Implied Cost of Capital Based Investment Strategies♦

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Abstract

In the recent literature on estimating expected stock returns, one of the most interesting approaches is the concept of the so-called implied cost of capital. Calculated as the internal rate of return that equates stock price with discounted future cash-flows, this method has been applied to estimating the market risk premium as well as forecasting individual stock returns. In this paper we investigate several implied cost of capital approaches in their intrinsic ability to predict stock returns. Using cross-sectional regression analysis and panel estimation, we confirm its hypothesised relation to stock returns, but detect qualitative differences among standard models employed.

JEL Classification: G11

Keywords: Implied cost of capital, implied return, portfolio management, expected stock returns, panel regressions, analysts' forecasts

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1. Introduction

Predicting the stock market or the returns of individual stocks has been an on-going effort in academia and the money management industry. Many different stock selection criteria and firm characteristics that might be useful for stock return prediction have been examined and analyzed thoroughly. Among the most prominent examples are past price and earnings momentum (Chan et al., 1996), firm size (Fama and French, 1992), valuation multiples such as the B/M ratio and the D/P ratio (Fama and French, 1988, 1992), and more fundamentally, the market beta of the CAPM. However, many of these characteristics are of an ad-hoc nature, and not derived by fundamental valuation analysis.

In this study we examine the capability of richer valuation models to predict cross-sectional returns. More precisely, we analyze the ability of the so-called implied cost of capital to accurately forecast stock returns. Calculated as the internal rate of return[1] that equates stock price with discounted expected cash-flows obtained from equity analysts, this rather new concept of estimating stock returns has been applied to determining the market risk premium as well as forecasting individual stock returns.

The underlying assumption of this methodology, the equalization of market price and fundamental firm value, can be justified when one is to accept market efficiency and negligible arbitrage costs. But even if we allow that price is only a noisy, cointegrated proxy for intrinsic firm value, the implied cost of capital should have some explanatory power to explain stock returns.

In a first step, we investigate the profitability of investment strategies based on various implied cost of capital (ICOC) estimates, such as the dividend discount model (DDM) or the residual income model (RIM), for a broad data sample of U.K. firms from 1995 to 2005. We find that ICOC-based investment strategies are profitable and provide significantly positive returns when derived from three-stage DDM and RIM approaches. However, the longer the investment horizon, the better the DDMs perform compared to the RIM, whose profitability deteriorates for

[1] In this study, the terms *implied cost of capital* (ICOC), *implied return*, and *internal rate of return* refer to the same concept and are used interchangeably.

time horizons longer than 6 months. Over 24 months, the portfolio with the highest implied cost of capital estimates based on the two-stage DDM following Damodaran (1999) performed on average about three times better than the one with the lowest expected returns. When examining the characteristics of the constructed portfolios, we find that all ICOC concepts are related to the Fama-French risk factors B/M-ratio and firm size. However, this strong relation might suggest that the implied cost of capital does not predict future returns itself, but only via its relation to these well-known risk factors. To analyze whether the ICOC has indeed an additional explanatory power for stock returns we run cross-sectional regressions as well as panel regressions of stock returns on firm characteristics and the implied cost of capital. The results confirm the hypothesis that the ICOC can contain some additional information for predicting stock returns. Especially RIM based ICOC estimates are always highly significant after controlling for market beta, B/M ratio and firm size.

Our study is related to several streams of literature. On the one hand, it takes up the pioneering works by Cornell (1999), and Claus and Thomas (2001) who applied the ICOC approach successfully to estimate an implied equity risk premium by aggregating firm estimates over entire markets. Among others, Gebhardt et al. (2001), Lee et al. (2003), and Easton et al. (2002) investigated implied returns for individual firms and its relation to firm characteristics. On the other hand, this paper refers to the earlier attempts to explain stock returns by Price-Value ratios. Lee at al. (1999) show that this inverse valuation multiple – where the intrinsic value is estimate with the help of comparable present value formulas – is related to Dow Jones stock returns. Although their approach is rather similar to the implied cost of capital, we opted in this study for the latter[2]. Finally, by mimicking investment portfolios using the ICOC as stock selection variable, this study uses techniques presented by the works on momentum strategies (Chan et al., 1996; Jegadeesh and Titman, 2001), or on contrarian investment (Lakonishok et al., 1994).

Despite its widespread use in both theory and practice, there are very little econometric foundations of the implied cost of capital methodology at the level of individual firms. As such, this work extents prior studies on the investigation of the implied cost of equity capital, such as

[2] We have several reasons for favoring the implied return concept. First, the implied return is essentially an implied discount factor which has a more intuitive interpretation as proxy for the shareholder's rate of expected return. As such, it is more easily compared to other common methods to estimate the firm's cost of capital. Second, the P/V approach requires in addition to the ICOC an estimate or assumption of the discount factor, which introduces another possible source of errors. Third, the ICOC is more prevalent in the literature, allowing better comparison to existing studies.

by Lee et al. (2003), who analysed the determinants of the ICOC at the firm level. A first paper that examines the ICOC's application to active portfolio management has been composed by Stotz (2005), although restricted to the rather small DJ Stoxx 50 data set. By using various econometric approaches to explain stock returns, this paper also contributes to the growing literature that investigates and compares the practical implementation of alternative estimation methods for individual stock returns. In fact, this study is one of the very few papers that carries out panel estimation methods on stock returns for a broad data set, comparable to Pandey (2001), or Subrahmanyam (2004). In contrast to these studies, we perform long-horizon regressions using overlapping stock returns, similar to Bauer et al. (2004). Moreover, this paper provides a details comparison of ICOC approaches commonly used, the residual income models and dividend discount models. In addition to existing models, we present a modified version of the RIM as proposed by Gebhardt et al. (2001) that is more coherent in the long run than existing RIM formulas.

This paper proceeds as follows. In the next section, we describe the methodology of the implied cost of capital in more detail and present the various estimation approaches employed in this study, the dividend discount model and the residual income model. Section 3 contains a brief description of our U.K. data sample. Then we present the results of buy-and-hold strategies, i.e. the returns of portfolio investments when we use the implied cost of capital estimate as stock selection variable, and analyze the characteristics of these portfolios. Finally, in section 5, we carry out cross-sectional and panel regression tests to show that even after controlling for common risk factors, the ICOC has some explanatory power to predict individual stock returns. Section 6 offers some concluding remarks.

2. Models for the Implied Cost of Capital

In this study, the cost of capital of individual firms is calculated using the methodology of the so-called implied cost of capital. The basic idea of this concept is to estimate the future cost of capital with the help of present value models. More precisely, the cost of equity is computed as the internal rate of return that equates discounted payoffs per share to current price, where expected cash flows are taken from equity analysts. In the literature, many different versions of the present value model are employed to calculate the implied cost of capital.

In this work, we resort to the models of most prominent studies on the implied cost of capital. On the one hand, we use the dividend discount model (DDM) in the versions of Cornell (1999) and Damodaran (1999). On the other hand, we rely on the residual income model (RIM) following the approaches of Claus and Thomas (2001) and Gebhardt et al. (2001). Moreover, we also present a new and slightly different implementation of the RIM and compare it to the existing models. In the following section, we describe the models and their implementation in more detail.

2.1. The Dividend Discount Model

The general DDM states that the price of a share should equal the discounted value of future dividend payments, and can be written as follows:

$$P_0 = \sum_{t=1}^{\infty} \frac{E[D_t]}{(1+k)^t} \tag{1}$$

where

P_0 = current share price, at the end of year 0,
$E[D_t]$ = expected dividends per share at the end of year t,
k = cost of capital or, equivalently, shareholders' expected rate of return.

Since exact predictions of future dividends cannot be made to infinity, one has to make assumptions about expected cash-flows when implementing the DDM in practice. The DDM following Cornell (1999) assumes an initial 5-year phase of high dividend growth, which is followed by a transition phase in which the growth rates decline linearly to a lower, stable growth g_l, which is then maintained ad infinitum. Thus, this model combines the plausible conjecture of a strong growth in the first years with realistic growth rates in the long run.

$$P_0 = \underbrace{\sum_{t=1}^{5} \frac{E[D_t]}{(1+k)^t}}_{\text{Growth Period}} + \underbrace{\sum_{t=6}^{20} \frac{E[D_t]}{(1+k)^t}}_{\text{Transition Period}} + \underbrace{\frac{E[D_{20}](1+g_l)}{(k-g_l)(1+k)^{20}}}_{\text{Stable Growth}} \quad (2)$$

In the initial phase, the dividend growth is assumed to equal the long-term consensus earnings growth rate, obtained from equity analysts[3]. In the stable phase following year 20, the dividend growth rate equals the estimated long-term GDP growth of the economy (Cornell, 1999). In this study, we assume adaptive expectations and calculate the expected GPD growth rate as the geometric nominal GDP growth rate over the past 5 years. Due to its three-stage structure, we refer to this model as *DDM3* hereafter.

It is well known that due to conflicts of interest, equity analysts tend to overstate long-term growth projections (see e.g. Chan et al. (2003)), which hence biases the ICOC estimates upwards. Since this study focuses on the analysis of implied costs of capital of individual firms, this bias would only cause problems if there were be some systematic relation between the degree of biases and some firm characteristic. We are not aware of any study documenting such a relation.

Damodaran (1999) proposes another, much simpler DDM, involving only two phases, an initial high dividend growth phase and a stable growth phase:

$$P_0 = \underbrace{\sum_{t=1}^{5} \frac{E[D_t]}{(1+k)^t}}_{\text{Growth Period}} + \underbrace{\frac{E[D_5](1+g_l)}{(k-g_l)(1+k)^5}}_{\text{Stable Growth}} \quad (3)$$

[3]The findings of Elton et al. (1981) suggest that analysts' forecasts are a good surrogate for investor expectations. The consensus growth rate is provided by IBES and is calculated as the median of the expected earnings growth rates of the contributing sell-side equity analysts. Note that estimating such earnings growth rates has a long tradition in the U.S., but not in European countries, where analysts have rarely published such forecasts until the last years but have concentrated on explicit earnings forecasts for the next years instead. Hence, the implementation of the Cornell (1999) approach for European markets leads to a considerable decrease in the available data set. Moreover, this growth rate is usually – if available – the median of very few analysts only.

Similar to the three-stage DDM, we use the consensus growth rate as provided by IBES as growth rate in the first phase and the expected long-term GDP growth rate of the economy after year 5. In the following, we refer to this model as *DDM2*.

Note that all presented DDM require the annual dividend D_0 which just has been paid out to the shareholders. Based on D_0 it is then possible to calculate the series of future dividend payments, beginning with D_1. In this study, we use the sum of all dividend payments over the last 12 months, also known as 12-months trailing dividends, as D_0.[4] We exclude all observations from the sample, where the 12-months trailing dividend equals 0.

2.2. The Residual Income Model

Another popular valuation formula is the RIM, stating that the value of the company equals the invested capital, plus the expected residual income from its future activities[5]:

$$P_0 = B_0 + \sum_{t=1}^{\infty} \frac{E[R_t]}{(1+k)^t} \tag{4}$$

with

$$E[R_t] = E[E_t] - k(B_{t-1}) = (roe_t - k)B_{t-1} \tag{5}$$

$$B_t = B_{t-1} + (1 - p_t)E[E_t] \tag{6}$$

where

B_t = book value of equity per share at the end of year t (B_0 being the current book value),

$E[R_t]$ = expected residual income per share in year t,

$E[E_t]$ = expected earnings per share in year t,

[4] There is some controversy in the literature about how to construct the right D_0 *or* D_1, see for example Harris and Marston (1992).

[5] When combined with the so-called clean surplus relation, the DDM can be transformed into the RIM (Feltham and Ohlson, 1995). This relation requires that all gains and losses affecting book value are also included in earnings. This condition is not always met, of course. Stock options and capital increases, e.g. can affect the book value of equity while leaving earnings unchanged. Still, the relation is approximately fulfilled in most cases.

roe_t = (expected) return on equity in year t,

p_t = payout ratio in year t.

Similar to the DDM, assumptions about the future growth in residual incomes or earnings have to be made when implementing the model in practice. One rather simple approach is proposed by Claus and Thomas (2001), who consider a two-stage RIM (abbreviated with *RIM2* in the following), assuming an initial phase of high earnings growth rates, followed by a stable growth of residual incomes after year five:

$$P_0 = B_0 + \underbrace{\sum_{t=1}^{5} \frac{E[E_t] - k(B_{t-1})}{(1+k)^t}}_{\text{Growth Period}} + \underbrace{\frac{E[R_5](1+g_l)}{(k-g_l)(1+k)^5}}_{\text{Stable Growth}} \tag{7}$$

Expected earnings for the first three years are taken from analysts forecasts, also provided by IBES. Earnings after year 3 are estimated by applying the IBES consensus earnings growth rate to the expected earnings of year 3.[6] The long-term growth rate in the second phase is presumed to equal the expected inflation rate calculated as the prevailing interest rate on 10-year treasury bonds less three percent, the assumed real-rate (Claus and Thomas, 2001, p. 1640). Future expected book values of equity are calculated using equation (6). To that end, we have to make assumptions regarding future payout ratios. In a slight variation to the methodology of Claus and Thomas (2001), we converge the current payout ratio geometrically towards 50% instead of using this ratio from the first prospective year on to project future book values. This approach seemed more realistic to us. Current payout rations are calculated by dividing the 12-months trailing dividends by the 12-months trailing earnings per share. This method ensures that the payments refer to the same time period as the earnings. Payout ratios above 1 are set to 1 in the first year, negative payout ratios are set to 0. If the payout ratio was missing due to missing dividend payments over the last 12 months, we equally set the payout ratio of year t=1 to 0.

[6] In the case where the expected earnings estimate of year 3 was missing, we also generated earnings in year 3 by applying the long-term consensus growth rate to expected earnings of year 2. If the projected earnings in year three were negative, we dropped the observation from the sample.

Gebhardt et al. (2001) rely also on the RIM to calculate the implied cost of capital. However, in contrast to Claus and Thomas (2001), they focus their assumptions not on future residual incomes, but more directly on the future return on equity (*roe* - see equation (5)), which they assume to converge to the industry median. More formally:

$$P_0 = B_0 + \underbrace{\sum_{t=1}^{3} \frac{E[roe_t] - k}{(1+k)^t} B_{t-1}}_{\text{Explicit Forecasts}} + \underbrace{\sum_{t=4}^{T} \frac{E[roe_t] - k}{(1+k)^t} B_{t-1}}_{\text{Transition Period}} + \underbrace{\frac{E[iroe_T] - k}{k(1+k)^{T-1}} B_{T-1}}_{\text{Terminal Value}} \quad (8)$$

where

T = is the forecast horizon of the transition period
$iroe_T$ = expected industry return on equity from period T onwards.

Similar to Gebhardt et al. (2001) we use explicit forecasts to calculate the expected return on equity for the next three years. Then we fade the *roe* to over $T-3$ years to the industry average. The industry average is calculated as the average *roe* over the past 60 months in the industry sector the company belongs to, using the industry sector codes of the GICS classification[7]. The calculation of future book values of equity and assumptions regarding future payout ratios are identical to those used in the RIM2 Claus and Thomas (2001) approach. Since the model by Gebhardt et al. (2001) is basically a three-stage RIM, we denote it by the abbreviation *RIM3*.

While the use of industry averages for the long-term return on equity has some appeal due to the findings of empirical analysis (Soliman 2004, Nissim and Penman 2001), the assumptions on future payout ratios in the literature as well as our implementation seem somewhat arbitrary to us. That is why we consider here another version of the RIM (denoted *RIM3'*) that avoids relying on assumptions for future payout ratios. Following the literature of sustainable growth rates in the long run, we use the following identity between payout ratio p, return on equity *roe* and the growth rate of the company g_l:

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[7] In our standard implementation we fix T=9. Instead of using the GICS classification, Gebhardt et al. (2001) rely on the 48 Fama and French (1997) industry classifications. We also tested other, more precise classifications such as the GICS Industry Group segmentation, or the Industry segmentation, but the results were much the same.

$$g_l \cdot roe = 1 - p$$
$$p = 1 - \frac{g_l}{roe} \tag{9}$$

In order to estimate future development of a company, one has to make to assumptions for two out of the three parameters. Instead of assuming the long-run payout ratio *p*, we opt to fix the long-term growth rate of the company g_l. By setting g_l equal to the expected GDP growth rate of the economy, we ensure that no company will persistently grow faster than the whole economy and eventually surpass it.

Hence, we calculate the RIM following Gebhardt et al. (2001) as presented in equation (8), but using different projected payout ratios. For each company, we calculate the long-term industry payout ratio using the relation (9), given the expected GDP growth of the economy and the industry roe_T. In the transition period, we then fade both payout ratio and return on equity towards their long-term levels.

2.3. Empirical Implementation

To calculate the implied cost of capital for the firms using the equations above, we employ the last available information as required by the formulas at the end of each calendar month. Firms with an incomplete data set, i.e. one or more missing input variables where we could not resort to approximations as explained above, have been ignored[8]. The solution of the equations is straightforward, since it is monotone in k, and can be solved iteratively.

3. Data

In our analysis, we focus on companies in the United Kingdom. We cover the MSCI universe from January 1990 to June 2005. The monthly data for prices, total return, book value per share, dividends per share, market capitalisation, and return on equity are taken from MSCI. All market

[8] Note that we do not carry out any time adjustment procedures similar to other studies on the implied cost of capital. Since we use a monthly data set, such adjustments would require the exact dividend payout dates and book value adjustments for all companies since 1990. Such data is not easy to get hold of nor it is reliable.

capitalisation data are free float adjusted. The earnings estimates as well as the long-term growth rate are taken from IBES median estimates. The data set contains 423 companies and over 41’000 monthly observations. We use the first five years to calculate the industry *roe* and can calculate the first expected returns starting January 1995, leaving us with 10 years of data. Since the number of companies included in the study changes over time, we have an unbalanced panel data set. As shown in Table 1, the industry group with the largest representation is Industrial Goods with 10-15% of the companies followed by Utilities, Materials, Retailing, and Household Products. The average company has a market cap £16.98bn and a book yield of 0.497.

The number of observations for the DDM2, DDM3 and RIM2 is constrained by the availability of the IBES long-term growth rate and the payout ratio. For the following analyses, we will use only the overlapping data set of 12,831 observations. However, using the more complete data set would result in the same results in most cases.

As Table 2 shows, the average expected return is fairly well clustered between 8.8% and 10.2% with the RIM3’ having the lowest average expected return at 8.88% and the DDM3 having the highest at 10.17%. However, the standard deviation is fairly low for the DDM2 model with only 2.54%. The standard deviation is somewhat higher for the DDM3 and RIM3 models with the RIM3’ having the highest standard deviation at 4.03%.

As was to be expected, the correlations between the structurally similar models DDM2 – DDM3 and RIM3 – RIM3’ are above 90%, rendering them to be essentially the same models as can be seen in Table 3. On the other hand, the correlations between the DDM and the RIM3 models are very low and generally are below 30%. The RIM2 models has similar correlations of around 40-50% with either group, being more correlated to the other RIM models using Pearson correlations, but being more correlated to the DDM models using Spearman Rank correlations.

4. Investment Strategies

In this section we explore whether it is possible to generate abnormal higher-than-average returns based on the investment strategies using the ICOC as stock selection variable. First, we illustrate our portfolio formation methodology. Then we compare the profitability of investment strategies based on the various ICOC approaches as presented in the previous section over different time horizons. Next we have a closer look at the relation between the ICOC and common risk factors, such as firm size, book-to-market ratio, and market beta as well as other firm characteristics. Finally, we examine whether the presented investment approach would also be profitable in practice by presenting a feasible trading strategy including transaction costs.

4.1. Portfolio Formation

Our analysis of the profitability of investment strategies using the ICOC as stock selection criteria follows in principle other well-known studies on investment strategies such as the work on price momentum strategies by Chan et al. (1996). At the end of each month, we rank all stocks in our sample based on the implied cost of capital estimates as described in the previous section. Then we group them into 8 equally weighted portfolios based on these rankings. Finally, we examine subsequent total returns, i.e. capital gains and dividend payments, over periods from 1 to 24 months. To increase the power of the analysis, we use – if not stated otherwise – overlapping holding periods. When we consider for instance a six months holding period, we use all possible portfolios that could be used such as those from January to July, from February to August, and so on.

4.2. Evaluation of Investment Strategies

In Table 4 we present the average buy-and-hold returns for all different implied cost of capital concepts over a subsequent holing period of 6 (overlapping) months. Portfolio 1 compromises the stocks with the lowest implied cost of capital estimate, and portfolio 8 consists of the high ICOC stocks. The line below indicates the average difference between the two extreme portfolios (P8-P1), i.e. the average return that could have been generated by an investment strategy consisting in a short position of the low-ICOC portfolio P1 and a long position in the high-ICOC portfolio P8. The t-statistic of this difference is given below, calculated by regressing the monthly overlapping differences (P8-P1) on a constant using Newey-West HAC standard errors with a lag length that equals the holding periods. In order to allow for a comparison of the models, we include only the observations where we have ICOC estimates for all selected approaches, reducing the sample size to 12831 observations[9].

Whereas all ICOC approaches exhibit a positive relation between cost of capital and subsequent stock returns, and thereby confirming the hypothesis of the ICOC's ability to predict stock returns, the table reveals large qualitative differences between the employed models. The difference between the two extreme portfolios, as shown in the line below the portfolio returns varies quite significantly between the models. Whereas the returns of the two extreme ICOC portfolios based on RIM3 and RIM3' do diverge up to 6.4% over six months on average, the RIM2 approach yields only a difference of 3.5%. In terms of statistical significance of this spread, the investment strategies using dividend discount models appear to be most reliable. Not surprisingly, the small spread of the RIM2 is statistically not significant. In addition, whereas most models exhibit in general monotonically increasing returns along with increasing implied returns, the RIM2 exhibits a large discontinuity in the two portfolios with the lowest expected returns (P1, P2).

Given the evidence for the positive relation between ICOC estimates and subsequent stock returns over a 6 month holding period, we next investigate the profitability of the investment strategies over different buy-and-hold periods. In order to compare the returns over time and to detect differences in the time structure between the ICOC models, we hence repeat the previous analysis for different investment horizons. Table 5 shows the average returns of the high (P8) and low (P1) ICOC portfolios, together with their average difference (P8-P1) and the t-stat thereof with holding periods of 1, 3, 6, 12, 18, and 24 months. The last two lines give the number of observations (decreasing with growing investment horizon) and the equally weighted return of the whole sample.

Table 5 indicates that all ICOC approaches yield a positive return, i.e. the difference between the high ICOC portfolio and the low ICOC portfolio is always positive, regardless of the buy-and-hold period of the portfolios. Over a holding period up to 6 months, the RIM3 models perform best, attaining a difference between the extreme portfolios up to 6.4% over 6 months. However, using longer rebalancing intervals, both DDMs show a better performance. Indeed, the statistical

[9] The in the subsequent portfolio analysis as well as the regression analysis in section 5, the sample size depends in addition of the number of holding periods and the availability of firm characteristics.

difference of a P8-P1 (DDM) investment strategy does not decrease over time, remaining significant at the 5% level. This compares to the RIM, where the return of an investment in a P8-P1 portfolio is not statistically different from zero if the rebalancing interval exceeds 6 months. In fact, after one year, the return spread between P8 and P1 does not grow anymore, suggesting that the RIM is indeed more of a short-term return indicator. Again, the RIM2 approach yields the worst, but still positive returns.

The better performance of the DDMs in predicting stock returns over long horizons might be explained by its informational advantage. Dividend policy seems to be a signalling process conveying information about future profits (e.g. Nissim and Ziv (2001)) that appears to increase the accuracy of ICOC estimates. Very clearly, RIM based approaches cannot capture this additional information included in dividend payments.

4.3. Firm Characteristics

From the preceding analysis, we found some evidence that ICOC estimates are related to subsequent stock returns, and can thus conclude that ICOC based investment strategies are profitable. Now we go further into the matter and investigate the characteristics of our investment portfolios. Along with the mean ICOC estimates and portfolio returns, we present in table 6 the mean B/M ratio, the median firm size (divided by the level of the stock market index), average market beta, and average price momentum of the 8 portfolios for some selected ICOC approaches. Price momentum is calculated as change in share prices over the past six months. The last row shows the overall averages (or means, respectively) over the whole sample size[10]. All firm characteristics are measured as of the portfolios formation date. We refrain from presenting the portfolio characteristics of the DDM2 and RIM3' models, since there are very similar to those of the DDM3 and RIM3 approach, respectively[11].

[10] The average market beta lies with 0.929 below the theoretical value of 1. This can be partly explained by the fact that due to missing long-term growth rates, our sample contains on average more large companies than the overall market, which usually tend to have lower beta values. From a practical perspective, it is not the average firm beta that is important, but the market beta of each portfolio, since individual correlations with the market might cancel out when pooling them into portfolios. However, estimates for portfolio betas did not differ significantly from the average firm beta of each portfolio.

[11] This can also be seen from the rather high correlations between the models as presented in Table 3.

Panel A of Table 6 displays the average characteristics of the portfolios when sorted according to the DDM3 estimates. There is a fairly close inverse relation between the ICOC and both past price momentum and firm size. Large firms, as well as firms that have seen a good share price performance over the last six months have on average smaller ICOC estimates. The negative relation of implied returns and firm size is in line with the findings of Fama and French (1992, 1993) that have detected size as priced risk variable. However, the two other firm characteristics that are usually known as risk factors, B/M ratio and market beta, are rather unrelated to the implied return estimates (with the exception of the B/M ratio for the portfolio with the highest ICOC which seems to contain rather cheap companies). The association with past price momentum can partly be explained by the nature of the present value formula: since current share price enters the equation, companies that have experienced a rise in share prices, have ceteris paribus a lower internal rate of return.

The ICOC obtained from the RIM2 exhibits similar relations to firm characteristics, as shown in Table 6, Panel B. However, firm size is now even stronger related to the ICOC estimates, and beta seems to have a slightly positive association to firm risk. Finally, the third panel (C) contains the characteristics of the RIM3 portfolios. The relationship between ICOC and firm characteristics is rather similar to those of the DDM3 and the RIM2, but the effects are more pronounced. Both B/M ratio and firm size are very strongly related to the ICOC estimate, market beta is not.

The close association of the implied return obtained from the RIM3 to the Fama-French risk factors and price momentum is striking, but in line with the findings of Lee et al. (2003), conducting regression tests of the determinants of the ICOC obtained from the RIM3 approach. Given that both B/M ratio and firm size are known to be priced risk factors, these results however question the validity of the ICOC as a separately priced factor. It could be that the ICOC is only a mere transformation of B/M ratio and firm size, and hence one would yield even better return predictions by directly using those well-known firm risk characteristics as stock selection principle. We will analyse this issue in the next section on regression analysis.

4.4. A Practical Example

The previous analysis makes a case for investing according to the ICOC stock selection principle. However, all presented results are based on two assumptions that are opposed to actual investment strategies. First, the – statistically significant – difference between the two extreme portfolios is calculated on the basis of overlapping holding periods. While the implementation of such a strategy is of course nor per se impossible, usually investment funds to invest most of their funds at once which makes the generation of such an overlapping investment strategy generally not feasible. Second, and more important, the regular portfolio adjustments do not come for free, but give rise to transaction costs.

Hence, in Table 7 we present the return on non-overlapping investment strategies with a holding period of 6 months, including transaction costs of 2% for each portfolio reshuffling[12]. The average return over the time period from January 1995 to June 2005 depends then of course on the starting month, ranging from January 1995 to June 1995 (at the beginning of July 1995, we reshuffle the January portfolio for the first time). We present two alternative investment strategies. One approach displays the previously cited long-short investment (P8-P1), the other one consists just in holding a long position in the high ICOC portfolio (P8). As a benchmark, the line below gives the equally weighted return of a portfolio of all shares in the sample. Since this is a passive investment strategy without rebalancing, its return is given net of transaction costs. All returns in the table are calculated as arithmetic averages over the 20 periods.

Investing in the P8 portfolio (also called long-only) and reshuffling after every six months yields for almost any starting month and any ICOC model higher returns than a passively managed buy-and-hold investment in the whole stock market. Hence, even when including transaction cost, long-only implied cost of capital strategies outperform the market. On the other hand, however, investing in a long-short portfolio (P8-P1) does not prove to be a profitable investment compared to the benchmark, with its average return being below the passive buy-and-hold strategy. We can conclude that whereas the high ICOC companies do indeed outperform the market significantly, the low ICOC companies do not under perform the market systematically.

[12] 1% for selling the portfolio and 1% for buying the new one. We abstract here form the possibility that some stocks may be kept in the portfolio at the rebalancing date. Hence, the presented returns indicate a lower bound for a possible actual range of returns.

5. Regression tests

The previous portfolio analysis indicates that the ICOC approach is useful to predict stock returns. However, in many cases, the characteristics of the portfolios formed according to the implied return concepts exhibit a strong relation to well-known risk factors such as B/M ratio or firm size. This observation casts doubts over the ICOC's intrinsic ability to predict stock returns, since its relation to subsequent returns might have its origin only in the ICOC's fairly close relation to underlying risk factors. We use regression analysis to disentangle the predictive power of ICOC estimates and risk factors to explain stock returns. In the literature, there are two common econometric approaches to carry out such tests: on the one hand, many asset pricing studies rely on the Fama-MacBeth (1973) cross-sectional regressions to analyse determinants of stock returns (e.g. Fama and French, 1992; Chan et al., 1996). Given the nature of our data set, we also perform panel regressions, in line with the more recent works on determinants of stock returns such as Pandey (2001) and Subrahmanyam (2005). Since the panel analysis makes use of the whole data set more efficiently, it usually provides more significant coefficient estimates (Baltagi, 2005)[13].

5.1. Cross-sectional Regressions

5.1.1. Methodology

For each month of our data set from January 1995 to August 2005, we first estimate cross-sectional regressions of actual stock return on the ICOC estimate, risk-factors, and other firm characteristics:

$$r_i = \alpha + \delta k_i + \gamma' X_i + u_i \qquad (10)$$

where r_i is the subsequent total stock return measured over different periods up to 24 months after having observed the risk-factors and firm characteristics. The ICOC estimate is denoted by k_i. X_i

[13] For a detailed comparison of the Fama-MacBeth (1973) and panel regression methods, see Petersen (2004).

is a vector of risk-factors, including market beta and firm characteristics, and u_i is the error term. In the next step, we then test whether the average coefficient estimates δ and γ' are significantly different from zero. The t-statistics are calculated by regressing the time series of the coefficient estimates on a constant. Since we use overlapping data, the t-statistic is calculated on the basis of heteroskedasticity- and autocorrelation-consistent (HAC) standard errors (Newey-West, 1987) with a lag-length corresponding to the number of months over which we measure the stock returns.

Note that we refrain from sorting the companies into portfolio before carrying out the Fama-MacBeth (1973) regressions. Instead we use individual firm data for our regressions, similar to the works of e.g. Brennman (1998), or Subrahmanyam (2005). This has several reasons: On the one hand, we want to include many different firm characteristics in our regression analysis. As Bauer et al. (2004) point out, the number of portfolios needed increases exponentially with the number of firm characteristics examined. With 5 groups for 5 different characteristics e.g., we would need 5^5 portfolios. Given our data, many of them would contain none ore few stocks. If we opted instead for choosing one or two characteristics as sorting variable only, we face the question which ones to select. Brennan et al. (1998) argue that selecting some out of many possible explanatory variables creates a "data-snooping bias that is inherent in all portfolio based approaches", since the selection of the sorting variable as well the sorting order can influence the results drastically. Especially the common practice to construct portfolios according to B/M-ratio and size is likely to overestimate the regression results (Lewellen et al., 2005). Finally, the use of few portfolios, i.e. employing only one or two sorting variables, reduces the sample size significantly, resulting in estimates with very low power[14].

5.1.2. Regression Results

Table 8 reports the time-series averages of the slope coefficients, along with their t-statistics. We again investigated the ICOC estimates obtained from the DDM3, RIM2, and RIM3. The dependent variable, the stock return r_i, is measured over 6 months after having observed the firm characteristics X_i .

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[14] This point has been put forward by Lee at al. (2003). They try to overcome this problem by forming country-industry portfolios to estimate a country-industry beta, thereby hoping to increase the accuracy of the beta estimate. Then they run, similar to us, individual firm regressions but include the industry beta as a proxy for the company beta as explaining variable. Fama and French (1992) rely on this procedure as well.

Regardless of the ICOC method employed, the average slope coefficients are rather small compared to their standard errors. Accordingly, the estimates are statistically not significantly different from zero. Still, compared to beta and other firm characteristics, the ICOC estimates are in many cases the most important explaining variable, with the RIM3 ICOC close to being significant when used as the only regressor. In all regressions, market beta and more interestingly, firm size, is not related to stock returns, which is against the evidence in the previous section and the findings of Fama and French (1992). The (weak) positive relation to price momentum is in line with Chan et al. (1996).

If one keeps in mind the common upward bias of coefficient estimates of portfolio regressions in many empirical studies (Lewellen et al., 2005), these rather poor results do not appear too disappointing, but must be put into perspective.

5.2. Panel Regressions

In line with more recent studies in the empirical finance literature we now refer to panel regressions to detect the predictive power of ICOC estimates on stock return after having controlled for common risk factors of the Fama-French model. Since the panel estimation procedure uses the whole information conveyed in the data in one regression step, we hope to increase the power of the estimates.

5.2.1. Methodology

The basic regression equation for stock returns and its explaining variables in a panel data set (pooled time-series cross-section) is given as follows:

$$r_{i,t} = \alpha + \delta k_{i,t} + \gamma' X_{i,t} + u_{i,t} \tag{11}$$

where the subscript i denotes the company (cross-section dimension) and t denotes the time period of the observation (time-series dimension). This general specification is known as pooled data set. In many cases however, the underlying assumption (when estimating the pooled data set by standard OLS) that the observation of a company at time t is independent an observation of the same company at a different point in time *s* is not met. Hence, the regression equation is modified for allowing for individual effects for each company. This individual effect can account for form characteristics that are not included in the regression equations such as the industry sector, or unobservable factors. This model is known as the one-way individual effects model:

$$r_{i,t} = \alpha_i + \delta k_{i,t} + \gamma' X_{i,t} + u_{i,t} \tag{12}$$

One of the most common approaches to estimate such an individual effects model is to assume that the individual effect α_i of each firm is constant over time. Relying on such a one-way fixed effect (FE) model hence implies that the returns of some companies are on average higher than the return of the market, whereas some other companies under perform the market on average. Another variant of the one-way individual effects model is the random-effects (RE) model, that assumes that the individual effect α_i is not constant, but fluctuates randomly over time with a zero mean.

To detect which model is appropriate for out data set, we carry out the several common statistical tests. First we rely on an F-test to see whether the estimated fixed effects are jointly significantly different from zero. If the H_0 of no significance of the individual fixed effects is rejected, we can conclude that a fixed-effect model is preferred to the simple pooled OLS estimation. Second, we perform a Breusch-Pagan test on the random effects model, to see whether the random effects are significantly different from zero. If the H_0 of no significance is rejected, we can conclude that a random-effect model is preferred to the simple pooled OLS estimation. Third, we conduct a Hausmann specification test, to see whether the coefficients of the FE and RE estimation differ significantly from each other. If the H_0 of no significant difference between the estimated coefficients is rejected, we can conclude that a fixed-effect model is preferred to the random effects estimation[15]. Note that we carry out these specification tests on non-overlapping data sets since the standard tests implemented by statistical packages do not correct for autocorrelation[16]. The test results of all samples showed that the fixed effects model is the preferred approach to estimate the panel regressions. We hence present only the results of the FE-panel regressions.

[15] Fixed-effects estimates are always consistent, but random-effects estimates might be more efficient.

[16] We conduct these tests for all possible non-overlapping panel data sets. In most cases however, the results do not differ across the different non-overlapping panels and lead to the same conclusion of employing a one-way fixed effects model.

In addition to the one-way individual effects model, we also could imagine a two-way individual effects model that allows not only for firm-specific effects, but includes a time-specific effect as well:

$$r_{i,t} = \alpha_i + \lambda_t + \delta k_{i,t} + \gamma' X_{i,t} + u_{i,t} \tag{13}$$

where λ_t is a time specific effect for each *t*. By adding a fixed time effect for each period, we reflect the fact that during the time period from 1995 to 2005, the capital markets in the U.K. have seen extreme movements, such as the record highs in 2000 and the subsequent market downturn up to 2003. The underlying determinants of stock returns might have changed over this period, e.g. due to changes in the expected equity risk premium that affects all stocks in the same way. The inclusion of a fixed time effect also helps to control for changes in stock returns that stem from the calendar time only.

We implement this time effect by adding *t-1* monthly regression dummies in the one-way FE regression model. Similar to the simple fixed effects model, we test the significance of the time effects by a joint F-test on all time dummies λ_t. Since the H_0 of no significance of all time dummies was rejected, we also adopt the two-way fixed effects model.

5.2.2. Results of the One-way Fixed Effects Model

Table 9 presents the regression estimates and t-statistics of the one-way fixed firm effects model of equation (12) for the same three ICOC estimates as in the Fama-MacBeth regression analysis. In addition to regression test on 6-month stock returns presented in panel A of the table, we also report regressions of 12-month returns (panel B). The regressions are carried out over whole overlapping panel data set. The t-statistics below the estimates are consequently calculated using the FE, heteroskedasticity robust and autocorrelated-adjusted standard errors following Rogers (1993). The explained variance of each the model is given in the last line.

As suggested earlier, the panel approach increases the power of the estimates decisively compared to the Fama-MacBeth procedure. In the 6-months return regressions displayed in panel

A, the ICOC coefficients (δ) are now highly significant, regardless of the method chosen to calculate them, even when including other risk variables and firm characteristics in to the regression equation. Similar to the Fama-MacBeth estimations, size is negatively related to stock returns, and market beta is again only weakly related to stock returns. However, using panel estimation, the coefficients of past price momentum are now negative. This compares to the positive coefficients of the previous Fama-MacBeth regressions and common studies on momentum strategies (Chan et al., 1996). This discrepancy between the panel and Fama-MacBeth estimation is due to varying sample sizes across the dataset. Since the sample compromises more stocks during periods when the market declines, the panel estimation puts relatively more weight on falling stocks. High market volatility together with many IPOs and delistings during the sample period might explain the difference to existing studies.

Interestingly, the three different ICOC models yield rather similar results. When using the ICOC as the only explaining variable, the RIM3 performs best, as can be seen easily from the R^2 value. When controlling for firm characteristics, the RIM2 yields the highest and most significant coefficient estimates[17].

What happens if we increase the forecasting horizon? The regression results of 12-months stock returns in panel B show some differences, notably for the RIM3 ICOC, which is no longer significantly related to stock returns after controlling for risk-factors and price momentum. This essentially confirms our claim in the portfolio analysis, that the RIM3 loses its predictive power over longer time periods. The statistical significance of price momentum also decreases over a longer forecasting horizon.

To conclude, the ICOC is not only a mere transformation or expression of the two risk-factors B/M-ratio and firm size (as hypothesised in the previous section), but adds significantly additional power in explaining stock returns. The RIM3 model however seems to loose some of its explanatory power over longer time horizons, presumably since it cannot make use of the information included in dividend payments.

[17] We have to add, however, that the rather good results obtained from the RIM3 are not robust to changes in the sample size. When using the whole data set available for RIM3 regressions (14151 observations instead of 10812), the RIM3 ICOC is no longer significant in explaining stock returns after controlling for the Fama-French factors. As mentioned earlier, the additional 3339 observations contain smaller companies (on average half the size) for which the RIM3 ICOC does not seem to be a good explanatory variable for stock returns. In fact, in panel regression tests of this sub-sample, the ICOC coefficient is negative and significantly different from zero.

5.2.3. Results of the Two-way Fixed Effects Model

Table 10 contains finally the regression results and t-statistics of the two-way fixed effects model as stated in equation (13). Again, we run the regressions on 6-months stock returns, using the whole overlapping panel data set. The t-statistics are calculated using heteroskedasticity robust and autocorrelated-adjusted standard errors following Rogers (1993). The last to lines contain the R^2 of each specification and the F-statistic of a joint significance test on all time dummies.

The estimates of Table 10 confirm the results of the previous one-way fixed effects model. The inclusion of a fixed time effect does note reduce the significance of all ICOC estimates as explanatory variables for stock returns. Similarly, the two Fama-French factors remain highly significant. On the other hand, the time dummies which prove to be very relevant as the F-statistic indicates, cause price momentum and market beta to get insignificant. In general, the fixed time effects increase the R-squared of the models up to 34%. Otherwise, the conclusion remains similar. When controlling for firm characteristics, the RIM2 yields the most significant coefficient estimates – taken alone, the RIM3 performs best[18].

6. Conclusion

The recently developed concept of the implied cost of capital has become popular tool for estimating expected stock returns both in theory and practice. By aggregating individual stock returns over the entire market, this approach is used thoroughly in research to derive a forward-looking equity risk premium estimate. Fund managers try to exploit the so-obtained expected returns to create investment portfolios that yield abnormal stock returns.

Surprisingly, a sound econometric foundation of this methodology at the level of individual firm data is still missing. In this paper, we employ portfolio analysis and regression test to answer the question whether the use of the implied cost of capital as proxy for expected stock returns can be substantiated by econometric evidence.

[18] We also conducted 2-way FE regressions on 12-month stock returns. The results were similar to the 1-way FE estimation: the coefficient of the ICOC from the RIM3 gets insignificant when controlling for firm risk.

In principle, our analysis confirm the implied cost of capital's hypothesised positive relation to stock returns, but detects large qualitative differences among several common models examined. We find that investment strategies based on the ICOC are profitable and provide significantly positive returns when derived from three-stage DDM and RIM approaches. However, the longer the investment horizon, the better the DDMs perform compared to the RIM, whose profitability deteriorates for time horizons longer than 6 months. When examining the characteristics of the constructed portfolios, we find that all ICOC concepts are related to the Fama-French risk factors B/M-ratio and firm size. On average, ICOC estimates of the DDM are less related to those risk factors. In the subsequent regression analysis, panel estimations - and to a weaker extent Fama-MacBeth regressions – show that the implied cost of capital helps to explain variations in stock returns even after controlling for other firm risk factors. However, its intrinsic explanatory power is rather small.

Our results have important practical implications for managers. On the one hand this study shows that the implied cost of capital offers indeed a powerful tool to estimate the firm's cost of equity, at least if taken jointly with other common risk factors. For portfolio mangers, on the other hand, this paper puts forward empirical evidence for the profitability of ICOC-based investment strategies. Still, large discrepancies between the models underpin the importance to carefully select the right approach.

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Table 1: Distribution of Industry Groups in the Sample

This table reports the distribution of the full data set over the different GICS industry groups. The first two columns include the whole sample from 1995 to 2005. The other two columns contain information over the industry affiliation in the first and last month of the sample, respectively.

	Industry Group	1995/01-2005/08		1995/01		2005/08	
		Obs.	Fract.	Obs.	Fract.	Obs.	Fract.
1010	Energy	610	2.4%	3	1.5%	7	3.1%
1510	Materials	1814	7.2%	8	4.0%	21	9.2%
2010	Industrial Goods	3191	12.6%	20	10.1%	34	14.8%
2020	Commercial Services & Supplies	1042	4.1%	14	7.0%	6	2.6%
2030	Transportation	1581	6.2%	12	6.0%	11	4.8%
2510	Automobile & Components	236	0.9%	2	1.0%	3	1.3%
2520	Consumer Durables & Apparel	1114	4.4%	12	6.0%	10	4.4%
2530	Consumer Services	1209	4.8%	13	6.5%	8	3.5%
2540	Media	1459	5.8%	14	7.0%	9	3.9%
2550	Retailing	1720	6.8%	13	6.5%	17	7.4%
3010	Food & Staples Retailing	662	2.6%	5	2.5%	5	2.2%
3020	Food, Beverage & Tobacco	1702	6.7%	10	5.0%	16	7.0%
3030	Household & Personal Products	209	0.8%	2	1.0%	2	0.9%
3510	Health Care Equipment & Services	409	1.6%	6	3.0%	3	1.3%
3520	Pharmaceuticals & Biotechnology	407	1.6%	2	1.0%	5	2.2%
4010	Banks	1296	5.1%	8	4.0%	11	4.8%
4020	Diversified Financials	801	3.2%	11	5.5%	5	2.2%
4030	Insurance	1030	4.1%	6	3.0%	11	4.8%
4040	Real Estate	904	3.6%	7	3.5%	8	3.5%
4510	Software & Services	499	2.0%	5	2.5%		0.0%
4520	Technology Hardware & Equipment	732	2.9%	6	3.0%	8	3.5%
4530	Semiconductor & Semi. Equipment	70	0.3%	1	0.5%		0.0%
5010	Telecommunication Services	826	3.3%	8	4.0%	3	1.3%
5510	Utilities	1841	7.3%	11	5.5%	26	11.4%

Table 2 : Descriptive Statistics

This table reports the maximum number of available observations as well as the mean implied return and standard deviation derived for the different valuation models. For the calculation of the mean and standard deviation, only observations with values for all five models were used (12831 observations).

	Number of available observations	Mean	Standard Deviation
DDM2	13763	9.15%	2.54%
DDM3	13760	10.17%	3.70%
RIM2	13280	8.93%	3.89%
RIM3	17076	9.33%	3.81%
RIM3’	17053	8.88%	4.03%

Table 3 : Correlation of Expected Returns

This table reports the correlation between the different valuation models using data for all years. Only observations with data for all valuation models were used (12831 observations). Pearson correlations are reported above the diagonal and Spearman Rank correlation below.

	DDM2	DDM3	RIM2	RIM3	RIM3’
DDM2		0.9123	0.3915	0.2854	0.2906
DDM3	0.9121		0.3631	0.1587	0.1633
RIM2	0.5183	0.4986		0.6972	0.6757
RIM3	0.1776	0.3087	0.4510		0.9901
RIM3’	0.1678	0.2951	0.4484	0.9871	

Table 4 : Returns from Buy-and-Hold Portfolios

This table reports the average, equally weighted buy-and-hold returns for portfolios constructed using various ICOC approaches as sorting variable. For each valuation model, the table shows the six-month overlapping returns for the eight portfolios. Portfolio 1 compromises the stocks with the lowest implied cost of capital estimate, and portfolio 8 consists of the high ICOC stocks. The second panel below indicates the average difference between the two extreme portfolios (P8-P1), i.e. the average return that could have been generated by an investment strategy consisting in a short position of the low-ICOC portfolio P1 and a long position in the high-ICOC portfolio P8. The t-statistic of this difference is given below, using Newey-West HAC standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is January 1995 to August 2005. The six-month equal-weighted return over all observations was 6.5%.

	DDM3	**DDM2**	**RIM2**	**RIM3**	**RIM3'**
P1 (low ICOC)	3.3%	2.8%	7.1%	4.5%	4.2%
P2	6.1%	5.5%	5.3%	5.0%	5.7%
P3	5.6%	6.2%	3.9%	5.0%	5.1%
P4	7.1%	6.1%	4.3%	6.3%	5.7%
P5	7.0%	6.7%	5.5%	5.9%	5.9%
P6	7.0%	7.7%	7.8%	6.4%	6.1%
P7	7.6%	8.9%	8.0%	8.5%	9.1%
P8 (high ICOC)	8.9%	8.8%	10.6%	10.8%	10.6%
P8-P1	5.6%**	5.9%**	3.5%	6.4%*	6.4%*
t statistic	(2.08)	(2.44)	(1.27)	(1.77)	(1.74)
EWA	6.5%				
Observations	10812				

Table 5 : Returns from Buy-and-Hold Portfolios with different Holding Periods

This table reports the average, equally weighted buy-and-hold returns of the high (P8) and low (P1) ICOC portfolios, together with their average difference (P8-P1) and the t-stat thereof over holding periods of 1, 3, 6, 12, 18, and 24 months. The t-statistic is calculated using Newey-West HAC standard errors. The last two lines give the number of observations (decreasing with growing investment horizon) and the equally weighted return of the whole sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is January 1995 to August 2005.

	Months	1	3	6	12	18	24
DDM3	P1	0.6%	1.5%	3.3%	6.6%	9.7%	14.1%
	P8	1.8%	5.0%	8.9%	15.6%	23.5%	32.9%
	P8-P1	1.3%**	3.5%***	5.6%**	8.9%**	13.8%**	18.8%**
	t-stat	(2.44)	(2.68)	(2.44)	(2.04)	(2.27)	(2.39)
DDM2	P1	0.5%	1.5%	2.8%	5.2%	8.1%	12.5%
	P8	1.9%	4.7%	8.8%	15.8%	24.2%	32.9%
	P8-P1	1.4%***	3.2%**	5.9%**	10.6%*	16.1%**	20.4%*
	t-stat	(2.66)	(2.17)	(2.08)	(1.95)	(2.09)	(1.90)
RIM2	P1	0.9%	3.3%	7.1%	14.1%	22.8%	32.5%
	P8	1.8%	5.4%	10.6%	18.8%	28.2%	37.8%
	P8-P1	0.9%*	2.1%	3.5%	4.7%	5.4%	5.3%
	t-stat	(1.68)	(1.42)	(1.27)	(0.78)	(0.53)	(0.30)
RIM3	P1	0.6%	2.3%	4.5%	8.9%	15.1%	21.8%
	P8	2.1%	5.6%	10.8%	18.9%	26.1%	33.3%
	P8-P1	1.5%***	3.3%*	6.4%*	10.0%	11.0%	11.5%
	t-stat	(2.68)	(1.85)	(1.77)	(1.32)	(0.85)	(0.58)
RIM3'	P1	0.6%	2.2%	4.2%	8.8%	15.5%	21.4%
	P8	2.0%	5.4%	10.6%	18.7%	25.7%	32.3%
	P8-P1	1.5%**	3.3%*	6.4%*	9.9%	10.2%	10.9%
	t-stat	(2.59)	(1.77)	(1.74)	(1.27)	(0.77)	(0.54)
Observations		11540	11255	10812	9923	9059	8237
EWA		1.2%	3.4%	6.5%	12.5%	18.4%	24.0%

Table 6: Firm Characteristics for Different Buy-and-Hold Portfolios for several Valuation Models

This table presents, along with the mean ICOC estimates and portfolio returns, the characteristics of the different buy-and-hold portfolios. Panel A reports firm characteristics of the DDM3 ICOC portfolios, panel B information on the RIM2 ICOC portfolios and panel information on the RIM3 ICOC investment portfolios. Portfolio 1 compromises the stocks with the lowest implied cost of capital estimate, and portfolio 8 consists of the high ICOC stocks. B/M is the mean book yield of the companies in a portfolio, SIZE is the median firm market capitalization (divided by the level of the stock market index), BETA is the average five year regressed sensitivity on the market portfolio, and MOMENTUM is the average historical six-month price return. The last row shows the overall averages (or means, respectively) over the whole sample size. All firm characteristics are measured as of the portfolios formation date.

Panel A: DDM3

	ICOC	RETURN	B/M	SIZE	BETA	MOMENTUM
P1	0.072	1.033	0.465	0.927	0.938	1.091
P2	0.085	1.061	0.475	0.922	0.868	1.083
P3	0.092	1.056	0.429	0.918	0.903	1.068
P4	0.098	1.071	0.451	0.903	0.902	1.043
P5	0.103	1.070	0.454	0.866	0.929	1.019
P6	0.111	1.070	0.499	0.744	1.015	1.005
P7	0.123	1.076	0.512	0.667	0.955	1.004
P8	0.170	1.089	0.672	0.587	0.929	0.976
Average	0.106	1.065	0.493	0.733	0.929	1.037
Observations	10812					

Panel B: RIM2

	ICOC	RETURN	B/M	SIZE	BETA	MOMENTUM
P1	0.049	1.071	0.599	1.054	0.892	1.085
P2	0.067	1.053	0.397	1.136	0.943	1.065
P3	0.080	1.039	0.421	1.070	0.903	1.059
P4	0.088	1.043	0.456	1.041	0.853	1.039
P5	0.095	1.055	0.422	0.914	0.906	1.035
P6	0.103	1.078	0.454	0.621	0.964	1.021
P7	0.115	1.080	0.514	0.514	0.984	1.002
P8	0.170	1.106	0.691	0.396	0.999	0.988
Average	0.095	1.065	0.493	0.733	0.929	1.037
Observations	10812					

Panel C: RIM3

	ICOC	RETURN	B/M	SIZE	BETA	MOMENTUM
P1	0.044	1.045	0.157	1.174	0.959	1.081
P2	0.062	1.050	0.250	1.307	0.996	1.053
P3	0.074	1.050	0.315	1.063	1.047	1.059
P4	0.084	1.063	0.378	0.873	0.919	1.049
P5	0.095	1.059	0.465	0.870	0.912	1.031
P6	0.108	1.064	0.606	0.710	0.855	1.024
P7	0.122	1.085	0.803	0.608	0.845	1.013
P8	0.163	1.108	1.029	0.379	0.890	0.981
Average	0.093	1.065	0.493	0.733	0.929	1.037
Observations	10812					

Table 7: Annualized Returns on Non-Overlapping Buy-and-Hold Portfolios with Half-Yearly Rebalancing including transaction Costs

This table shows the equal-weighted returns on non-overlapping ICOC based investment strategies with a holding period of 6 months, including transaction costs of 2% for each portfolio reshuffling. The returns are shown for each different starting month, from January 1995 to June 1995. We present two alternative investment strategies. One approach displays the previously cited long-short investment, i.e. each portfolio consists of a long position of companies with the highest internal rate of return, and a short position in the portfolio with the lowest internal rate of return (P8-P1). The other approach consists just in holding a long position in the high ICOC portfolio (P8). As a benchmark, the line below ("All") gives the equally weighted return of a portfolio of all shares in the sample. Since this is a passive investment strategy without rebalancing, its return is given net of transaction costs. All returns in the table are calculated as arithmetic averages over the 20 periods (January 1995 – January).

		JAN	FEB	MAR	APR	MAY	JUN
DDM3	P8	1.063	1.074	1.107	1.066	1.056	1.053
	P8-P1	1.040	1.056	1.094	1.053	1.047	1.041
	All	1.068	1.073	1.075	1.065	1.058	1.060
RIM2	P8	1.074	1.097	1.106	1.078	1.067	1.069
	P8-P1	1.008	1.017	1.026	1.013	1.004	1.010
	All	1.066	1.071	1.073	1.062	1.057	1.059
RIM3	P8	1.068	1.094	1.120	1.092	1.078	1.074
	P8-P1	1.020	1.042	1.068	1.036	1.037	1.041
	All	1.066	1.070	1.075	1.065	1.057	1.057

Table 8 : Results of Different Fama-MacBeth Regression correcting for Bias and in the Fama-French Factors

This table shows the results of different Fama-MacBeth regressions, the average slope coefficient of the cross-sectional regressions along with their t-statistics. For each valuation model, three different regression specifications are estimated, including different risk factors regressed on the subsequent 6-month return using overlapping periods. The first regresses only the internal rate of return (ICOC) on the subsequent total stock return. The second specification uses in addition the three Fama-French factors, B/M being the book yield, SIZE the market capitalization divided by the level of the stock market index, and BETA is the five year regressed sensitivity on the market portfolio. The last model adds the historical six month price return (MOM). The t-statistic is calculated on the basis of heteroskedasticity- and autocorrelation-consistent (HAC) standard errors following Newey-West (1987). The regressions are run over the full cross-section of companies. None of the variables were statistically significant at the 10% level.

	DDM3			RIM2			RIM3		
ICOC	0.23	0.24	0.19	0.31	0.26	0.21	0.41	0.43	0.34
t-stat	(1.00)	(1.35)	(1.12)	(1.31)	(1.25)	(1.04)	(1.41)	(1.17)	(0.97)
BETA		0.01	0		0.01	0		0.01	0.01
t-stat		(0.29)	(0.18)		(0.45)	(0.27)		(0.42)	(0.17)
B/M		0.02	0.02		0.03	0.03		0	0.01
t-stat		(0.86)	(1.11)		(1.49)	(1.76)		(0.1)	(0.4)
MCAP		0	0		0	0		0	0
t-stat		(0.47)	(0.52)		(0.35)	(0.5)		(0.39)	(0.55)
MOM			0.04			0.03			0.03
t-stat			(1.0)			(0.72)			(0.75)

Table 9 : Panel Regression with One-Way Fixed Effects

This table presents the regression estimates and t-statistics of the one-way fixed firm effects model:

$$r_{i,t} = \alpha_i + \delta k_{i,t} + \gamma' X_{i,t} + u_{i,t} \quad (12)$$

For each valuation model, three different regression specifications are estimated, including different risk factors regressed on the subsequent stock return using overlapping periods. The first regresses only the internal rate of return (ICOC) on the subsequent total stock return. The second specification uses in addition the three Fama-French factors, B/M being the book yield, SIZE the market capitalization divided by the level of the stock market index, and BETA is the five year regressed sensitivity on the market portfolio. The last model adds the historical six month price return (MOM). The explained variance of each the model is given in the last line

The regressions are carried out over whole overlapping panel data set. The t-statistic is calculated on the basis of heteroskedasticity- and autocorrelation-consistent (HAC) standard errors following Rogers (1993). The regressions are run over the full cross-section of companies. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. Panel A reports the regression estimates on 6-month stock returns, panel B the results of 12-months return regressions.

Panel A: 6-month forecast horizon

	DDM3			RIM2			RIM3		
ICOC	1.03***	0.62***	0.56**	1.71***	1.30***	1.15***	2.27***	1.14***	0.89**
t-stat	(2.79)	(2.79)	(2.58)	(4.26)	(4.32)	(3.90)	(6.61)	(2.94)	(2.28)
BETA		0.03*	0.04*		0.03	0.03		0.03	0.03
t-stat		(1.83)	(1.80)		(1.27)	(1.32)		(1.55)	(1.61)
B/M		0.25***	0.23***		0.24***	0.23***		0.18***	0.18***
t-stat		(6.81)	(6.34)		(6.75)	(6.44)		(4.38)	(4.35)
SIZE		-0.02***	-0.02***		-0.02***	-0.02***		-0.02***	-0.02***
t-stat		(-5.63)	(-5.78)		(-6.12)	(-6.21)		(-6.55)	(-6.55)
MOM			-0.07***			-0.05**			-0.07***
t-stat			(-3.62)			(-2.62)			(-3.31)
R-squared	0.02	0.10	0.10	0.03	0.11	0.11	0.06	0.10	0.10

Panel B: 12-month forecast horizon

	DDM3			RIM2			RIM3		
ICOC	1.59***	0.95**	0.89**	2.76***	2.04***	1.99***	3.70***	1.40*	1.16
t-stat	(2.64)	(2.54)	(2.41)	(4.05)	(3.99)	(3.75)	(6.00)	(1.70)	(1.37)
BETA		0.04	0.04		0.01	0.01		0.03	0.03
t-stat		(0.81)	(0.80)		(0.30)	(0.32)		(0.65)	(0.68)
B/M		0.42***	0.41***		0.41***	0.40***		0.34***	0.34***
t-stat		(6.22)	(5.87)		(5.92)	(5.75)		(3.66)	(3.66)
SIZE		-0.04***	-0.04***		-0.04***	-0.04***		-0.04***	-0.04***
t-stat		(-5.94)	(-6.03)		(-6.50)	(-6.53)		(-6.74)	(-6.74)
MOM			-0.05*			-0.02			-0.05*
t-stat			(-1.88)			(-0.62)			(-1.77)
R-squared	0.03	0.14	0.14	0.04	0.15	0.15	0.07	0.13	0.13

Table 10 : Panel Regression with Two-Way Fixed Effects

This table presents the regression estimates and t-statistics of the two-way fixed firm and time effects model:

$$r_{i,t} = \alpha_i + \lambda_t + \delta k_{i,t} + \gamma' X_{i,t} + u_{i,t} \tag{13}$$

where λ_t is a time specific effect for each t. For each valuation model, three different regression specifications are estimated, including different risk factors regressed on the subsequent 6-month return using overlapping periods. The first regresses only the internal rate of return (ICOC) on the subsequent total stock return. The second specification uses in addition the three Fama-French factors, B/M being the book yield, SIZE the market capitalization divided by the level of the stock market index, and BETA is the five year regressed sensitivity on the market portfolio. The last model adds the historical six month price return (MOM). The last to lines contain the R^2 of each specification and the F-statistic of a joint significance test on all time dummies λ_t.

The regressions are carried out over whole overlapping panel data set. The t-statistic is calculated on the basis of heteroskedasticity- and autocorrelation-consistent (HAC) standard errors following Rogers (1993). The regressions are run over the full cross-section of companies. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

	DDM3			RIM2			RIM3		
ICOC	0.74**	0.43**	0.41**	1.07***	0.84***	0.81***	2.08***	1.1***	1.05**
t-stat	(2.58)	(2.32)	(2.25)	(3.09)	(3.00)	(2.84)	(5.79)	(2.65)	(2.47)
BETA		0.01	0.01		0	0		0	0
t-stat		(0.46)	(0.45)		(0.11)	(0.12)		(0.01)	(0.03)
B/M		0.21***	0.21***		0.21***	0.21***		0.15***	0.15***
t-stat		(6.64)	(6.63)		(6.58)	(6.66)		(3.82)	(3.83)
SIZE		-0.02***	-0.02***		-0.02***	-0.02***		-0.02***	-0.02***
t-stat		(-4.49)	(-4.55)		(-4.85)	(-4.87)		(-4.94)	(-4.96)
MOM			-0.03			-0.01			-0.02
t-stat			(-1.33)			(-0.66)			(-0.85)
R-squared	0.28	0.33	0.33	0.28	0.34	0.34	0.31	0.33	0.33
F-test	72.27	57.42	58.5	66.79	61.6	61.24	61.15	58.37	57.45