnings of small firms, highly sensitive to both internal and external conditions. Furthermore, I expect that some SME specific characteristics will influence the level of predictiveness of future realized returns. Gebhardt et al. (2001) show that several firm characteristics have an impact on the one-year and two-year ahead ICC and additionally confirmed by Wang (2015). Additionally, I aim to expand HVZ's study timeframe to provide more updated results and capture potential trends of the HVZ model over the years and specific macroeconomic environments, such as crisis periods. By doing so, this study will not only address gaps in existing models but also provide insights into developing more accurate, SME-specific approaches, bridging theoretical advancements with practical applications for these firms.

Based on my analysis, I find that the HVZ model is not less suitable for small-sized firms and that differences in the predictive power of the method are not large, therefore suggesting the accuracy of the model. However, by studying the spread between predicted and realized returns, the model presents several limitations that lead to significant differences between the two dimensions of returns. Secondly, I find that the correlation between the size and the cost of equity is always positive, independently of the size of the firm. Finally, my results show that during crisis periods the applicability of the HVZ model is compromised as the regression variables are able to explain a smaller portion of the future earnings.

In section 2 I will provide the details of my data and the adopted methodology; in section 3 I conduct a review of the existing literature on the topic and develop my hypotheses; in section 4 I report the results of the analysis; in section 5 I provide the main limitations of my study and in the final section I conclude.

2. Data and Methodology

For consistency, I initially employ the same timeframe as in Hou et al.'s (2012) study retrieving the data from the intersection of the CRSP monthly returns file from July 1963 to 2009 and the Compustat fundamentals annual file from 1963 to 2009 as well. However, due to data availability, I am not able to include NYSE, Amex, and Nasdaq listed securities with sharecodes 10 or 11. To overcome this difference, I clean my database by including in the filters “securitytype”, “securitysubtype”, “sharetype” and “primaryexch”. This way I am still able to exclude REITs, Utilities and ADRs from my dataset. Furthermore, I expand the timeframe including data until 2024.

The variable definitions are retrieved from Hou et al.'s study as well and are as follows: (i) earnings is income before extraordinary items from Compustat; (ii) book equity is Compustat stockholder's equity; (iii) total assets and dividends are also from Compustat. Prior to 1988, accruals are calculated using the balance sheet method as the change in non-cash current assets less the change in current liabilities excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expense. Starting in 1988, I use the cash flow statement method to calculate accruals as the difference between earnings and cash flows from operations. I will also include data from the period after 2009 in the study timeframe. Finally, I will create a subsample dividing each year the firms in terciles based on their amount of total assets, as a measure of size. This involves creating three classes, named “Low Sized Firms”, “Medium Sized Firms” and “Large Sized Firms”.

The model used to forecast earnings of individual firms is the same as the one adopted by Hou et al. (2012). This consists in applying the following regression using the previous ten years of data:

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

Where $E_{i,t+\tau}$ denotes the earnings of firm i in year $t + \tau$, ($\tau = 1$ to 5), $A_{i,t}$ is the total assets, $D_{i,t}$ is the dividend payment, $DD_{i,t}$ is a dummy variable that equals 1 for dividend payers and 0 otherwise, $NegE_{i,t}$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise, and $AC_{i,t}$ is accruals.

All explanatory variables are measured as of year t . Consistent with the study, for each firm i and each year t in the sample, I multiply the independent variables as of year t by the coefficients obtained from the pooled regression estimated using data from the previous ten years. This approach ensures that the earnings forecasts are entirely out-of-sample. Furthermore, I only require firms to have non-missing values for the independent variables in year t to compute their earnings forecasts, minimizing the impact of survivorship bias.

For the estimation of the ICC, I apply the same analysis conducted by Hou et al. (2012), which is based on a “composite” measure calculated as the average of the individual ICC estimates of Gebhardt et al. (GLS, 2001) and Gordon and Gordon (Gordon, 1997) models. I exclude from the calculation the Claus and Thomas (CT, 2001), Easton (MPEG, 2004), and Ohlson and Juettner-Nauroth (OJ, 2005) models because of the numerical and economic instability of the output. I compute each ICC estimate for each firm at the end of June of each year t using the end-of-June market equity and the model-based earnings forecasts for up to five years into the future and I impose a minimum reporting lag of three months. To estimate the ICC, I finally match the earnings forecasts to the market equity at the end of June of year t .

For the analysis of the applicability of the model overtime, I divide the total timeframe into decades. This leads to the creation of six different periods: 1968-1977; 1978-1987; 1988-1997; 1998-2007; 2008-2017; 2018-2024. To analyze crisis periods, I create additional three periods: 2000-2002; 2007-2009; 2019-2021. By applying the same analysis methodology adopted by Hou et al. I am able to replicate their study and make cross-sectional comparisons that include the additional years considered in this research.

3. Literature review

The estimation of the cost of capital has been widely explored in the financial literature, with various models and approaches developed to assess its determinants and implications. Yet, there is no generally accepted method to calculate this measure. (Echterling et al., 2015). According to Lee et al. (2009), a reliable proxy for expected returns should be correlated with future realized returns, as any unexpected shocks are, by definition, unpredictable. Most of the studies use the ex-post realized returns as proxies for the ex-ante expected returns. However, this measure represents a noisy proxy and, therefore, not a reliable one (Elton, 1999). Traditional asset pricing models such as the CAPM or the Fama-French 3 and 5 factor models lead to imprecise estimates, and which use would be invalid for empirical problems (Fama and French, 1997, 2004; Elton, 1999).

To address the mentioned inadequacy, more recent literature proposes the Implied Cost of Capital (ICC), a forward looking approach for the estimation of the equity cost capital (Gebhardt et al., 2001). However, also this method has its limitations, as the underlying assumption of a constant cost of capital (Callen and Lyle, 2019) or its heavy reliance on the precision of the earnings forecast (Richardson et al., 2001). Furthermore, the evidence on the relationship between realized returns and the implied cost of capital (ICC) is mixed (Wang, 2021). Some studies report a positive relationship (e.g., Gode and Mohanram, 2003; Hou et al., 2012; Li et al., 2013; Li and Mohanram, 2014; Callen and Lyle, 2019), while others find no significant relationship (e.g., Gebhardt et al., 2001; Easton and Monahan, 2005; Guay et al., 2011). Notably, Ang and Aadka (2017) even document a negative relationship. Finally, small firms and financially distressed ones are underrepresented (La Porta, 1996; Hong et al., 2000; Diether et al., 2002).

The ICC is defined as the internal rate of return (IRR) that equates the current stock to the present value of all future cash flows (ex. expected dividends, earnings and book-values) to common shareholders. Several ICC methods, either following a firm-level or a portfolio-level approach, have been proposed in the finance literature, including the Dividend Discount Model (DDM), the Residual Income Method (RIM), and the Abnormal Earnings Growth Model (AEGM) (Echterling et al., 2015). The best-known include the Malkiel (1979), the Gordon & Gordon (1979) and the Botosan and Plumlee (2002), for their contributions to the DDM; Claus and Thomas (2001), Gebhardt (2001)

and Daske et al. (2006) for the RIM; Easton (2004) and Ohlson et al. (2005) for the AEGM.

The applicability of the ICC extends to several corporate finance settings, such as the relationship between risk and return (e.g., Botosan and Plumlee, 2005; Pástor et al., 2008) and return predictability (e.g., Li et al., 2013) or the impact of corporate governance on cost of capital (e.g., Botosan, 1997; Francis et al., 2005; Ashbaugh-Skaife et al., 2009), the relation between earnings attributes and cost of capital (Francis et al., 2004), the impact of accounting restatements on cost of capital (Hribar and Jenkins, 2004), and the relationship between investment and cost of capital (Frank and Shen, 2016). Finally, it can be used for investment purposes (Simon, 2024).

The most common approach is to use analysts' earnings forecasts to proxy for cash flow expectations, which can be retrieved from Thomson Reuters Institutional Brokers Estimate System (IBES) (Echterling et al., 2015). Evidence shows that the performance of such model presents deficiencies (Gebhardt et al., 2001; Easton and Monahan, 2005; Guay et al., 2011) and that analysts tend to be overly optimistic (O'Brien, 1988; Mendenhall, 1991; Abarbanell, 1991; Brown, 1993; Francis and Philbrick, 1993; Dugar and Nathan, 1995; Hayes, 1998; Doukas et al., 2002; Abarbanell and Levahy, 2003; Easton and Sommers, 2007). However, some authors show that the forecast errors can be predicted (Ali et al., 1992; Hughes et al., 2008). Furthermore, analyst forecasts typically cover only a subset of firms, leaving nearly half without coverage. The firms lacking analyst representation are predominantly small and young, the ones of greatest interest to researchers studying information asymmetry, earnings quality, and disclosure issues (Li and Mohanram, 2014). This is confirmed by Echterling et al. (2015), who state that analysts select and cover only larger enterprises and in a more advanced life cycle.

The alternatives to analysts' forecasts rely on two different regression-based models: time-series models and cross-sectional models. The first use either a linear or exponential smoothing approach and rely on past earnings (Ball and Brown, 1968; Brown et al., 1987). However, their produced forecasts are neither accurate nor biased (Azevedo et al., 2021). On the other hand, Hou et al. (2012) propose a mechanical forecast and their results show that, overall, their model (HVZ) is a better proxy for future earnings. This model, which follows a pooled cross-sectional regression, uses the average of five different ICC estimates (Claus and Thomas, Easton, Gebhardt et al., Gordon and Gordon,

and Ohlson and Juettner-Nauroth) to define its “composite” ICC measure. The cross-sectional model explains a large fraction of the variation in the expected profitability across firms and estimates for up to 5 years into the future. Furthermore, the model appears to be less accurate, but it also presents a lower level of systematic bias compared to the analyst-based one (Simon, 2024). The main advantages of this approach consist in its generation of statistical power by using the large cross-section of individual firms to compute the earnings forecasts and in its significant coverage, shown to be higher than the analysts-based model’s one. The study concludes, by comparing the different ERC (Earnings Response Coefficient) parameter scores which capture the reaction of stock prices to unexpected earnings.

The HVZ model represents a better proxy for market expectations of future earnings. Their results are further confirmed by the relationship with the ex-post realized returns, a finding reinforced by Li et al. (2013). However, Hou et al.’s study also shows that the predictive power of their model-based ICC is less suitable for specific subclasses of firms, respectively small firms, firms with high leverage, default probabilities or analyst dispersion and with low analyst coverage. Despite this, the HVZ model serves as a basis-point for numerous future studies aspiring to reach higher validity, such as the ones proposed by Gerakos and Gramacy (2013), referred to as “RW model” , Li and Mohanram (2014) or Hess and Wolf (2022) and continues to be extensively used in empirical studies on accounting based valuation (e.g. Chang et al, 2012) and ICC (e.g., Lee et al., 2011; Patatoukas, 2011; Jones and Tuzel, 2012) (Li and Mohanram, 2014).

Particularly, Li and Mohanram (2014) criticize the absence of a comparison of the HVZ model with other cross-sectional models as well as the failure to study the relationship between the ICC estimates and the future returns at the firm level, as Gebhardt et al.’s (2001) or Gode and Mohanram’s (2003) prior studies did. Additionally, they recognize the presence of anomalous relationships between the ICC estimates and risk factors, such as the negative correlation with systematic and idiosyncratic risk represent a limit of the model and present two new models: the “EP” model and the “RI” model which both outperform the HVZ (as well as Gerakos and Gramacy’s 2013 naïve random walk model) in terms of forecast accuracy, forecast bias, ERC, correlations between ICC proxies and future returns and risk factors. Most importantly, the

improvement in the forecast accuracy is 45% in small firms and firms without analyst coverage.

Other studies (e.g. Hansen and Thimsen, 2020; Cao and You, 2021; Chen et al., 2022; Van Binsbergen et al., 2023; Hess et al., 2022) have proposed new approaches, differentiating from the past simple linear approaches (Simon, 2024). For instance, Ball and Ghysels (2017) introduce their MIDAS model, which relies on mixed data sampling regression methods and integrates high-frequency time-series data to forecast earnings. Despite the model outperforming raw analysts' earnings forecasts, given its constraints to short-term forecasting, it is not suitable for the ICC estimation. For this reason, Azevedo et al. (2021) extend the MIDAS model and build their CM model, a cross-sectional model based on analysts' forecasts, gross profits, and past stock performance. This approach shows higher accuracy than cross-sectional models and better ERC, and bias scores compared to the AF (raw analysts' forecasts), CSAF (cross-sectional analysts' forecasts), HVZ, EP, RI and RW models. However, this approach shares the main limitation of Hou et al.'s 2012 study: worse performance for small firms as the functioning of this model applies exclusively to firms with an analyst following (Azevedo et al., 2021).

Furthermore, Hess and Wolf (2022) propose a new machine-learning model which retrieves the firm's most updated earnings trends from their current quarterly reports. This approach aims to solve believed general cross-sectional models' limitations, such as the firm-unspecific estimation parameters for past earnings and other accounting variables and the neglect of firm-specific past changes in earnings, as well as the ones of Li and Mohanram's (2014) model, such as the allocation of the same growth coefficient to all firms, ignoring firm-specific nuances. The model, by introducing an interim earnings growth variable, outperforms the HVZ, EP and RI models both in terms of general accuracy and systematic distortion, which is not considered in the HVZ model. However, when considering a longer time forecast framework, the differences become less pronounced (Hess et al., 2022).

As previously stated, the main limitation of Hou et al.'s (2012) and others' studies are the limited applicability to specific subclasses of firms, such as small-sized ones. In fact, Harris and Wang (2019) demonstrate that the HVZ model, which is a pure accounting-based model that does not incorporate market information and is exclusively

based on historical accounting variables, faces some general limitations in the earnings forecast, reason for which they propose a new model for future earnings estimation. However, they also find that, for both analysts-based or model-based, large firms register a higher level of accuracy compared to small companies at all forecast horizons, implying that the size of a firm plays a significant role in the predictions of its future cash flows, supporting Lee and So's (2017) theory that the size of a firm is strongly related to financial analysts' forecasts. This relationship is further confirmed by Hess et al. (2019), who demonstrate that SMEs face more difficulties in forecasting future earnings as well as by Preussner et al. (2022) that provide evidence of a higher accuracy in the prediction for larger firms and with a higher level of corporate governance and management skills and other studies (e.g. Choi and Ziebart, 2004; Beekes and Brown, 2006; Rostamy et al., 2008; Hurwitz, 2018). This is particularly relevant as earnings predictions are strongly related to the reliability of ICCs (Easton and Monahan, 2005).

In fact, the HVZ model uses earnings as a proxy for cash flows expectations (Hou et al., 2012), and its regression, as discussed in the methodology section, is based on four different variables: total assets, dividends, historical earnings and accruals. For this reason, each variable's treatment and consideration becomes essential. According to S&P's Compustat User Guide (2003), total assets are defined as current assets plus net property, plant, and equipment plus other noncurrent assets (including intangible assets, deferred items, and investments and advances).

In particular, intangible assets play a significant role for many SMEs (Watson, 2010) as a source of competitive advantage (Teece, 2000). However, high costs lead to a limited desirability in SMEs in identifying and reporting such items (Watson, 2010). This idea is also supported by Citron et al. (2004) who empirically show the intangibles limited inclusion in SME's accounting balance sheets. Secondly, large companies are associated with a higher probability of distributing dividends (Redding, 1997) and a higher payout (Chen and Dhiansiri, 2009). Additionally, Hess et al. (2019) suggest that small firms have more volatile earnings and less reliable accounting information. Finally, according to Dechow and Dichev (2002), accrual quality is positively related to firm size. Despite this, the HVZ model shows a positive and significant 10-1 spread for all subclasses of firms, suggesting a good level, on a general basis of the ICC's predictive power the model and a correct ranking of the firms in deciles. However, based on the literature, I expect that

the variables' relationship with size, will lead to less accurate earnings forecast for small-sized firms, and consequently to a lower reliability of the entire model to such subclass. In fact, the higher spread resulting in the low-information subset does not necessarily imply a higher accuracy of the model for such firms. For this reason, I aim to study the accuracy of the HVZ model also by analyzing the differences between the realized returns of the firms classified among the 1st and the 10th decile and I expect the model to achieve higher accuracy for larger firms than for smaller confirming the hypothesis that it is less suitable for small-sized firms.

H1: The HVZ model shows a higher level of accuracy for large-sized firms than small-sized ones.

This result would be in contradiction to the study of Wang (2015), based on the GLS, which introduces the concept of ICC measurement errors, defined as the difference between a firm's ICC and its "true expected returns". Particularly, he develops a framework to assess whether these errors are randomly noisy or systematically intrinsic and finds that the measurement errors are positively and significantly correlated with several firm characteristics, such as the size. This result would suggest that the ICC is a worse proxy for larger firms.

Additionally, the size of a firm represents one of the key characteristics which relationship with returns is highly debated (Fama and French, 1993). Banz (1981) is believed to be the first to introduce the "size effect", demonstrating its negative relationship with returns (Embong et al., 2012). Berk (1995) exhibits higher returns for small firms compared to larger ones. Many other studies (e.g. Fama and French, 1992; Lau et al, 2002; Lam, 2002) find a significant and negative relationship between size and returns. However, other studies (e.g. Davis and Desai, 1998; Morelli, 2007) show that such "size effect" is not significant.

In the HVZ model, Hou et al. (2012) find a negative and significant relationship between size and the expected return. Potential explanations for the negative relationship between size and expected returns are widely discussed. These typically include compensation for higher risk-taking, for trading costs and/or liquidity risk, and the assumed rationality of investors. (van Dijk, 2011). However, Hou et al. (2012) also find

that this relationship is not significant when analyzed with the realized returns, meaning that the expectations are not always met. One potential explanation of this mismatch, considering the existence of the previously discussed size effect in the development of the expected returns, could be the incorporation of a size-premia. This could be in line with more recent empirical evidence which suggests that the size effect seems to vary or disappear, especially after the 1980s (Crain, 2011), consistent with Fama and French (2011) study which finds no existence of a size premium in any of the four regions analyzed and with Dimson et al.'s study (2011) which that the superior returns of smaller firms disappear over time. Furthermore, other research (e.g. Horowitz et al., 2000; Fama and French, 2008; Michou et al., 2010) show that the size effect is not distributed across all firms or it is exclusively concentrated in smaller ones (Crain, 2011).

For this reason, I aim to study whether the correlation between realized returns and the size of a firm remains non-significant also when decomposing the size in small, medium and large. Potential differences in the significance of such relationship across the subclasses would imply the existence of a driver in Hou et al's (2012) non-significant result. Based on the previous literature, I would expect small firms to show a negative and significant correlation with the realized returns.

H2: Small-sized firms show a negative and significant correlation with realized returns.

Finally, I aim to study how the predictive power of the HVZ model may vary over time, especially during periods of crisis. In fact, macroeconomic variables affect the cost of equity and long-term returns in equity markets (Dichev and Piotrowski, 2001). These factors may include information availability, information quality and financial disclosure, and their effect is significant during both crisis and post-crisis period (Natalia, 2011). Other variables that influence the cost of equity comprise interest rates (Miller and Modigliani, 1958; Antoniou et al., 1998; Gregory and Michou, 2009), as well as firm-specific characteristics such as beta, idiosyncratic volatility, book-to-market ratio, leverage, long term earnings growth rate, stock price momentum (Ke, 2022) and audit quality (Khurana and Raman, 2004; Mansi et al., 2004; Pittman and Fortin, 2004).

However, not all variables can be forecasted and controlled, such as confidence of customers, firms and investors, financial regulations and monetary policies (Natalia, 2011). According to Chen, Roll and Ross (1986) systematic forces that influence the pricing operator (expected cash flows and the discount factor) are the ones that determine the asset returns. They demonstrate that unexpected changes in the risk-free rate and in the risk premium, and both expected and unexpected inflation impact the expected cash flow. On the other hand, the discount rate is influenced by the level of interest rates, the term-structure spreads, and by the risk premium. In particular, the latter varies over time, making the estimation of the cost of equity more difficult. Grabowski and Pratt (2008) find that the Equity Risk Premium (ERP) during a crisis can lead to an underestimation of the cost of capital.

In fact, Peksyk et al. (2023) find that the cost of equity during the 2008-2009 crisis was increasingly volatile, between 9% and 10.5% in the US (Kroll, 2023) and higher than the canonical range of 3.5-6 % considered by Grabowski and Pratt (2008). Their results are shown to be similar to the ones of the pandemic crisis. Finally, they suggest that over the last 15 years market participants apply alternative methods to modify traditional asset pricing models, such as the CAPM. This is consistent with the inclusion of a market volatility factor proposed by Fama and French (2015), the analysis of the tax shield and its effect on the volatility of the cost of equity (Fernandez, 2004) and Salisu et al.'s (2020) modified model which comprehends a health news parameter for the estimation of the returns. In general, when assessing the cost of equity under uncertain circumstances, different approaches such as adjustments or scenario methods, are used to take into account the new conditions (Peksyk et al., 2023).

For these reasons, and consistent with Affleck-Graves et al. (2002) who demonstrate that firms with less predictable earnings have a higher cost of equity, I propose the following hypothesis:

H3: During crisis periods, the predictive power of the HVZ model will be lower, and the cost of equity higher.

In the following section, I describe the main results of my research.

4. Results

4.1. Replication of Hou's study

The following section presents the results of empirical analyses conducted to evaluate the predictive ability of the regression model of future earnings proposed by Hou et al. (2012). Since the time-horizon subject to the analysis in my dataset is larger, I first identify the differences in the average values of the key variables used as inputs to estimate the future earnings. These values are shown in Table 1.

In particular, I find that the earnings in my dataset are almost double (92,76 vs 49,07), as well as the total assets (3250.31 vs 1529.78 and the dividends (38.29 vs 19.11). The dividend dummy and the negative earnings, on the other hand, register similar values, whereas my accruals are significantly lower (-119.93 vs -43.14). These differences can be considered attributable to the larger time horizon considered in my analysis and the different economic scenarios that occurred between 2008 and 2024. In fact, when limiting the analysis to the same period of Hou et al. (Panel B), such differences become significantly narrower and almost eliminated, indicating that the datasets, despite the differences explained in the methodology section, are comparable.

Table 1 – Summary statistics

Table 1: Summary Statistics of Regression Variables

Panel A – Full Sample							
	Mean	1%	25%	Median	75%	99%	STD
Earnings (ib)	92.76	-382.20	-0.65	3.35	30.26	2,970.00	394.07
Assets (at)	3,250.31	1.48	34.36	183.40	1,160.98	92,082.00	11,796.81
Dividends (dvc)	38.29	0.00	0.00	0.00	5.86	1,191.00	153.89
Dividend Dummy (DD)	0.45	0.00	0.00	0.00	1.00	1.00	0.50
Negative Earnings Dummy (NegE)	0.29	0.00	0.00	0.00	1.00	1.00	0.45
Accruals	-119.93	-3,449.90	-41.15	-4.83	-0.37	248.10	454.49
Panel B – Sample 1968–2008							
	Mean	1%	25%	Median	75%	99%	STD
Earnings (ib)	59.05	-197.76	-0.20	2.76	19.70	1,488.00	287.31
Assets (at)	2,099.91	1.48	25.11	115.83	667.66	48,429.00	9,001.72
Dividends (dvc)	23.62	0.00	0.00	0.00	3.79	578.48	111.01
Dividend Dummy (DD)	0.45	0.00	0.00	0.00	1.00	1.00	0.50
Negative Earnings Dummy (NegE)	0.27	0.00	0.00	0.00	1.00	1.00	0.44
Accruals	-73.21	-1,821.00	-20.45	-2.80	-0.27	104.40	336.71

Therefore, these results indicate that my data are appropriate to study the accuracy of the cross-sectional model. By computing the regression expressed in the Methodology, I find that, overall, the model is able to explain a high proportion of the future earnings over the three-time periods, registering adjusted R-squared values ranging between 95% and 98%. These results not only support the soundness of the cross-sectional model in forecasting future cash flows but also suggest a larger predictive power than the one estimated by Hou et al. (2012). Furthermore, analyzing the single average coefficients, I find that the intercept, the accruals variable and the negative earnings dummy exhibit an opposite sign compared to Hou et al (2012). However, the coefficients of the negative earnings dummy are not statistically significant in my estimates, reducing the divergence.

On the other hand, the directional effects, although with differences in magnitude, of the total assets, the current earnings, the dividends, and the dividend dummy register are the same. Results are shown in Table 2.

Table 2 – Cross-sectional model’s coefficients

Table 2: Coefficient estimates of the cross-sectional earnings model

LHS	Type	Intercept	A_t	D_t	DD_t	E_t	Neg E_t	AC_t	Adj. R^2
E_{t+1}	Coefficient	0.0610	0.0002	0.0225	0.3680	0.9770	-0.0643	-0.0080	0.9829
	t-stat	2.2100	10.3000	20.8000	11.8000	1253.0000	-1.0300	-15.7000	
E_{t+2}	Coefficient	0.1280	0.0004	0.0451	0.7340	0.9550	-0.1200	-0.0160	0.9664
	t-stat	2.3100	10.3000	20.9000	11.9000	610.0000	-0.9570	-15.7000	
E_{t+3}	Coefficient	0.1960	0.0006	0.0679	1.1000	0.9320	-0.1650	-0.0239	0.9505
	t-stat	2.3400	10.4000	21.1000	11.8000	397.0000	-0.8750	-15.7000	

Verified and confirmed the applicability and the functioning of the cross-sectional model, I proceed calculating the implied cost of capital by applying the Gordon model and the GLS model. I exclude the additional models (CT, OJ and MPEG) from the composite ICC mainly because of the numerical and economic structural instability of the output. The excluded models feature non-linear relationships in their formula, causing earnings inflation and extreme sensitivity to disproportionate relationships between expected earnings and market capitalization.

By contrast, the Gordon and GLS models incorporate natural stabilizers, producing economically and statistically meaningful estimates of the ICC. Therefore, calculating the composite ICC, I find an average value of 11% (Table 3) compared to the 15% found by Hou et al. (2012). To verify whether the difference may result from the additional twenty-five years of analysis, I decompose the estimate into multiple time frames (Table 4). Interestingly, I find that my results are lower in each time horizon, with a peak in the difference (7,2%) in the 1989-1993 observation. Such differences could be attributable to the different method of estimating the composite ICC itself.

Furthermore, although both estimates over time show volatility and significant deviations between periods, it is important to note that Hou’s results exhibit larger magnitude changes between time observations.

Table 3 – ICC Estimates

Table 3: Summary Statistics of Implied Cost of Capital (ICC) Estimates

Model	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Gordon	0.0022	0.0382	0.0657	0.0941	0.1098	0.5000
GLS Model	0.0505	0.0639	0.0828	0.0938	0.1133	0.2448
Composite	0.0454	0.0705	0.0930	0.1104	0.1320	0.3491

Table 4 - Composite ICC over time

Table 4: Composite ICC Estimates by Period (1968–2024)

Period	N	Mean	P25	Median	P75
1968–1973	1701	0.115	0.0756	0.102	0.141
1974–1978	3164	0.125	0.0904	0.119	0.149
1979–1983	2683	0.118	0.0777	0.109	0.148
1984–1988	1673	0.0966	0.0684	0.0839	0.107
1989–1993	1583	0.0983	0.0687	0.0834	0.108
1994–1998	1958	0.0942	0.0642	0.0786	0.102
1999–2003	1078	0.115	0.0654	0.0888	0.131
2004–2008	1277	0.101	0.0628	0.0774	0.109
2009–2024	674	0.122	0.0690	0.0911	0.141
1968–2024	1434	0.110	0.0705	0.0930	0.132

To evaluate the quality of the model-based ICCs as proxies for the expected returns, I follow Gebhardt et al (2001), Easton and Monahan (2005) and Guay et al. (2011) and examine the relationship between the composite ICC and the future realized returns. At the end of June of each year, I rank companies into decile portfolios based on their composite ICC. Subsequently, I calculate the equally weighted annual buy-and-hold returns (and the related Newey-West statistics) for each portfolio for the following one, two, and three years. Finally, I evaluate the time-series average of the annualized buy-and-hold returns of the decile portfolios sorted on the composite ICC, as well as the return spreads between the highest-ranked decile and the lowest-ranked one.

The results (Table 5) highlight a statistically significant difference between the 10th decile and the first one for all three the time horizons, suggesting that the HVZ model accurately predicts the future returns, confirming Hou et al. (2012) findings.

Table 5 – ICC spread

Table 5: ICC estimates and future realized returns

ICC Decile	1-Year		2-Year		3-Year	
	Return	t-stat	Return	t-stat	Return	t-stat
1	0.0178	0.62	0.145	3.56	0.303	5.79
2	0.0264	1.01	0.176	4.57	0.355	6.60
3	0.0618	2.24	0.225	5.82	0.416	7.91
4	0.0812	2.90	0.242	6.14	0.418	8.19
5	0.0994	3.63	0.257	6.63	0.439	8.21
6	0.1160	4.23	0.277	7.12	0.447	8.97
7	0.1300	4.79	0.294	7.60	0.451	9.42
8	0.1500	5.22	0.313	8.05	0.490	9.75
9	0.1800	6.00	0.356	8.53	0.512	9.56
10	0.2460	7.21	0.449	8.38	0.615	8.77
10–1	0.2280	8.02	0.304	5.83	0.312	4.11

Based on the results discussed, I can confirm that, despite the differences in the dataset, in the time subject of analysis, and in the computation of the composite ICC, the HVZ model is indeed capable of forecasting future earnings and a reliable solution to estimate the cost of equity of the firms.

4.2. Applicability to small-sized firms

Extending Hou et al's study, one of the purposes of my study is to discover whether the HVZ model maintains its predictive ability regardless of the size of the firm. For this reason, I aim to replicate the analysis conducted in Section 4.1 by dividing the sample into three different categories: small-size ("Low"), medium-size ("Medium") and large-size ("High"), where the size, consistent with Hou et al. (2012) is the natural logarithm of the end-of-June market equity.

Summary statistics for each subsample are reported in Table 6.

Table 6 – Summary Statistics by firm size

Table 6: Summary Statistics of Variables by Firm Size

Panel A – Low Size Firms							
Variable	Mean	1%	25%	Median	75%	99%	STD
Earnings (ib)	2.0932	-102.978	-2.312	0.235	1.668	135.3980	94.2745
Assets (at)	441.807	1.484	11.662	30.585	103.699	4650.510	4093.374
Dividends (dvc)	3.0972	0.000	0.000	0.000	0.071	56.5252	36.5721
Dividend Dummy (DD)	0.2640	0.000	0.000	0.000	1.000	1.0000	0.4408
Negative Earnings Dummy	0.4332	0.000	0.000	0.000	1.000	1.0000	0.4955
Accruals	-15.1345	-246.489	-4.494	-0.970	-0.132	34.2890	143.2667
Panel B – Medium Size Firms							
Variable	Mean	1%	25%	Median	75%	99%	STD
Earnings (ib)	23.9306	-255.568	-0.673	4.346	13.800	665.8405	209.7718
Assets (at)	1471.122	5.093	62.453	172.661	640.020	23483.369	7546.034
Dividends (dvc)	14.1346	0.000	0.000	0.000	2.782	298.477	86.8009
Dividend Dummy (DD)	0.4583	0.000	0.000	0.000	1.000	1.0000	0.4983
Negative Earnings Dummy	0.2646	0.000	0.000	0.000	1.000	1.0000	0.4411
Accruals	-52.0440	-1052.108	-23.513	-4.873	-0.722	139.628	278.4170
Panel C – High Size Firms							
Variable	Mean	1%	25%	Median	75%	99%	STD
Earnings (ib)	279.5667	-382.1970	16.824	59.887	221.899	2970.000	632.1488
Assets (at)	8642.1556	50.8260	515.300	1835.000	6496.152	92082.000	18437.230
Dividends (dvc)	107.4321	0.0000	0.000	12.644	71.277	1191.000	248.0203
Dividend Dummy (DD)	0.7106	0.0000	0.000	1.000	1.000	1.0000	0.4535
Negative Earnings Dummy	0.1125	0.0000	0.000	0.000	0.000	1.0000	0.3160
Accruals	-307.8456	-3449.900	-230.575	-54.912	-9.509	248.101	706.4321

By computing the adjusted R-squared of the HVZ model regarding the estimation of the forecasted future earnings, I find that, although the bigger firms register a higher explanatory power, the difference with the smaller firms is not so large. In fact, for time

$t+1$, the High subsample has a 98.2% R-squared whereas the Low subsample 97.0% (Table 7). The same conclusion applies for the other time observations.

These results suggest that the input variables are able to explain almost all the value of the future earnings, independent of the size of the firm taken into consideration. However, it is important to note that the adjusted R-squared tends to decrease over time, for each subsample, potentially leading to the conclusion that the model might become less accurate and useful for too much in the future observations.

Table 7 – Cross-sectional coefficients by firm size

Table 7: Coefficient Estimates of the Cross-Sectional Earnings Model by Firm Size

LHS	Type	Intercept	A_t	D_t	DD_t	E_t	Neg E_t	AC_t	Adj. R^2
Panel A: Low Size Firms									
E_{t+1}	Coefficient	-0.0561	0.0002	0.0225	0.0170	0.9740	-0.160	-0.0084	0.970
	t-stat	-4.19	3.71	11.2	1.02	517.0	-4.80	-9.13	
E_{t+2}	Coefficient	-0.1080	0.0005	0.0451	0.0282	0.9490	-0.323	-0.0167	0.942
	t-stat	-4.04	3.70	11.4	0.83	249.0	-4.78	-9.11	
E_{t+3}	Coefficient	-0.1610	0.0007	0.0679	0.0456	0.9230	-0.481	-0.0251	0.916
	t-stat	-4.04	3.70	11.5	0.91	160.0	-4.73	-9.10	
Panel B: Medium Size Firms									
E_{t+1}	Coefficient	-0.2290	0.0004	0.0170	0.0926	0.9840	-0.111	-0.0059	0.973
	t-stat	-6.77	5.27	3.38	3.48	418.0	-1.72	-4.39	
E_{t+2}	Coefficient	-0.4600	0.0008	0.0340	0.1920	0.9680	-0.213	-0.0119	0.948
	t-stat	-6.77	5.28	3.37	3.61	205.0	-1.67	-4.41	
E_{t+3}	Coefficient	-0.6880	0.0012	0.0512	0.2920	0.9510	-0.309	-0.0179	0.926
	t-stat	-6.78	5.28	3.37	3.67	134.0	-1.61	-4.47	
Panel C: High Size Firms									
E_{t+1}	Coefficient	0.6720	0.0002	0.0241	0.3730	0.9780	1.340	-0.0071	0.982
	t-stat	3.83	8.79	19.1	3.55	1230.0	5.81	-14.3	
E_{t+2}	Coefficient	1.3600	0.0004	0.0483	0.7340	0.9560	2.720	-0.0142	0.965
	t-stat	3.86	8.82	19.2	3.50	600.0	5.87	-14.3	
E_{t+3}	Coefficient	2.0600	0.0006	0.0727	1.0700	0.9330	4.160	-0.0213	0.948
	t-stat	3.89	8.89	19.3	3.42	390.0	5.95	-14.3	

To further investigate the role of size and its impact on the cost of capital, I study the relationship between size and expected and realized returns. Contrary to the results of Hou et al. (2012), I find that this relationship is positive and significant with both expected and realized returns.

To get a better idea, I study this relationship by decomposing the sample and find that it is so in all three subsamples. These results fit into the line of thought that size premiums do not actually play a role, and, additionally, the positive relationship suggests that the size effect is reversed. As shown in Table 8, for the complete sample, as well as for the three subsamples I find a positive and significant relationship between size, and both expected and realized returns. However, it is possible to notice that the smallest firms have the lowest correlation with the ICC proxies compared to the other subsamples, whereas this trend is reversed when studying the relationship with the realized returns, with big firms registering the lowest correlation coefficient.

Hypothesis 2, which suggests that the correlation between the size and the future realized returns is negative and statistically significant, therefore, is rejected. A potential reason could be that investors' behavior after 2008 may have changed, preferring larger and more liquid companies.

Table 8 – Size and realized and expected returns

Table 8: Relationship Between Firm Size and Realized vs. Expected Returns

	Low		Medium		High		Full Sample	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Realized Return	1.090	4.63	0.709	2.94	0.368	2.17	0.418	3.36
Expected Return (ICC)	0.134	7.32	0.144	6.42	0.171	11.7	0.172	19.0

However, as a robustness check, I replicate Hou's study in examining the relationship by restricting myself to considering the horizon between 1968 and 2008. Once again, my unreported results suggest a positive and significant relationship between size and expected and realized returns, meaning that the opposite sign is not driven by the additional time frame considered. Thus, the different investors' behavior is not the cause. An alternative explanation could be the fact that the size may proxy for additional firm characteristics. In fact, due to data availability, I did not include in the regression variables such as analyst coverage, idiosyncratic volatility, or firm-level risk and quality factors.

Therefore, the observed size relationship could incorporate additional correlated effects with other variables.

Finally, to evaluate the accuracy of the HVZ model's predictive power, as previously, I divided the subsample's ICC in deciles and measured the 10-1 spread for each subsample, consistent with Hou et al.'s (2012) methodology. The results highlight a positive and significant spread for each size category, initially suggesting that the cross-sectional model works for all types of firms, regardless of their size.

However, by extending the study of Hou et al. (2012), I first create the deciles for the three different size categories of the sample and compute the 10-1 spread (Table 9). The results show that per each category, this spread is positive and statistically significant, suggesting the accuracy of the model per subsample. Furthermore, I create the deciles not only based on the average hold-and-buy return but also based on the average of the composite ICCs (Table 10). By calculating the spread between the corresponding deciles in one table and the other, I am able to estimate the actual difference between the predicted and the realized returns and, thus, assess the accuracy of the model. The analysis shows that significant differences exist for both smaller and larger companies.

Overall, based on the 10-1 spread, the HVZ model works well for both small-sized, medium and larger ones, therefore I reject Hypothesis 1. However, when I compute the spread between the correspondent deciles, the results highlight some significant errors in the accuracy of the prediction, with peaks in the first decile and in the last decile, meaning that the errors occur for both small firms and large ones. More in detail, as shown in Table 10, the ICC model tends to underestimate the cost of equity for companies in the lower deciles, i.e., smaller companies, and tends to overestimate that of companies in the higher deciles, i.e., larger companies.

These results suggest that the composite model-based ICC is an accurate model in categorizing firms into deciles based on their projected returns, but not entirely efficient in estimating these. This outcome is consistent with several aforementioned studies in the literature review section which suggest that new models are more accurate than the HVZ one.

Table 9 – ICC spread for size subsamples

Table 9: ICC estimates and future realized returns — Subsamples by Firm Size

Panel	ICC Decile	1-Year		2-Year		3-Year	
		Return	t-stat	Return	t-stat	Return	t-stat
Low	1	0.0197	1.18	0.0430	1.72	0.0874	2.66
	2	0.0370	2.04	0.0824	2.96	0.1320	3.82
	3	0.0403	2.43	0.0725	3.04	0.1310	4.04
	4	0.0382	1.50	0.0749	2.86	0.1080	3.38
	5	0.0516	3.13	0.0987	3.69	0.1500	3.79
	6	0.0517	3.37	0.1080	4.40	0.1390	4.31
	7	0.0681	3.18	0.1110	3.81	0.1410	3.96
	8	0.0742	3.42	0.1530	3.34	0.1840	4.43
	9	0.0455	2.01	0.1090	2.92	0.1690	3.17
	10	0.0700	2.94	0.1770	4.28	0.2260	3.98
	10–1	0.0503	2.69	0.1340	3.64	0.1390	3.30
Medium	1	0.0009	0.05	0.0260	0.98	0.0699	2.07
	2	-0.0043	-0.27	0.0158	0.69	0.0559	1.93
	3	0.0178	1.31	0.0532	2.51	0.0978	3.46
	4	0.0230	1.64	0.0607	2.73	0.1090	3.52
	5	0.0358	2.32	0.0816	3.34	0.1300	3.99
	6	0.0477	3.07	0.0967	4.18	0.1470	4.56
	7	0.0436	3.03	0.0998	4.09	0.1450	4.42
	8	0.0568	3.41	0.1020	4.32	0.1450	4.44
	9	0.0748	4.15	0.1370	4.95	0.1730	4.70
	10	0.0807	4.11	0.1590	4.30	0.2040	4.64
	10–1	0.0798	4.21	0.1350	3.74	0.1370	3.58
High	1	-0.0071	-0.45	0.0093	0.41	0.0392	1.39
	2	-0.0054	-0.38	0.0153	0.71	0.0584	2.05
	3	0.0033	0.24	0.0397	2.01	0.0737	2.95
	4	0.0103	0.81	0.0487	2.77	0.0889	3.94
	5	0.0066	0.51	0.0461	2.33	0.0862	3.46
	6	0.0285	2.03	0.0688	3.60	0.1040	4.64
	7	0.0246	1.92	0.0697	3.69	0.1040	4.13
	8	0.0303	2.27	0.0713	3.82	0.1060	4.46
	9	0.0453	3.34	0.0982	4.88	0.1380	5.39
	10	0.0627	4.19	0.1270	5.44	0.1620	5.68
	10–1	0.0698	6.63	0.1180	5.94	0.1230	5.68

Table 10 – Effective accuracy test

Table 10: Comparison Between ICC-Based and Realized Return Deciles

Decile	Avg BHR (ICC Decile)	Avg BHR (Realized Return Decile)	Spread (ICC – Realized)	<i>t</i> -stat
1	0.0039	0.4540	-0.4501	-24.0
2	0.0045	0.2070	-0.2025	-25.2
3	0.0159	0.1280	-0.1121	-21.1
4	0.0232	0.0749	-0.0517	-11.8
5	0.0271	0.0327	-0.0056	-1.67
6	0.0362	-0.0064	0.0425	11.7
7	0.0371	-0.0465	0.0836	22.5
8	0.0429	-0.0927	0.1356	21.9
9	0.0522	-0.1550	0.2072	25.6
10	0.0681	-0.2910	0.3591	28.3

4.3. Predictive power over the years

The final goal of my analysis is to evaluate the HVZ model and its predictive power over the years within the time frame being investigated. Firstly, by dividing the latter into 10-year time lags, I have the opportunity to assess any trends in the key variables of the cross-sectional model. Specifically, as shown in Table 11, the average of all variables continuously increases in absolute value, except for the number of dividend-paying companies, which, overall, decreases. In addition, by focusing on and extracting from the sample three historical periods of financial-economic crises, such as the 2000 Dotcom bubble, the 2007 financial crisis and the 2019 pandemic crisis, it can be noted that all variables in these sub-periods record a lower absolute value than the average of the time frame in which they are placed.

Table 11 – Mean of variables during pre, during and post crisis

Table 11: Mean of Key Financial Variables by Decade and Crisis Periods

Period	Net Income	Total Assets	Dividends	Dividend Dummy	Negative Earnings	Accruals
1968–1977	19.839	534.139	8.025	0.657	0.094	-15.213
1978–1987	31.644	1058.132	13.360	0.508	0.223	-29.933
1988–1997	49.995	1918.796	21.504	0.388	0.289	-56.719
1998–2007	112.038	3792.497	40.659	0.385	0.313	-133.479
2008–2017	190.453	6549.738	80.220	0.455	0.327	-233.999
2018–2024	225.733	8006.968	96.336	0.413	0.429	-268.327
Dotcom 2000–2002	76.644	3494.424	33.321	0.361	0.362	-145.234
Fin. Crisis 2007–2009	151.981	5273.161	62.772	0.427	0.343	-212.743
Covid 2019–2021	211.013	7923.570	92.795	0.409	0.437	-272.409

The analysis of these variables is important because they are the inputs to the regression used to estimate future returns. Consequently, they have a significant impact on the outcome and predictive ability of the model. For this reason, I study the average coefficients of them for each decade and their relationship to the predicted returns (Table 12). To limit the number of tables, I report only the results of them in relation to the first expected return ($t+1$).

The results show a positive and statistically significant relationship between current earnings and the forecast, with relatively stable coefficients over the years. A positive and significant relationship is also found when considering total assets and the amount of dividends, while the coefficient of dividend paying companies is positive, but since 2008 it stops being significant. Accruals maintain a negative and significant relationship with expected returns in all time frames. Finally, negative earnings show a less stable trend and predominantly negative coefficients.

These results are in line with those contained in Table 2, where the analysis is conducted over the total period except precisely for negative earnings, which had a negative but not statistically significant relationship. Focusing on crisis periods, we see that all coefficients of current returns are positive and significant, but smaller given the uncertainty. On the other hand, accruals, as well as negative earnings (except for the financial crisis) penalize even more the stability of expected returns during such periods. Finally, dividend payments (for the pandemic crisis) and the amount of dividends distributed send a positive signal to the market, while total assets maintain a limited impact on the forecast.

Table 12 – Coefficients by period

Table 12: Cross-Sectional Coefficients with Significance by Period (Forecast E_{t+1})

Period	Intercept	A_t	D_t	DD_t	E_t	Accruals	Neg E_t
1968–1977	0.0339	$1e - -04^{***}$	0.0276 ^{***}	0.1682 ^{***}	0.9813 ^{***}	-0.0113 ^{***}	0.0612
1978–1987	-0.0911 ^{**}	$6e - -04^{**}$	0.0123 ^{***}	0.3587 ^{***}	0.9827 ^{***}	-0.0019 [*]	0.2379 ^{***}
1988–1997	-0.1335 ^{**}	$2e - -04^{**}$	0.0225 ^{***}	0.3864 ^{***}	0.9787 ^{***}	-0.0077 ^{***}	0.2096 ^{***}
1998–2007	-0.0981 [*]	0 ^{***}	0.0188 ^{***}	0.9881 ^{***}	0.9788 ^{***}	-0.011 ^{***}	-0.3032 ^{**}
2008–2017	0.3786 [*]	$2e - -04^{**}$	0.0233 ^{***}	0.1875	0.9702 ^{***}	-0.0076 ^{***}	-0.4569 ^{**}
2018–2024	0.4839	$3e - -04^{***}$	0.0224 ^{***}	0.5293	0.9704 ^{***}	-0.0092 ^{**}	-1.746 ^{***}
Dotcom (2000–2002)	-0.1529	$1e - -04^{***}$	0.0358 ^{***}	0.4438	0.9676 ^{***}	-0.012 ^{***}	-0.9901 ^{**}
Fin. Crisis (2007–2009)	-0.0921	$1e - -04^{***}$	0.0318 ^{***}	-0.3662	0.9676 ^{***}	-0.012 ^{***}	0.2822
COVID (2019–2021)	0.7346	$3e - -04^{***}$	0.0248 ^{***}	1.6389 ^{**}	0.9655 ^{***}	-0.012 ^{***}	-2.3609 ^{***}

Finally, I study the average expected returns and R-squared for each decade, focusing on the projections of times $t+1$, $+2$ and $+3$, as done previously. This analysis allows me to assess the predictive ability of the HVZ model over the years.

The results, shown in Table 13, show that the projected returns increase over the years, in line with the increase in current returns discussed earlier, and that the model maintains good predictive ability across the decades, albeit decreasing over them. In each crisis, the R-squared coefficient is lower than for the corresponding time frame. This implies that the model is less efficient in estimating future returns in crisis periods, confirming the first part of Hypothesis 3.

Table 13 – Forecast per Period

Table 13: Summary of Forecasted Earnings and Model Fit by Period

Period	N	Mean E_{t+1}	R^2_{t+1}	Mean E_{t+2}	R^2_{t+2}	Mean E_{t+3}	R^2_{t+3}
1968–1977	375,387	20.048	0.993	20.257	0.987	20.469	0.981
1978–1987	577,254	31.982	0.987	32.325	0.973	32.678	0.961
1988–1997	769,697	50.459	0.981	50.935	0.964	51.423	0.946
1998–2007	718,357	112.781	0.974	113.549	0.958	114.337	0.938
2008–2017	546,491	191.928	0.980	193.427	0.960	194.938	0.941
2018–2024	325,844	226.632	0.968	227.539	0.952	228.480	0.928
Dotcom (2000–2002)	220,955	77.260	0.963	77.909	0.937	78.562	0.907
FinCr (2007–2009)	174,052	152.272	0.967	152.561	0.944	152.863	0.918
COVID (2019–2021)	170,445	212.964	0.968	214.898	0.938	216.852	0.909

In order to definitively confirm hypothesis 3, I study the extent of the average ICC composite across the time frame being investigated (Table 14). This decreases until 1997 and then gradually rises before the 2000s until 2024. During the early 2000s' Dotcom bubble, there is an average cost of equity capital of 11.3%, higher than the 10.3% for the baseline decade. For the next two crises the result does not change, showing an average cost approximately 1.3% higher during the financial crisis, and 1.2% higher during the pandemic, respectfully to their correspondent decade.

The results obtained, put together, demonstrate and consequently confirm Hypothesis 3 to the extent that during crisis periods the cross-sectional model performs worse in terms of predictive ability and that the cost of equity is higher.

Table 14 – ICC across Periods

Table 14: Distribution of Composite ICC by Period

Period	N	Mean	P25	Median	P75
1968–1977	2,274	0.120	0.0824	0.111	0.145
1978–1987	2,326	0.113	0.0746	0.101	0.141
1988–1997	1,791	0.0959	0.0666	0.0802	0.105
1998–2007	1,355	0.103	0.0630	0.0803	0.113
2008–2017	760	0.116	0.0664	0.0863	0.131
2018–2024	631	0.125	0.0708	0.0949	0.147
Dotcom (2000–2002)	942	0.113	0.0634	0.0831	0.130
Financial Crisis (2007–2009)	1,010	0.115	0.0705	0.0899	0.131
COVID (2019–2021)	510	0.137	0.0799	0.110	0.170
1968–2024 (Full Sample)	1,434	0.110	0.0705	0.0930	0.132

4.4. Discussion of results

Taken together, my empirical analysis concludes that the mechanical cross-sectional model proposed by Hou et al. (2012) is not less suitable for small-sized firms. In fact, the predictive power of the model presents slight differences in the adjusted R-squared values, suggesting a general applicability of the method to each subsample. Therefore, the chosen explanatory variables are able to cover in a large part the forecast for future earnings. Furthermore, when classifying each subsample in 10 deciles, the 10-spread coefficient is positive and significant for each size subclass, confirming the applicability of the HVZ as a reliable ICC estimation model.

Developing Hou et al’s 2012 analysis, I categorize the sample of firms into deciles also based on the average ICC estimate and consequently make a comparison with the correspondent realized returns deciles. The results show significant differences between the expected returns and the realized returns, questioning the accuracy of the model.

Interestingly, and contrary to the results of Hou et al. (2012), I find a positive and significant relationship between the size of a firm and both its expected and realized returns. This relationship is confirmed also in my robustness check, but, due to data availability, the size parameter might incorporate additional dimensions and, therefore, mislead the result.

Finally, I demonstrate that the HVZ model loses part of its predictive power in difficult macroeconomic environments, such as financial and/or economic crisis like the 2000 Dotcom bubble, the 2007 financial crisis and the 2019 pandemic. During such periods the adjusted R-squared is lower compared to the correspondent decade and the resulting cost of equity estimation higher, in line with my expectations.

5. Limitations

It should be acknowledged that this study, while representing a reliable replication and extension of the study conducted by Hou et al. (2012), has some limitations, in addition to those mentioned by the original authors.

First, due to data constraints, different, although consistent, parameters and filters were used to retrieve the dataset from the merged CRSP and Compustat databases, which, albeit to a limited extent, may have influenced the results.

Second, due to data limitations, I created the size variable based on firms' total assets, failing to consider additional important variables, such as analyst coverage, idiosyncratic volatility and firm-specific risk measures. These dimensions could then be incorporated into the variable, potentially affecting its relationship with the future earnings (both forecasted and realized).

Finally, unlike the original HVZ model, I considered only two ICC models: the Gordon and the GLS. Despite the exclusion of the CT, MPEG and OJ models avoids instability, the results obtained might not be generalizable to these other ICC methods.

6. Conclusion and Future Research

Despite its relevance in several corporate finance settings, there is no well-established and accurate estimation method for the cost of equity in the existing literature (Echterling et al., 2015). The HVZ model proposed by Hou et al. (2012) is widely used as a basis point and recognized as a benchmark methodology for a large number of studies. However, according to the authors of the model themselves as well as other studies, one of its main limitations is its level of suitability for smaller sized firms.

For this reason, the first objective of my analysis is to find out whether the HVZ model has lower predictive power, and is therefore less efficient for smaller firms, as Hou et al. (2012) suggest in their study. To assess the applicability of the cross-sectional model, I first divide the sample into three categories based on firms' total assets. Second, I replicate Hou's methodology and calculate the adjusted R-Squared of the pooled regression for each subsample. Despite the differences in values across these, such differences are small, thus suggesting that the predictive power of the coefficients holds regardless of the size of the companies.

Finally, I calculate the 10-1 decile spread, consistent with Hou et al. (2012), for each subsample. My results show positive and significant spreads for each subclass, thus definitively rejecting the hypothesis that the HVZ model is less suitable for smaller firms.

However, I also introduce an alternative way to assess the accuracy of the model by dividing the firms into deciles based also on the average of the composite ICCs, allowing me to calculate the difference between expected and realized returns. Based on this additional analysis, I demonstrate that the HVZ model has several limitations, independently of the size of the firms analyzed.

To further comprehend the results of my analysis, I investigate the relationship between the size of a firm and the realized and expected returns. Interestingly, and contrary to Hou et al. (2012), but in line with many other studies, I find that this relationship is positive and significant. However, due to data availability, it may be possible that the size factor in my correlation incorporates additional dimensions, therefore misleading the true relationship between the size of a firm and its expected and realized returns.

The final goal of the analysis is to understand whether the model loses predictive power and accuracy during periods of crisis. To evaluate these potential trends, I focus on the analysis of three specific economic crisis: the Dotcom Bubble, the Financial Crisis and the Covid-19 pandemic. The results I obtain suggest that during difficult moments, the model becomes less efficient as its predictive power is lower. Furthermore, during such periods, the cost of equity estimated registers a rise, compared to the baseline decade.

Overall, my study contributes to existing literature of the cost of equity estimation and the ICC. My empirical analysis highlights that the HVZ model is not less suitable for smaller subclasses of firms, registering a similar predictive power capability across different firms. However, by expanding Hou et al.'s 2012 study, I introduce an alternative way to assess the accuracy of such estimations and show and confirm, as previous studies, that the model does have several limitations with this regard. Finally, I find that the HVZ model becomes less applicable during crisis periods and leads to higher expected returns.

Future research might investigate whether the HVZ model loses efficiency with respect to other specific subclasses of the sample, such as firms with high leverage and/or a poor information environment. Secondly, the accuracy of the model could be studied across different industries, focusing on the potential need of inclusion of new variables in the future earnings estimation regression. Additionally, the accuracy of the combination of different ICC methods should be explored to determine the prevalence of one model among the others. This could also be analyzed considering periods of crisis, or particular macroeconomic environments.

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