The role of market efficiency on implied cost of capital estimates: an international perspective

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Abstract
This study examines the role of market efficiency on international differences in the usefulness of the implied cost of capital (ICC) to measure expected stock returns. The analysis exploits cross-country differences in market efficiency around the world using a variety of empirical measures of market efficiency. A key methodological contribution of this paper is to assess the quality of the ICC as estimate of expected returns by evaluating its forecast error for subsequent stock returns. The results show that the accuracy of the ICC as measure of expected stock returns is positively associated with the countries’ level of market efficiency.

Keywords Implied cost of capital · Expected stock returns · Market efficiency · Analyst forecasts · Mispricing · Cross-country study

JEL Classification G12 · G14 · G15 · G18 · K00 · M41

1 Introduction

The implied cost of capital (ICC) is the internal rate of the return that equates a firm’s market price to discounted earnings forecasts. Since the first articles appeared, the ICC has been used as estimate of expected returns in many different areas in accounting.
and finance. As the computation of the ICC explicitly relies on equity market prices, any price distortions caused by market inefficiencies are expected to reduce the quality of ICC estimates. However, there is little empirical evidence about the link between market efficiency and the ICC so far, especially in an international context.

This paper thus examines international differences in the usefulness of the implied cost of capital (ICC) to measure expected stock returns across 30 countries. In particular, this study investigates whether the ability of the ICC to predict the cross-section of stock returns is systematically related to the countries’ degree of market efficiency. The analysis exploits cross-country differences in market efficiency around the world using a variety of empirical measures of a country’s level of market efficiency, including autocorrelation patterns of stock market returns, transaction costs and analyst coverage.

Prior research by Griffin et al. (2010) and Kristoufek and Vosvrda (2013) documents large cross-country differences in market efficiency. Using various concepts of market efficiency, these studies show that equity markets in developed economies tend to be more efficient relative to emerging economies. The standard explanation of these differences is that developed markets have lower transaction costs, better access to reliable company-specific information, and lower costs of information acquisition. Taken together, these factors improve the informational efficiency of financial markets (Griffin et al. 2010). Another reason for developed economies having more efficient markets is the legal and regulatory environment. Information provided to investors depends to a large extent on company disclosure requirements, which vary significantly across countries (La Porta et al. 1998; DeFond et al. 2007). More timely and more accurate information improves the efficiency of financial markets. However, it is not clear how and whether these differences in market efficiency across countries translate into the accuracy, and hence usefulness, of the ICC as measure of expected stock returns.

A recent paper by Rusticus (2014) investigates the impact of market inefficiencies on the firms’ ICC estimates for the U.S. equity market. Using firm-level data, Rusticus (2014) shows that mispricing of equity shares can indeed cause significant biases of ICC estimates. However, it is an open question how these insights obtained from U.S. firm-level data apply to other equity markets with different levels of market efficiency. This is especially important in light of the growing number of studies that rely on the ICC as measure of expected stock returns around the globe (Hail and Leuz 2006; Lee et al. 2009). The objective of this study is therefore to obtain a better understanding of the empirical link between market efficiency and the accuracy of the ICC as estimate of expected stock returns around the world.

In a first step, I compute the firms’ implied cost of equity capital for a large international data set from 1995 to 2008 covering 30 countries around the globe. In line with the most important studies in the literature, the implied cost of capital is computed using share prices and analyst earnings forecasts following the model by Gebhardt et al.¹

¹ Among others, Cornell (1999), Gebhardt et al. (2001) and Claus and Thomas (2001) use the ICC to estimate an expected equity risk premium. Botosan (1997) uses the ICC to analyze corporate finance decisions of firms. Lee et al. (2009) employs the ICC to test asset pricing models, while Pástor et al. (2008) and Chava and Purmanandam (2010) analyze the risk-return trade-off of shares. Li et al. (2013) and Esterer and Schröder (2014) use the ICC to predict stock returns.
Similar to Hail and Leuz (2006), there are large cross-country differences in the firms’ average ICC estimates.

I then examine, for each country separately, the ability of the ICC to predict the cross-section of stock returns using a variety of empirical approaches. Following the literature (Li and Mohanram 2014), I use portfolio sorts and firm-level regressions to examine the predictive power of the ICC for stock returns. Under the premise that expected returns equal realised returns on average, these analyses allow assessing the quality of the ICC as measure of expected stock returns. However, if stock returns are generated by a factor model (as the CAPM), stocks with high expected returns will have low realised returns during periods where the factor (as the market factor) is negative (Pettengill et al. 1995). Put differently, there will be a negative relation between expected and realised returns. In such situations, sorts and cross-sectional regressions might lead to the conclusion that the ICC is a poor estimate of expected stock returns, even if the ICC is accurate. Against this backdrop, I also examine the accuracy of the ICC by measuring its forecast error for stock returns (Diebold 2006), which is largely immune to such reversal effects. This analysis reveals substantial differences in the predictive power of the ICC for stock returns across countries. In line with conventional wisdom, the ICC’s forecasts errors for stock returns tend to be significantly larger in emerging markets relative to developed equity markets.

Then I turn to the cross-country analysis on the effect of market efficiency on the ability of the ICC to predict the cross-section of stock returns. To measure market efficiency, I resort to various empirical measures proposed in the literature. Besides a market efficiency index derived from the autocorrelation pattern of stock market returns, informational market efficiency is measured by transaction costs and analyst coverage. Since the accuracy of the ICC also depends on the quality of analyst earnings forecasts, I include the absolute consensus analyst forecast error as measure of analyst forecast quality. The analysis is carried out using a simple cross-country regression, as well as using panel regressions that allows for time-varying parameters, with the exception of the market efficiency index for which I have only one observation for the entire sample period.

I find a positive relation between the ability of the ICC to predict the cross-section of stock returns and a country’s level of market efficiency, especially if measured by average transaction costs. The results thus triangulate the findings of Rusticus (2014) obtained at the firm-level, showing that ICC biases caused by market efficiencies can be substantial, especially for firms that are less liquid and that face higher transaction costs. Furthermore, and in line with Guay et al. (2011), more accurate analyst forecasts improve the reliability of ICC estimates to predict stock returns.

Finally, I examine to what extent these results can be explained by cross-country differences in the countries’ regulatory and legal framework. This is essential as La Porta et al. (1998) highlight the importance of such institutional factors on the quality and functioning of equity and debt markets. The results shows that such factors are indeed related to the accuracy of the ICC to predict stock returns. Nevertheless, various proxies for market efficiency remain significantly related to the accuracy of the ICC to predict stock returns if such institutional factors are being controlled for. A limitation of this additional analysis is that the variables capturing these institutional factors are not time-varying, similar to the market efficiency index.
Taken together, this study highlights the importance of efficient capital markets for the accuracy of the firms’ ICC as measure of expected stock returns. Only in equity markets where investors have access to reliable information and can actually trade upon this news, the ICC is a reliable estimate of expected stock returns.

This study is related to the growing literature examining the usefulness of the ICC as proxy for expected stock returns. This literature either examines the association between ICC estimates and standard equity risk factors (Gebhardt et al. 2001; Gode and Mohanram 2003; Botosan and Plumlee 2005), the relation between the ICC and subsequent stock returns (Easton and Monahan 2005; Guay et al. 2011; Lee et al. 2020), or both (Botosan et al. 2011). Focusing the analysis on the U.S. equity market, these studies come to different conclusions about the usefulness of a firm’s ICC estimate to proxy for expected returns. While Botosan et al. (2011) find some support for using the ICC as measure of expected returns, Easton and Monahan (2005, 2010) and Guay et al. (2011) rather question the suitability of the ICC as empirical measure of expected stock returns.

This study contributes to this literature in two ways. On the one hand, I make a methodological contribution. In light of the well-known problems of using portfolio sorts and regression analysis when examining the relation between expected and realised returns (Pettengill et al. 1995), I propose measuring the quality of the ICC as measure of expected stock returns by its forecast error for stock returns (Diebold 2006). The second contribution is of empirical nature. To my knowledge, this is the first study that evaluates the ICC as proxy for expected stock returns for a large set of countries around the globe. This is especially important in light of the increasing literature that uses the ICC as estimate of expected stock returns in many countries around the globe. The results suggest that the ICC is not a good proxy for expected stock returns in countries with inefficient financial markets.

This study also builds on the literature in accounting and financial economics examining and explaining cross-country differences in market efficiency (Griffin et al. 2010; Kristoufek and Vosvrda 2013), transaction costs (Eleswarapu and Venkataraman 2006), the firms’ costs of equity capital (Hail and Leuz 2006), and the quality of accounting figures (Ball et al. 2000; Hung 2001; Leuz et al. 2003). The common trait of these studies is to link cross-country differences in the variables of interest to more fundamental properties of the underlying financial markets, such as the regulatory and legal framework (La Porta et al. 1998). This study contributes to this literature by showing that differences in the reliability of the firms’ ICC estimates to proxy for expected stock returns are equally related to some key aspects of financial markets, especially market efficiency, transaction costs, and information availability.

Finally, this paper is related to earlier studies that aim at detecting and analysing estimation errors and biases of the firms’ ICC estimates. With the exception of Rusticus (2014), this literature has focused on the impact of erroneous or biased analyst forecasts on the accuracy of ICC estimates. These studies both assess the magnitude of biases

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2 For a detailed discussion of the various approaches, see, e.g., Easton and Monahan (2016) and Lee et al. (2020).
and forecast errors on ICC estimates as well as suggest methods to correct the ICC estimates for such distortions.³

This paper develops as follows. The next section describes the estimation of the firms’ ICC for the international data sample. Section 3 examines the ability of the ICC to predict the cross-section of stock returns in 30 countries around the globe. Section 4 presents the main results of this study, showing that the predictive power of the firms’ ICC for stock returns is systematically related to cross-country differences in the country’s degree of market efficiency. Additional analyses and robustness checks are presented in Sect. 5. Section 6 offers some concluding remarks and implications.

2 Implied cost of capital around the world

This section presents the estimation of the firms’ implied cost of capital (ICC) and describes the international data sample. The implied cost of capital estimates for the 30 countries covered in this study are presented in Sect. 2.3.

2.1 Estimation

I follow the literature and use a residual income model (RIM) to estimate the firms’ ICC. The RIM states that the value of a company equals the book equity capital plus the expected discounted residual income from future activities.

Definition 1 (Residual income, residual income model): Let $b_t$ denote the book value of equity per share at the end of year $t$, $e_t$ the earnings per share in year $t$, $roe_t$ the return on equity, and $k$ the cost of equity capital. Then the residual income per share $ri_t$ is defined as

$$ri_t = e_t - k(b_{t-1}) = (roe_t - k)b_{t-1}.$$ (1)

The price of a share $P_0$ is then given by

$$P_0 = b_0 + \sum_{t=1}^{\infty} \frac{E_0[ri_t]}{(1+k)^t} = b_0 + \sum_{t=1}^{\infty} \frac{E_0[roe_t] - k}{(1+k)^t} b_{t-1}.$$ (2)

Since it is not possible to forecast earnings (or, equivalently, the return on equity) until infinity, one has to make assumptions about expected earnings in the long run when implementing the model in practice. This study follows the seminal works by Gebhardt et al. (2001), Pástor et al. (2008), and Chen et al. (2013) using a three-stage version of the RIM:⁴

³ See, e.g., Francis et al. (2000), Easton and Sommers (2007), Guay et al. (2011), Hou et al. (2012), Larocque (2013) and Mohanram and Gode (2013). Kothari et al. (2016) provides an excellent review.

⁴ Alternative implementations of the RIM are by Claus and Thomas (2001), Gode and Mohanram (2003) or Easton (2004). Botosan and Plumlee (2005), Easton (2006) and Botosan et al. (2011) provide a good overview of the different formulae and model assumptions. Additional tests in Sect. 5.2 show that the main results of this paper are robust to alternative implementations of the RIM.
Definition 2 (Three-stage residual income valuation:) Let $E_0[iroe]$ denote the expected long-term industry return on equity. Then the price of a share is given by

$$
P_0 = b_0 + \sum_{t=1}^{3} \frac{E_0[roe_t] - k}{(1+k)^t} b_{t-1} + \sum_{t=4}^{9} \frac{E_0[roe_t] - k}{(1+k)^t} b_{t-1} + E_0[iroe] \frac{k}{k(1+k)^8} b_8. \quad (3)
$$

Explicit forecasts Transition period Terminal value

In the explicit forecast period of three years, expected earnings are directly taken from equity analysts. In the transition period of six years, a company’s return on equity is assumed to geometrically converge to its long-term industry average. This assumption is based on the notion that over longer time periods, all competitive advantages are arbitraged away, so that no company within an industry achieves higher returns than its peers. For a detailed description of the implementation of the residual income model, see appendix A.

The ICC is obtained by solving the residual income model (3) for the internal rate of return, given the prevailing share price and the expected earnings per share. Since the RIM is monotone in $k$, the solution can be obtained iteratively.

2.2 Data and sample selection

This study analyses the role of market efficiency on implied cost of capital estimates across international capital markets. For a country to be included in the study, I require a minimum of 1,000 firm-month ICC observations and the availability of the market efficiency index by Kristoufek and Vosvrda (2013). These restrictions leave a sample of 30 countries.

Equity analyst earnings forecasts and long-term earnings growth predictions are collected from IBES. I use the consensus forecasts of all contributing sell-side analysts, which are published once a month. To ensure that the ICC estimates are based on publicly available information, share price data are of the same day, equally provided by IBES. Book value data are obtained from Worldscope. Monthly data on total stock returns are taken from Datastream. All data are denoted in local currency.

I include all firms for which there are enough data to estimate the firms’ ICC. Observations with a negative book value of equity are excluded from the sample. To reduce the impact of outliers, all observations with ICC estimates above 100%, as well as the highest (lowest) 0.5% of the ICC estimates per country and month are dropped. To avoid that non-traded stocks affect the results, stocks with a net return of 0% are removed. In addition, observations with a share price below 1 unit of local currency (penny stocks) are excluded. Furthermore, firms that are covered by fewer

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5 Instead of using equity analyst earnings forecasts, Hou et al. (2012) and Li and Mohanram (2014) suggest regression-based earnings forecasts. However, the relatively small data samples in many countries covered in this study do not allow to reliably estimating the forecasting model parameters, resulting in noisy earnings forecasts.

6 Since the market efficiency index by Kristoufek and Vosvrda (2013) is only available for a limited set of countries, a few important equity markets are not included in this study, such as Australia, Ireland, New Zealand, Norway, Sweden and Portugal. For more details on the efficiency index, see Sect. 4.1.
than 3 equity analysts are also removed. In a last step, I require a minimum of 15 observations for a given country and month as well as the availability of transaction costs data as provided by Griffin et al. (2010). Table 1 provides an overview of the sample selection procedure and the number of observations available after each filter.

### 2.3 Implied cost of capital around the world

Table 2 provides an overview on the international data sample. The analysis covers the time from January 1995 to January 2009. The study includes around 820,000 firm-month observations. With more than 300,000 firm-month observations, the data sample is the largest in the United States. The smallest data sample is from Hungary, with just about 1000 observations.

Given the large heterogeneity of countries, there are considerable differences in average ICC estimates, ranging from 3.6% in Japan to 12.2% in Indonesia. Hail and Leuz (2006) show that these differences can be attributed to cross-country differences in the level of interest rates and (expected) inflation rates, different average risk profiles of the firms included in each of the samples, and differences in the institutional framework across countries, such as disclosure requirements. For example, the deflationary environment in Japan with low interest rates explains the low average ICC estimates in this country. In contrast, high interest rates in Indonesia, especially during the Asian financial crisis in 1997/98 give reasons for the high average ICC estimates in this country. Although these estimates tend to be lower than those reported in Hail and Leuz (2006), the overall pattern is similar.7

There is also some considerable variability of ICC estimates over time. In line with the global business cycle and movements in interest rates and risk premia, the countries’ average ICCs were with 9.5% the highest in 2001, right at the bottom of the global recession in the early 2000s. The global ICC reached with 6.5% its low in 2006,

7 Hail and Leuz (2006) cover the period from 1992 to 2001 when average inflation and interest rates were higher.
## Table 2
Summary statistics

| Country code | Country code | Currency code | Firm-month observations | Implied cost of capital (%) | Interest rates (%) | Inflation rates (%) |
|--------------|--------------|---------------|-------------------------|-----------------------------|-------------------|---------------------|
|              |              |               |                         | Mean | Lowest | Highest |                       |                   |
| Argentina    | AR           | ARS           | 1663                    | 9.54 | 7.75   | 10.72   | 11.38                   | N/A               |
| Austria      | AT           | EUR           | 3694                    | 6.32 | 5.18   | 8.00    | 3.47                    | 1.75              |
| Belgium      | BE           | EUR           | 8363                    | 7.32 | 5.72   | 9.04    | 3.27                    | 1.93              |
| Canada       | CA           | CAD           | 37,167                  | 7.30 | 6.12   | 10.12   | 3.82                    | 1.93              |
| Chile        | CL           | CLP           | 1306                    | 8.81 | 7.22   | 10.49   | 2.81                    | 4.54              |
| China        | CN           | CNY           | 20,466                  | 8.33 | 4.43   | 10.54   | 7.02                    | 1.95              |
| Denmark      | DK           | DDK           | 9065                    | 6.29 | 4.93   | 7.85    | 3.88                    | 2.12              |
| Finland      | FI           | EUR           | 9838                    | 8.17 | 6.51   | 10.97   | 3.58                    | 1.57              |
| France       | FR           | EUR           | 38,032                  | 6.84 | 5.85   | 8.62    | 3.44                    | 1.54              |
| Germany      | DE           | EUR           | 30,064                  | 5.96 | 4.51   | 8.46    | 3.25                    | 1.48              |
| Greece       | GR           | EUR           | 7062                    | 6.36 | 3.19   | 8.62    | 6.51                    | 3.77              |
| Hong Kong    | HK           | HKD           | 16,381                  | 11.15| 8.63   | 15.85   | 3.67                    | 0.68              |
| Hungary      | HU           | HUF           | 1006                    | 12.05| 9.39   | 13.91   | 10.25                   | 9.09              |
| India        | IN           | INR           | 16,248                  | 10.70| 7.80   | 14.72   | 7.53                    | 6.41              |
| Indonesia    | ID           | IDR           | 7365                    | 12.22| 7.94   | 17.96   | 16.00                   | 12.68             |
| Italy        | IT           | EUR           | 14,704                  | 6.51 | 5.64   | 8.55    | 4.41                    | 2.31              |
| Japan        | JP           | JPY           | 86,880                  | 3.61 | 2.73   | 5.39    | 0.27                    | –0.02             |
| Malaysia     | MY           | MYR           | 18,871                  | 7.69 | 5.05   | 10.41   | 3.91                    | 2.57              |
| Mexico       | MX           | MXN           | 5060                    | 8.95 | 6.32   | 12.74   | 16.51                   | 9.97              |
| Netherlands  | NL           | EUR           | 17,448                  | 8.93 | 7.01   | 11.84   | 4.76                    | 2.11              |
| Philippines  | PH           | PHP           | 4975                    | 9.67 | 5.66   | 13.51   | 8.56                    | 5.34              |
| Poland       | PL           | PLN           | 2511                    | 9.50 | 6.20   | 12.95   | 12.90                   | 6.39              |
| Singapore    | SG           | SGD           | 11,139                  | 6.35 | 4.74   | 8.97    | 1.61                    | 1.29              |
| South Africa | ZA           | ZAL           | 14,488                  | 11.70| 9.30   | 14.48   | 11.17                   | 6.38              |
| South Korea  | KR           | KRW           | 29,323                  | 9.42 | 6.25   | 13.21   | 6.85                    | 3.49              |
| Spain        | ES           | EUR           | 12,478                  | 6.00 | 4.00   | 7.82    | 4.11                    | 2.81              |
| Switzerland  | CH           | CHF           | 17,606                  | 5.53 | 4.37   | 7.50    | 1.45                    | 0.84              |
| Thailand     | TH           | THB           | 14,091                  | 9.89 | 7.74   | 12.48   | 5.17                    | 3.16              |
| United Kingdom | UK     | GBP           | 61,850                  | 8.67 | 7.34   | 10.08   | 5.10                    | 1.83              |
| United States | US       | USD           | 300,769                 | 6.62 | 5.91   | 7.28    | 3.69                    | 2.48              |

The table reports the number of firm-month observations for each country included in the study, the average implied cost of capital, as well as the lowest and the highest annual average implied cost of capital. In addition, the table reports the average short-term interest and inflation rates over the examined time period (1995–2008). Data on short-term interest rates and inflation rates are obtained from the IMF (data on inflation rates for Chile are from the OECD; inflation rates in Argentina are not considered reliable).

just at the peak of the business cycle in the eve of the Great Recession. This pattern is in line with theory that suggest a counter-cyclical equity risk premium (Campbell and Cochrane 1999) and is similar to the empirical results by Li et al. (2013).
3 Implied cost of capital and expected stock returns

Under the premise that analyst earnings forecasts reflect the marginal investor’s expectations and that markets are efficient (i.e., prices reflect fundamental values), the ICC is an unbiased measure of expected stock returns (Botosan and Plumlee 2005).8 This section examines and compares the accuracy of the firms’ ICC to proxy for expected stock returns around the world.

Assessing the accuracy of the ICC to measure expected returns faces the challenge that expected returns are essentially unobservable. To circumvent this problem, the literature has proposed several indirect methods to evaluate empirical estimates of expected returns. This study follows Guay et al. (2011) and assesses the accuracy of the ICC as estimate of expected stock returns by testing its ability to predict the cross-section of subsequent, realised stock returns. This approach is based on the notion that in equilibrium, expected returns equal realised returns.

In practice, however, realised returns differ from expected returns because of the arrival of new information over time, such as cash-flow or discount-rate (expected return) news (Campbell 1991; Voulteenaho 2002). As a result, the returns of individual equity shares are very noisy, almost following a random walk over the short horizon (Kendall 1953). Empirical tests comparing expected returns to realised returns are therefore usually performed not for individual shares, but by aggregating shares into portfolios or by examining the entire cross-section of equity markets.9 If firm-specific information surprises cancel out across firms, expected returns equal realised returns on average.

A further complication is that realised returns can differ from expected returns even across firms because of aggregate information surprises (Elton 1999; Fama and French 2002). Such aggregate information surprises affect the returns of the entire equity market. As a consequence, realised returns differ from expected returns for all firms by some similar margin, thereby introducing a market-wide, systematic prediction or forecast error. To account for aggregate information surprises, the empirical tests used in this study allow disentangling market-wide prediction errors from firm-specific prediction errors. Since the focus of the paper is on predicting and comparing the ICC’s ability to predict the cross-section of stock returns across countries, firm-specific prediction errors are most relevant for the main results of this study.

There are various approaches to examine the ability of the firms’ ICC to predict stock returns. In an attempt to draw a comprehensive picture of the relation between the firms’ ICC and stock returns, this section resorts to the most common techniques. These approaches differ from each other because of different loss functions associated with the ICC’s forecast errors. Section 3.1 uses portfolio sorts on the firms’ ICC. Section 3.2 analyses the cross-section of firm-level stock returns using regression

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8 This study uses the terms cost of capital, required return, and expected rate of return interchangeably. Some authors, such as Lewellen (2010), consider the ICC as estimate of expected stock returns if markets are efficient, and as required rate of return if markets are not efficient. In the terminology of this paper, the latter would be a biased estimate of expected stock returns.

9 Easton and Monahan (2005) propose an empirical approach to isolate expected stock returns from cash-flow and discount-rate news. Yet, this approach is only feasible when using regression analysis to assess the ICC’s ability to predict the cross-section of stock returns.
analysis. In light of the well-known problems of using portfolio sorts and regression analysis when analysing the relation between expected and realised returns (Pettengill et al. 1995), Sect. 3.3 assesses the accuracy of the ICC by its forecast error for stock returns.10

3.1 Portfolio sorts

As a first assessment of how average returns vary depending on the firms’ ICC estimates I employ portfolio sorts, similar to Hou et al. (2012) and Li and Mohanram (2014). Portfolio sorts are simple to compute, and their non-parametric nature avoids imposing any functional form on relation between ICC estimates and stock returns. Portfolio sorts based on the firms’ ICC have also the advantage of being largely immune to aggregate forecast biases caused by, e.g., aggregate information surprises or systematic biases of analyst forecasts. Such market-wide effects tend to affect the companies’ ICC estimates in a similar way, such that they have little impact on the relative ranking of the firm’s ICC. Hence, the composition of the portfolios generally remains unchanged.

At the end of each month, all stocks are ranked according to their ICC estimate and grouped into five equal-weight and value-weight portfolios (for each country separately). Then I measure the subsequent total portfolio returns (i.e., capital gains plus dividend yield) for a holding period of one month.

Table 3 shows the average returns of zero-cost long-short investment (hedge) portfolios that buy stocks with high ICC estimates, and short sell stocks with low ICC estimates. The left column reports the returns of equal-weight portfolios; the right column reports the returns of value-weight portfolios. If the ICC accurately predicts stock returns, this long-short strategy should yield positive average returns.

The table allows for several conclusions. First, there is considerable cross-country variability in long-short portfolio returns across countries. Average monthly returns range from $-0.73\%$ in Germany to $+2.09\%$ in Hungary using equal-weight portfolios. When using value-weight portfolios, cross-country differences are even larger, ranging between $-2.41\%$ in Germany to $+1.22\%$ in Poland. This finding suggests some considerable heterogeneity in the ICC’s ability to predict stock returns across countries.

More important is the finding that in almost all countries the long-short portfolio returns are not significantly different from zero. When using value-weight portfolios, stocks with high ICC estimates do not significantly outperform stocks with low ICC estimates in any country. This result suggests that the ICC is a poor predictor for stock returns in many equity markets around the globe. Although this result might appear surprising, it is in line with prior research. Using portfolio sorts, Hou et al. (2012) find no significant relation between the firm’s analyst-based ICC and stock returns in the U.S. market either.

10 The ICC is—similar to a bond’s yield to maturity—the constant rate of return that an investor would receive by holding the equity share until infinity. Put differently, the ICC is a long-term, constant expected rate of return. If true short-term expected returns are time-varying, the ICC is not an unbiased estimate of expected returns (Hughes et al. 2009). Since expected returns of individual stocks are mainly time-varying due to market-wide, aggregate information surprises, such biases are unlikely to have a significant effect on the results of this paper.
### Table 3  Portfolio sorts

| Country      | Equal-weight | t-stat. | Value-weight | t-stat. |
|--------------|--------------|---------|--------------|---------|
| Argentina    | 0.03%        | (0.27)  | -1.43%       | (-0.76) |
| Austria      | -0.69%       | (-1.47) | -0.99%       | (-1.25) |
| Belgium      | -0.40%       | (-1.39) | -0.03%       | (-0.05) |
| Canada       | -0.53%*      | (-1.85) | -0.57%       | (-1.06) |
| Chile        | 2.08%***     | (2.73)  | 0.77%        | (0.35)  |
| China        | -0.19%       | (-0.63) | 0.10%        | (0.08)  |
| Denmark      | 0.18%        | (0.47)  | -0.39%       | (-0.38) |
| Finland      | -0.13%       | (-0.35) | -0.56%       | (-0.63) |
| France       | -0.32%       | (-0.95) | -0.05%       | (-0.09) |
| Germany      | -0.73%**     | (-2.00) | -2.41%***    | (-2.72) |
| Greece       | 0.66%        | (1.49)  | -0.32%       | (-0.33) |
| Hong Kong    | 0.10%        | (0.23)  | -0.48%       | (-0.77) |
| Hungary      | 2.09%*       | (1.71)  | -0.16%       | (-0.10) |
| India        | -0.03%       | (-0.06) | 0.53%        | (0.73)  |
| Indonesia    | 1.12%        | (1.36)  | -0.08%       | (-0.05) |
| Italy        | 0.11%        | (0.40)  | -0.74%       | (-1.18) |
| Japan        | 0.49%        | (1.30)  | 0.82%        | (1.35)  |
| Malaysia     | 0.30%        | (0.72)  | 0.20%        | (0.23)  |
| Mexico       | 0.03%        | (0.06)  | 0.12%        | (0.17)  |
| Netherlands  | 0.01%        | (0.03)  | -0.47%       | (-0.80) |
| Philippines  | 0.72%        | (1.05)  | -0.18%       | (-0.13) |
| Poland       | 1.36%        | (1.59)  | 1.22%        | (0.86)  |
| Singapore    | 0.10%        | (0.27)  | 0.83%        | (0.98)  |
| South Africa | 0.45%        | (1.02)  | -0.54%       | (-0.74) |
| South Korea  | 0.50%        | (0.94)  | -0.97%       | (-1.04) |
| Spain        | 0.36%        | (1.29)  | 0.32%        | (0.54)  |
| Switzerland  | -0.20%       | (-0.76) | -1.30%       | (-1.36) |
| Thailand     | 0.63%        | (1.36)  | -0.55%       | (-0.54) |
| United Kingdom| 0.12%       | (0.37)  | -0.33%       | (-0.84) |
| United States| -0.12%       | (-0.35) | -0.61%*      | (-1.65) |

The table reports the time-series average returns of monthly zero-cost long-short investment portfolios that invest in stocks with high a ICC, and short sell stocks with a low ICC, together with their statistical significance. The left column reports the returns of equal-weight portfolios, the right column reports the returns of value-weight portfolios. T-statistics are given in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

If expected returns equal realised returns on average, these results suggest that (i) the usefulness of the ICC as measure of expected stock returns varies significantly across countries, and (ii) that ICC is not a reliable estimate of expected stock returns across international equity markets.
However, this interpretation is not clear-cut. If stock returns are generated by a factor pricing model (such as the CAPM), firms with high expected returns will have low realised returns during periods where the factor (such as the market factor) is negative (Pettengill et al. 1995). That is, high expected returns imply low realised, actual returns. If the ICC captures true expected stock returns indeed, long-short investment portfolios based on the firms’ ICC are expected to generate negative returns in such periods. As a consequence, the negative long-short portfolio returns reported in some of the portfolio sorts might actually not be a sign that the ICC is an inaccurate measure of expected stock returns. In countries like Austria, Germany or Italy for example, average market excess returns were rather low over the sample period. Low returns of long-short ICC portfolios in these counties are therefore not incompatible with the ICC being an accurate measure of expected stock returns.

3.2 Cross-sectional regressions

Another possibility to assess the ability of the firms’ ICC estimates to predict the cross-section of stock returns is to run cross-sectional regressions of individual firm data. Following Guay et al. (2011) and Li and Mohanram (2014), I regress monthly stock returns $r_{i,t+1}$ on the firms’ ICC estimates $k_{i,t}$,

\[ r_{i,t+1} = \alpha + \beta k_{i,t} + u_{i,t+1}, \]

where $k_{i,t}$ is the ICC estimate of firm $i$ in month $t$, $r_{i,t}$ is the firm’s subsequent monthly stock return, and $u_{i,t+1}$ is the disturbance term. In line with the literature, equation (4) is estimated using the two-pass Fama and MacBeth (1973) regression approach.\textsuperscript{11}

Similar to portfolio sorts, cross-sectional regressions allow to disentangle aggregate and individual forecast errors. The regression intercept $\alpha$ measures the ICC’s average forecast error, while the regression coefficient $\beta$ captures the association between ICC and stock returns for individual firms. A significantly positive slope coefficient indicates a positive association between the ICC and stock returns.

The results, presented in Table 4, largely confirm the findings of the portfolio sorts. First, a large variation in slope coefficients shows that there is a considerable cross-country variation in the ICC’s ability to predict the cross-section of stock returns. Second, the regression analysis confirms that in many countries, the relation between a firm’s ICC and stock returns is rather weak and not significant. In many countries there is even a negative association between the ICC estimates and stock returns, especially in Canada, France, Germany, and Switzerland. Only in Chile, Hungary, the Philippines and Thailand, the ICC coefficient is positively significant, as conjectured.

By and large, the results are consistent with the previous analysis. Countries with high long-short portfolio returns tend to have larger ICC coefficients (Chile, Hungary), while countries with low long-short portfolio returns tend to have small ICC coefficients (Germany).

\textsuperscript{11} Expected returns (i.e., the ICC) and realised returns are expressed over different time horizons. While the ICC is an annual expected return estimate, stock returns are measured over one month. To make the two measures comparable, the firms’ ICC estimate is divided by 12.
Table 4 Cross-sectional Fama and MacBeth (1973) regressions

| Country     | Constant | t-stat. | ICC coefficient | T-stat. | R² (%) |
|-------------|----------|---------|-----------------|---------|--------|
| Argentina   | 0.004    | (0.26)  | −0.496          | (−0.70) | 6.46   |
| Austria     | 0.005    | (0.95)  | −0.860          | (−1.30) | 4.52   |
| Belgium     | 0.007*   | (1.77)  | −0.276          | (−0.77) | 3.07   |
| Canada      | 0.098*** | (3.20)  | −0.498**        | (−2.29) | 1.27   |
| Chile       | −0.020** | (−2.07) | 3.664***        | (3.50)  | 6.71   |
| China       | 0.004    | (1.03)  | −0.305          | (−0.71) | 5.82   |
| Denmark     | 0.005    | (1.03)  | 0.386           | (0.69)  | 3.10   |
| Finland     | 0.010**  | (2.00)  | −0.113          | (−0.24) | 3.20   |
| France      | 0.011*** | (2.97)  | −0.872***       | (−2.70) | 1.83   |
| Germany     | 0.005    | (1.04)  | −0.908**        | (−2.43) | 1.65   |
| Greece      | 0.003    | (0.36)  | 1.072           | (1.37)  | 3.59   |
| Hong Kong   | 0.007    | (1.31)  | −0.019          | (−0.07) | 2.70   |
| Hungary     | −0.016   | (−1.18) | 1.958*          | (1.68)  | 8.67   |
| India       | 0.011*   | (1.90)  | −0.194          | (−0.50) | 3.83   |
| Indonesia   | 0.005    | (0.58)  | 0.565           | (1.40)  | 3.69   |
| Italy       | 0.006    | (1.29)  | −0.283          | (−1.20) | 1.64   |
| Japan       | −0.002   | (−0.41) | 0.761           | (0.81)  | 2.27   |
| Malaysia    | 0.005    | (0.93)  | 0.122           | (0.26)  | 2.90   |
| Mexico      | 0.014**  | (2.48)  | 0.116           | (0.21)  | 5.37   |
| Netherlands | 0.005    | (1.13)  | 0.222           | (0.58)  | 2.56   |
| Philippines | −0.004   | (−0.58) | 1.090**         | (2.11)  | 6.24   |
| Poland      | −0.009   | (−0.75) | 0.889           | (0.84)  | 7.86   |
| Singapore   | 0.005    | (1.03)  | −0.197          | (−0.42) | 2.69   |
| South Africa| 0.010*   | (1.70)  | 0.325           | (0.73)  | 4.16   |
| South Korea | 0.005    | (0.55)  | 0.129           | (0.39)  | 2.42   |
| Spain       | 0.009**  | (2.27)  | 0.182           | (0.42)  | 2.11   |
| Switzerland | 0.011**  | (2.49)  | −0.825**        | (−1.96) | 1.82   |
| Thailand    | −0.004   | (−0.58) | 0.678**         | (2.02)  | 2.20   |
| United Kingdom | 0.007** | (2.15)  | −0.017          | (−0.09) | 0.91   |
| United States | 0.014*** | (3.67)  | −0.392          | (−1.35) | 0.75   |

The table reports the intercept and the ICC coefficient when regressing monthly stock returns on the firms’ ICC estimate using the Fama and MacBeth (1973) cross-sectional regression approach. T-statistics are given in parenthesis. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Again, these findings suggest that the ICC is a poor predictor for stock returns in many equity markets around the globe. This result is, however, in line with the findings of Easton and Monahan (2005) and Guay et al. (2011) that similarly use regression analysis to evaluate the ICC as predictor of stock returns.

Similar to the portfolio sorts, this finding does not necessarily imply that the ICC is a poor estimate of expected stock returns. If returns are generated by a factor model, negative factor returns in a given period reverse the relation between expected and actual returns.
realised returns. Insignificant or negative slope coefficients might simply result from a large fraction of cross-sections (months) with negative factor returns—and not because of erroneous ICC estimates.

To some extent, such an inverse relation should be picked up by the regression intercept. Since the regression imposes a linear relation between expected and realised returns, an inverse relation between these two measures mechanically generates a positive intercept (assuming a positive interest rates). This effect can be observed in the data: the correlation between intercept and slope coefficient is with $-0.84$ strongly negative. With a few exceptions, countries with significantly negative slope coefficients exhibit a large, significant intercept.

### 3.3 Forecast errors

Given the conceptual problems when using portfolio sorts and regression analysis to evaluate the suitability of the ICC to proxy for expected stock returns, this section analyses the ICC’s ability to predict stock returns by calculating the ICC’s average forecast errors. Following the forecasting literature (Diebold 2006), I calculate for each monthly cross-section the (equal-weight) mean absolute forecast error (MAE) and the root mean squared forecast error (RMSE),

$$\text{MAE}_t = \frac{1}{I} \sum_{i=1}^{I} |r_{i,t} - k_{i,t-1}| \quad \forall t \in [0, T]$$

$$\text{RMSE}_t = \sqrt{\text{MSE}_t} = \sqrt{\frac{1}{I} \sum_{i=1}^{I} (r_{i,t} - k_{i,t-1})^2} \quad \forall t \in [0, T].$$

Again, the ICC estimate is divided by 12 to make it comparable to the monthly stock return data. Then the MAE and the RMSE are averaged over time. Both the MAE and the RMSE have a symmetric loss function, i.e., positive and negative forecast errors of the ICC for stock returns are punished equally.

To disentangle aggregate forecast errors from firm-specific forecast errors, the mean squared forecast error (MSE) is decomposed into its two components, error variance (EV) and mean error (ME):

$$\text{MSE}_t = \text{EV}_t + \text{ME}_t^2$$

The mean error captures the ICC’s average forecast error, caused by aggregate information surprises that influence the returns of the entire stock market as well as systematic biases of analyst forecasts. By contrast, the error variance measures the dispersion of individual forecast errors (Diebold 2006). Again, for each country, the mean error and error variance are averaged over time.

Since MAE and RMSE treat positive and negative forecast errors equal, the error variance—the measure of idiosyncratic forecasts errors—is immune to any market wide biases. Different from portfolio sorts and cross-sectional regressions, an inverse
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relation between expected and realised returns is largely picked up by the mean error. The symmetric nature of these forecast metrics, however, comes at a cost: a low error variance does not necessarily imply that the firms’ ICC is positively related to subsequent stock returns. However, in many applications, academics and practitioners are less concerned about the accuracy of point estimates of expected returns but about a positive association between expected and realised stock returns (Elliott and Timmermann 2008).\(^\text{12}\)

Table 5 reports, for each country, the time-series averages of the various forecast error metrics. All time-series averages are significant at the 1% level for all countries, with the exception of the mean error (ME). In line with previous analyses, there are considerable cross-country differences in the forecast accuracy of the firms’ ICC estimates for stock returns. In terms of MAE, RMSE and MSE, the ICC is most accurate in forecasting stock returns in Belgium and China. In contrast, in Indonesia and South Korea, average MAE, RMSE and MSE are considerably larger. With some exceptions, forecast errors tend to be lower in developed equity markets relative to developing markets. As expected, these three forecast metrics are very similar, with pair-wise correlation coefficients of 0.95 or higher.

As argued before, the ICC can have large forecast errors for stock returns either because of aggregate, systematic deviations, or because of a large dispersion of idiosyncratic forecast errors. The decomposition of the mean squared error (MSE) into error variance (EV) and (squared) mean error allows disentangling firm-specific forecast errors from systematic forecast errors. Note that while the mean error (ME) indicates the systematic forecast error over the entire time horizon, the squared mean error (ME\(^2\)) allows assessing the magnitude of the systematic forecast error for each monthly cross-section.\(^\text{13}\)

In the majority of countries, there is a negative average forecast error (ME). This means that the ICC overstates average realised returns over the sample period. Since, ceteris paribus, high earnings forecasts increase a firm’s ICC estimate, this finding is consistent with the literature documenting systematic positive biases of analyst earnings forecasts (Chan et al. 2007). The average forecast error is most pronounced in Poland, reaching more than 0.8% in absolute terms. In contrast, in countries like Mexico, the average forecast error is positive, which means that the ICC understates average stock returns in these countries. Yet, in most countries the average forecast bias is rather small. Only in China and the United States, the average forecast bias is significantly different from zero. The average squared mean error (ME\(^2\)) is with 0.07% the smallest in China. Hence, despite a significant mean error (ME), the ICC is a rather accurate predictor of average monthly stock returns in this country. In contrast, the average squared mean errors are the highest in Indonesia.

With a correlation coefficient of 70%, the two components of the MSE, error variance and squared forecast error are positively related, see panel B of Table 6. This means that countries with larger idiosyncratic errors tend to exhibit also larger systematic biases. Yet, there are some exceptions. For example, in Canada and the United

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\(^{12}\) Different from the forecast error metrics, portfolio sorts and cross-sectional regressions assess whether the ICC is on average positively or negatively related to stock returns or not.

\(^{13}\) Monthly mean errors can cancel out over time. In this case, the time-series average mean error is close to zero, while the time-series average squared mean error can still be substantial.
Table 5  Average ICC forecast errors

| Country       | MAE (%) | RMSE (%) | MSE (%) | EV (%) | $ME^2$ (%) | ME (%) |
|---------------|---------|----------|---------|--------|------------|--------|
| Argentina     | 9.61    | 11.86    | 1.68    | 0.91   | 0.77       | −0.72  |
| Austria       | 6.79    | 9.00     | 0.90    | 0.65   | 0.25       | −0.51  |
| Belgium       | 6.10    | 8.11     | 0.73    | 0.54   | 0.19       | −0.03  |
| Canada        | 7.90    | 11.29    | 1.37    | 1.18   | 0.19       | 0.06   |
| Chile         | 7.51    | 9.26     | 0.95    | 0.56   | 0.40       | −0.11  |
| China         | 2.14    | 3.53     | 0.30    | 0.22   | 0.07       | −0.43  |
| Denmark       | 7.25    | 9.50     | 0.98    | 0.75   | 0.24       | 0.10   |
| Finland       | 7.57    | 9.85     | 1.05    | 0.78   | 0.28       | 0.21   |
| France        | 7.77    | 10.34    | 1.19    | 0.89   | 0.29       | 0.12   |
| Germany       | 8.93    | 11.86    | 1.59    | 1.21   | 0.39       | −0.46  |
| Greece        | 9.23    | 11.72    | 1.68    | 0.90   | 0.78       | 0.22   |
| Hong Kong     | 8.94    | 11.89    | 1.70    | 1.12   | 0.58       | −0.24  |
| Hungary       | 9.14    | 11.56    | 1.50    | 0.91   | 0.59       | −0.59  |
| India         | 10.32   | 13.29    | 1.94    | 1.26   | 0.68       | 0.17   |
| Indonesia     | 12.56   | 15.76    | 3.10    | 1.94   | 1.16       | 0.22   |
| Italy         | 6.94    | 8.91     | 0.91    | 0.58   | 0.32       | −0.13  |
| Japan         | 8.07    | 10.40    | 1.17    | 0.88   | 0.29       | −0.21  |
| Malaysia      | 8.41    | 10.93    | 1.50    | 0.85   | 0.65       | −0.05  |
| Mexico        | 8.49    | 10.81    | 1.34    | 0.87   | 0.47       | 0.72   |
| Netherlands   | 7.30    | 9.70     | 1.04    | 0.77   | 0.27       | −0.02  |
| Philippines   | 10.12   | 12.91    | 2.06    | 1.27   | 0.79       | −0.54  |
| Poland        | 9.74    | 12.06    | 1.66    | 1.02   | 0.64       | −0.85  |
| Singapore     | 7.96    | 10.51    | 1.33    | 0.84   | 0.49       | −0.05  |
| South Africa  | 8.35    | 10.82    | 1.29    | 1.00   | 0.28       | 0.34   |
| South Korea   | 11.95   | 15.18    | 2.67    | 1.67   | 1.00       | −0.10  |
| Spain         | 6.50    | 8.50     | 0.82    | 0.55   | 0.27       | 0.60   |
| Switzerland   | 6.79    | 8.96     | 0.89    | 0.62   | 0.27       | 0.26   |
| Thailand      | 10.96   | 14.20    | 2.52    | 1.60   | 0.92       | −0.65  |
| United Kingdom| 7.44    | 9.97     | 1.09    | 0.89   | 0.20       | 0.03   |
| United States | 9.32    | 12.91    | 1.79    | 1.55   | 0.24       | 0.67   |

The table reports, for each country, the time-series averages of the monthly mean absolute forecast error (MAE), the root mean squared forecast error (RMSE), the mean squared forecast error (MSE), the error variance (EV), the squared mean error ($ME^2$), and the forecast bias (mean forecast error, ME). For a definition of the various metrics, see Sect. 3.3.

The time-series averages of all forecast error metrics are significant at the 1% level for all countries, with the exception of the mean error (ME). The mean error is generally not significantly different from 0. The only exceptions are China (significance at the 5% level) and the United States (significance at the 10% level).
States, the squared mean error is rather low, while the error variance is high. The opposite is true for Malaysia, where the error variance is rather low, but the squared mean error is considerable. This observation shows that the distinction between the two components of the MSE is important indeed.

Overall, this section establishes some considerable heterogeneity in the ICC’s ability to predict stock returns across countries. If expected returns equal realised returns on average, this result implies that the usefulness of the ICC as measure of expected stock returns varies significantly across equity markets as well. To better understand these cross-country differences, the next section explores whether different degrees of market efficiency and analyst forecast quality—the two data sources to compute the ICC—can explain these cross-country differences. In light of the shortcomings of portfolio sorts and regression analysis, the remainder of this study relies on the forecast error metrics presented in this sub-section as measure of the ICC’s ability to predict stock returns.

4 Implied cost of capital and market efficiency

Under the premise that markets are efficient and that analyst forecasts reflect investor expectations, the ICC is an unbiased estimate of expected stock returns. In practice these assumptions are rarely fulfilled. First, markets are not always efficient. Information about a company’s earnings (Ball and Brown 1968) or recommendations of equity analysts (Michaely and Womack 1999; Green 2006) do not seem immediately impounded in prices. Furthermore, fully efficient markets are also impossible from a theoretical perspective. As long as information is costly to acquire and trading itself is costly, Grossman and Stiglitz (1980) show that prices cannot perfectly reflect the information which is available. Second, although a series of papers (Griffin 1976; Elton et al. 1981; Park and Stice 2000) demonstrates the usefulness of analyst forecasts as surrogate for market expectations, these forecasts might be erroneous and systematically biased due to conflicts of interests of equity analysts (Chan et al. 2007). As a consequence, the ICC is not an unbiased measure of expected stock returns. This section thus examines whether different degrees of market efficiency and analyst forecast quality can explain cross-country differences in the ICC’s ability to predict stock returns. The conjecture is that the ICC is a better predictor of stock returns in countries with higher levels of market efficiency and analyst forecast accuracy.

Estimating the impact of market inefficiencies on the relation between ICC and subsequent stock returns faces several empirical challenges, however. First of all, since the firms’ true fundamental values are unobservable, it is not possible to directly measure market inefficiencies (i.e., price deviations from fundamental values) at the firm level. Second, quantifying the impact of market inefficiencies on the accuracy of the ICC as measure of expected stock returns by analysing the relation between ICC and stock returns of individual firms is problematic since deviations of market prices from fundamental values affect both ICC estimates and subsequent stock returns. For example, if a share trades below fundamental value, the ICC overstates its true expected return. If the share subsequently converges to its fundamental value, the share’s actual return is also higher than its true expected return. In this case, the ICC might accurately
predict stock returns, although it is not an accurate measure of expected returns. In contrast, if the share price reflects fundamental value, the ICC accurately measures the expected stock return. But if the price then diverges from fundamental value, expected and realised returns differ. In this case it would be wrong to interpret the resulting forecast error as sign of an erroneous ICC estimate since the ICC estimate was effectively accurate.\footnote{See also Rusticus (2014) for more discussion.}

To circumvent this problem, Rusticus (2014) examines the relation between ICC and stock returns around earnings announcements. This is a common technique to isolate mispricing from risk effects in stock returns. Rusticus (2014) shows that a large fraction of ICC-based hedge portfolios returns occur in fact around the firms’ earnings announcements. This suggests that mispricing plays an important role in explaining the relation between the ICC and stock returns.

This paper avoids the problems related to using firm-level data illustrated above by analysing the impact of market inefficiencies on the accuracy of the ICC at the country level. Under the premise that idiosyncratic, firm-specific price fluctuations around the firms’ fundamental values cancel out across firms, the ICC’s average forecast accuracy in a country depends only on the market-wide level of market efficiency.

The second data component to calculate a firm’s ICC are analyst earnings forecasts. Different from market inefficiencies, the quality of these forecasts can be verified once a company’s earnings figures are released. As a consequence, it is easier to measure and account for analyst earnings forecast quality, both for individual companies and entire equity markets.\footnote{Another source of errors of the ICC can be the valuation model used to extrapolate expected earnings after the initial period of earnings forecasts (Rusticus 2014). There is also a possibility that pricing errors and analyst forecast errors are correlated. However, if market participants believe in erroneous analyst forecasts, pricing and forecast errors cancel out, such that the ICC is an unbiased estimate of expected stock returns.}

The next section presents the empirical measures of a country’s level of market efficiency and analyst forecast quality. Section 4.2 then analyses whether these measures can explain cross-country differences in the ICC’s ability to predict stock returns. Given the small sample size of simple cross-country regressions, Sect. 4.3 uses a panel date set to explore the determinants of a country’s average ICC forecast accuracy.

### 4.1 Measures of market efficiency and analyst forecast quality

To measure a country’s overall degree of market efficiency, this study resorts to the market efficiency index by Kristoufek and Vosvrda (2013). Different from other measures used in the literature,\footnote{Common measures of efficiency mainly exploit short-term and long-term autocorrelation patterns of stock returns. Examples include the size of short-term reversals (Jegadeesh 1990), momentum strategies (Jegadeesh and Titman 1993), and variance ratios (Lo and MacKinley 1988).} the index by Kristoufek and Vosvrda (2013) has the advantage of combining short-term and long-term autocorrelation patterns as well as a herding measure in one single figure.

Griffin et al. (2010), however, question the suitability of such indices to measure the efficiency of capital markets. As such, the lack of autocorrelation of stock returns is consistent with fully efficiency markets: if all information is immediately incorporated...
in prices, there is no room for systematic price patterns. However, the absence of any autocorrelation of stock returns is also consistent with completely inefficient markets: if market prices are entirely determined by uninformed noise traders, price movements are also entirely random although no news is incorporated into prices whatsoever.

Against this backdrop, this study follows Griffin et al. (2010) and uses two alternative, indirect indicators of a country’s level of market efficiency: (i) transaction costs and (ii) the access to relevant information. The rationale of using transaction costs as measure of market efficiency is that high transaction costs impede trade and thus limit relevant information to be incorporated in market prices. The higher average transaction costs, the less efficient are capital markets. Average transaction costs also reflect the activity and competition in the market. To measure transaction costs, I resort to estimates of round-trip transaction costs following Lesmond et al. (1999), as provided by Griffin et al. (2010). Since transaction costs are negatively related to firm size and since the size of companies listed on stock markets differs across countries, I use the median transaction costs in a calendar year as measure of a country’s transaction costs (Griffin et al. 2010).

Besides, the efficiency of capital markets is likely to depend on the availability of reliable information. Only if important information is readily available, markets participants can incorporate such news into prices, leading to more efficient markets. Similar to Griffin et al. (2010), information costs and information quality is measured by average analyst coverage. Analyst coverage is measured by the sum of all analyst forecasts for a given firm. The intuition is that competition among analysts is likely to increase the timeliness and quality of their forecasts.

Finally, to measure the accuracy of analyst forecasts, I compute the absolute consensus analyst forecast error of all firms covered in this study. The absolute consensus forecast error is defined as the absolute difference between the actual earnings per share and the median consensus forecasts of earnings per share in the last month before the earnings announcement, standardized by the share price:

$$AFE_t = \frac{|e_t - E_{t-1}[e_t]|}{P_{t-1}}$$

To reduce the impact of outliers, the highest and lowest 0.5% of the absolute forecast errors are removed before calculating the average for a given year. The conjecture is that lower consensus forecast errors will lead to better ICC estimates, and therefore to a higher ability of the firms’ ICC to predict stock returns.

Panel A of Table 6 gives an overview on the various measures of market efficiency and analyst forecast quality for each country (the columns on the left). The market efficiency index by Kristoufek and Vosvrda (2013) goes from zero to one. A low index value indicates a high level of efficiency, while a high index value corresponds to inefficient markets. According to this measure, the Japanese and Danish equity markets are most efficient. In contrast, Malaysian and Chilean equity markets are least efficient. Round-trip transaction cost data are obtained from Griffin et al. (2010). Investors in the Philippines and Indonesia face the highest median round-trip transaction costs. Yet, in most countries transaction costs are much lower. Next, the table shows that there is also some substantial variation in analyst coverage across countries. In Hong
Table 6  Market efficiency, analyst forecast accuracy, and institutional factors  

Panel A: Descriptive statistics by country

| Country   | Efficiency index | Transaction costs (%) | Analyst coverage | Analyst forecast errors (%) | Efficiency of judicial system | Rule of law | Financial disclosure index |
|-----------|------------------|-----------------------|------------------|-----------------------------|-------------------------------|-------------|----------------------------|
| Argentina | 0.219            | 10.95                 | 24.4             | 2.77                        | 6                             | 5.35        | N/A                        |
| Austria   | 0.143            | 3.11                  | 16.5             | 1.84                        | 9.5                           | 10          | 62                         |
| Belgium   | 0.080            | 1.70                  | 22.4             | 1.40                        | 9.5                           | 10          | 68                         |
| Canada    | 0.119            | 15.60                 | 19.9             | 1.21                        | 9.25                          | 10          | 75                         |
| Chile     | 0.289            | 11.63                 | 15.7             | 1.30                        | 7.25                          | 7.02        | N/A                        |
| China     | 0.230            | 0.56                  | 28.8             | 1.93                        | N/A                           | N/A         | N/A                        |
| Denmark   | 0.071            | 4.50                  | 20.6             | 2.24                        | 10                            | 10          | 75                         |
| Finland   | 0.099            | 2.68                  | 24.9             | 1.87                        | 10                            | 10          | 83                         |
| France    | 0.124            | 2.58                  | 27.5             | 1.59                        | 8                             | 8.98        | 78                         |
| Germany   | 0.076            | 3.49                  | 32.4             | 2.26                        | 9                             | 9.23        | 67                         |
| Greece    | 0.181            | 0.94                  | 16.6             | 1.27                        | 7                             | 6.18        | N/A                        |
| Hong Kong | 0.188            | 4.85                  | 36.6             | 2.65                        | 10                            | 8.22        | 73                         |
| Hungary   | 0.075            | 1.40                  | 26.4             | 1.88                        | N/A                           | N/A         | N/A                        |
| India     | 0.121            | 2.10                  | 20.2             | 1.61                        | 8                             | 4.17        | 61                         |
| Indonesia | 0.258            | 18.98                 | 23.5             | 8.21                        | 2.5                           | 3.98        | N/A                        |
### Panel A: Descriptive statistics by country

| Country       | Efficiency index | Transaction costs (%) | Analyst coverage | Analyst forecast errors (%) | Efficiency of judicial system | Rule of law | Financial disclosure index |
|---------------|------------------|------------------------|------------------|-----------------------------|-------------------------------|-------------|--------------------------|
| Italy         | 0.107            | 0.52                   | 28.5             | 1.87                        | 6.75                          | 8.33        | 66                       |
| Japan         | 0.066            | 1.83                   | 18.0             | 0.86                        | 10                            | 8.98        | 71                       |
| Malaysia      | 0.310            | 3.03                   | 30.4             | 2.37                        | 9                             | 6.78        | 79                       |
| Mexico        | 0.183            | 2.12                   | 21.9             | 2.95                        | 6                             | 5.35        | N/A                      |
| Netherlands   | 0.105            | 1.12                   | 34.2             | 1.79                        | 6                             | 10          | 74                       |
| Philippines   | 0.231            | 21.49                  | 24.5             | 4.90                        | 4.75                          | 2.73        | 64                       |
| Poland        | 0.177            | 1.68                   | 18.5             | 1.24                        | N/A                           | N/A         | N/A                      |
| Singapore     | 0.131            | 5.48                   | 34.2             | 1.69                        | 10                            | 8.57        | 79                       |
| South Africa  | 0.117            | 7.74                   | 16.2             | 1.65                        | 6                             | 4.42        | 79                       |
| South Korea   | 0.166            | 1.04                   | 23.9             | 6.33                        | 6                             | 5.35        | N/A                      |
| Spain         | 0.111            | 0.57                   | 34.3             | 1.21                        | 6.25                          | 7.8         | 72                       |
| Switzerland   | 0.110            | 1.74                   | 24.6             | 1.84                        | 10                            | 10          | 80                       |
| Thailand      | 0.136            | 4.82                   | 24.2             | 7.68                        | 3.25                          | 6.25        | 66                       |
| United Kingdom| 0.140            | 7.99                   | 22.3             | 0.78                        | 10                            | 8.57        | 85                       |
| United States | 0.170            | 1.03                   | 19.2             | 0.47                        | 10                            | 10          | 76                       |
Table 6 continued

Panel A: Descriptive statistics by country

| Country | Efficiency index | Transaction costs (%) | Analyst coverage | Analyst forecast errors (%) | Efficiency of judicial system | Rule of law | Financial disclosure index |
|---------|------------------|-----------------------|------------------|-----------------------------|------------------------------|------------|---------------------------|

Panel B: Correlation statistics

|                      | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  | (10) |
|----------------------|------|------|------|------|------|------|------|------|------|------|
| n = 30               |      |      |      |      |      |      |      |      |      |      |
| (1) Mean square error (MSE) | 1.00 |      |      |      |      |      |      |      |      |      |
| (2) Error variance (EV)                      | 0.95 | 1.00 |      |      |      |      |      |      |      |      |
| (3) Squared mean error (ME²)                   | 0.90 | 0.70 | 1.00 |      |      |      |      |      |      |      |
| n = 30               |      |      |      |      |      |      |      |      |      |      |
| (4) Efficiency index                                   | 0.30 | 0.15 | 0.45 | 1.00 |      |      |      |      |      |      |
| (5) Transaction costs                                 | 0.40 | 0.39 | 0.33 | 0.43 | 1.00 |      |      |      |      |      |
| (6) Analyst coverage                                   | −0.08 | −0.12 | −0.02 | −0.07 | −0.19 | 1.00 |      |      |      |      |
| (7) Analyst forecast errors                           | 0.77 | 0.67 | 0.78 | 0.32 | 0.42 | 0.09 | 1.00 |      |      |      |
| n = 20               |      |      |      |      |      |      |      |      |      |      |
| (8) Efficiency of judicial system                     | −0.56 | −0.48 | −0.59 | −0.21 | −0.31 | 0.08 | −0.70 | 1.00 |      |      |
| (9) Rule of law                                        | −0.67 | −0.55 | −0.71 | −0.49 | −0.45 | 0.13 | −0.45 | 0.72 | 1.00 |      |
| (10) Financial disclosure index                       | −0.35 | −0.27 | −0.40 | 0.05 | −0.03 | 0.13 | −0.35 | 0.42 | 0.32 | 1.00 |

Panel A presents the summary statistics of the various measures of market efficiency, analyst forecast errors, and legal and institutional factors by country. Panel B presents the correlation statistics. Because of missing data for some of the countries, the correlation matrix including legal and institutional factors can only be calculated for a subset of 21 countries.

The market efficiency index is provided by Kristoufek and Vosvrda (2013). A low index value corresponds to a high degree of market efficiency. Transaction costs are calculated following the round-trip transaction cost measure by Lesmond et al. (1999), and are obtained from Griffin et al. (2010). Since transaction costs are negatively related to firm size and since the size of companies listed on stock markets differs across countries, median transaction costs per calendar year are used as measure of a country’s transaction costs. The table reports the time-series average of the so-obtained transaction cost measure. For more discussion, see Griffin et al. (2010). Analyst coverage is measured by the sum of all analyst forecasts for a given firm. The table reports the time-series average of the yearly mean analyst coverage. Analyst forecast quality is measured by the absolute analyst consensus forecast error for the most recent annual earnings figures. The table reports the time-series mean of the absolute analyst consensus forecast error. The scores of a country’s efficiency of the judicial system and the rule of law as taken from La Porta et al. (1998). In addition, the table reports the index of financial disclosure from the CIFAR (DeFond et al. 2007). All indices are increasing in the quality of the respective legal and institutional factor. The scores measuring the efficiency of the judicial system and the rule of law are out of 10 points; the index of financial disclosure is out of 100 points.
Kong and Spain, there are for each company on average around 35 separate forecasts available. In contrast, there are only around 16 individual forecasts in Chile and South Africa, on average. The last column reports the analyst forecast errors of the countries. According to this metric, analysts in Japan, the United Kingdom, and the United States are most accurate. In contrast, in Indonesia, the Philippines, South Korea and Thailand, analysts are least reliable.

The upper part of panel B of Table 6 presents the correlation statistics for the various measures of market efficiency and analyst forecast errors for the 30 countries covered in this study. As conjectured, there is a positive association between the various ICC forecast error metrics (MSE, EV, $ME^2$) and the efficiency index, transaction costs and analyst forecast errors. In addition, the matrix confirms a negative relation between ICC forecast errors and analyst coverage.

### 4.2 Cross-country regressions

This section examines the determinants of cross-country differences in the ICC’s ability to predict stock returns at the country level. To this end, I regress the country’s ICC forecast error metrics $y_j$ (estimated in Sect. 3.3) on the countries’ market efficiency index $EI_j$, transaction costs $TC_j$, analyst coverage $COVERAGEx_j$, and analyst forecast errors $AFE_j$.

$$y_j = \alpha + \beta_1 EI_j + \beta_2 TC_j + \beta_3 COVERAGEx_j + \beta_4 AFE_j + u_j,$$

where $j$ indicates the country.\(^{17}\) The market efficiency index, transaction costs and analyst forecast errors are transformed in natural logarithms to reduce their skewness.

Table 7 presents the results. In panel A, the dependent variable is the ICC’s mean squared error (MSE); panels B and C present the results when decomposing the ICC’s MSE in error variance (EV) and squared mean error ($ME^2$). Each panel presents univariate regressions for each of the predictors, as well as a multiple regression including all explanatory variables. Since the ICC’s forecast errors for stock returns are estimated in the previous section, they might not be free from estimation errors. To mitigate the impact of outliers caused by potentially imprecise estimates, the regression equation (5) is also estimated using robust standard errors following Rogers (1993) and iteratively reweighted least squares.

As conjectured, there is a positive relation between forecast errors (MSE) and a countries’ market efficiency index. The higher the Kristoufek and Vosvrda (2013) index, the less efficient is a capital market. Hence, the positive relation between the efficiency index and the ICC mean squared error underlines the importance of efficient capital markets for the reliability of ICC estimates. When using a country’s average transaction costs as alternative proxy for market efficiency, the picture is similar. In countries with high transaction costs, the ICC tends to be less accurate, as the mean

\(^{17}\) This study only presents the regression results when measuring the ICC’s forecast accuracy by the mean squared error (MSE), and its two components, error variance (EV) and squared mean error ($ME^2$). The results are quantitatively and qualitatively very similar to the mean squared error (MSE) when using the mean absolute error (MAE) and the root mean squared error (RMSE) to measure the ICC’s forecast quality. The results are available on request.
Table 7  Cross-country regressions

### Panel A: Mean squared error (MSE)

| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------|-----|-----|-----|-----|-----|-----|-----|
| Estimation    | OLS | OLS | OLS | OLS | OLS | Robust | IRWLS |
| Market efficiency index | 0.005* | 0.002 | 0.002 | 0.001 |   |   |   |
|                | (1.82) | (0.72) | (0.59) | (0.35) |   |   |   |
| Transaction costs | 0.002** | 0.001 | 0.001 | 0.001 |   |   |   |
|                | (2.05) | (0.60) | (0.54) | (0.85) |   |   |   |
| Analyst coverage | −0.000 | −0.000 | −0.000 | −0.000 |   |   |   |
|                | (−0.45) | (−1.16) | (−1.54) | (−1.05) |   |   |   |
| Analyst forecast errors | 0.006*** | 0.006*** | 0.006** | 0.007*** |   |   |   |
|                | (4.14) | (3.52) | (2.74) | (4.43) |   |   |   |
| $R^2$        | 10.6% | 13.1% | 0.7% | 37.9% | 45.4% | 45.4% | 55.1% |

### Panel B: Error variance (EV)

| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------|-----|-----|-----|-----|-----|-----|-----|
| Estimation    | OLS | OLS | OLS | OLS | OLS | Robust | IRWLS |
| Market efficiency index | 0.002 | −0.000 | −0.000 | −0.001 |   |   |   |
|                | (1.00) | (−0.05) | (−0.04) | (−0.77) |   |   |   |
| Transaction costs | 0.001** | 0.001 | 0.001 | 0.001 |   |   |   |
|                | (2.14) | (1.07) | (1.02) | (1.60) |   |   |   |
| Analyst coverage | −0.000 | −0.000 | −0.000 | −0.000 |   |   |   |
|                | (−0.65) | (−0.95) | (−1.36) | (−0.83) |   |   |   |
| Analyst forecast errors | 0.003** | 0.003** | 0.003 | 0.004*** |   |   |   |
|                | (2.71) | (2.26) | (1.49) | (3.87) |   |   |   |
| $R^2$        | 3.5% | 14.1% | 1.5% | 20.8% | 29.3% | 29.3% | 50.1% |

### Panel C: Squared mean error (ME²)

| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------|-----|-----|-----|-----|-----|-----|-----|
| Estimation    | OLS | OLS | OLS | OLS | OLS | Robust | IRWLS |
| Market efficiency index | 0.003** | 0.002* | 0.002 | 0.002** |   |   |   |
|                | (2.72) | (1.96) | (1.63) | (2.32) |   |   |   |
| Transaction costs | 0.001 | −0.000 | −0.000 | −0.000 |   |   |   |
|                | (1.53) | (−0.42) | (−0.34) | (−0.63) |   |   |   |
| Analyst coverage | −0.000 | −0.000 | −0.000 | −0.000 |   |   |   |
|                | (−0.10) | (−1.26) | (−1.38) | (−1.48) |   |   |   |
| Analyst forecast errors | 0.003*** | 0.003*** | 0.003** | 0.003*** |   |   |   |
|                | (5.55) | (5.00) | (7.36) | (5.41) |   |   |   |
| $R^2$        | 20.8% | 7.7% | 0.0% | 52.4% | 61.7% | 61.7% | 64.2% |

The table reports the regression results of the average ICC mean squared error (MSE), error variance (EV), and squared mean error (ME²) for 30 countries on the various measures of market efficiency and the absolute analysts consensus forecast error (AFE). The market efficiency index, transaction costs and analyst forecast errors are transformed in natural logarithms to reduce their skewness. Specifications 1 to 5 are estimated with OLS. Specification 6 is estimated with OLS using robust standard errors following Rogers (1993). Specification 7 is estimated with iteratively re-weighted least squares (IRWLS). T-statistics are given in parenthesis, *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.
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Fig. 1 ICC mean squared error and market efficiency index. The graph plots the linear regression of the countries’ ICC mean squared errors (MSE) on the log market efficiency index by Kristoufek and Vosvrda (2013)

... squared errors are higher in these countries. In contrast, the average number of analysts contributing to the consensus forecasts—the measure of information quality and information availability—has little explanatory power for cross-country differences in the ICC’s predictive power for stock returns. Although there is a negative relation between analyst coverage and forecast errors (suggesting that more analysts lead to better ICC estimates), this relation is not significant. Finally, and in line with Easton and Monahan (2005) and Guay et al. (2011), the table shows that larger forecast errors of analysts, as measured by the absolute consensus forecast error, directly translate into a lower explanatory power of the ICC for stock returns. Figures 1, 2, 3 and 4 plot these univariate regressions for each of the explanatory variables. When including all four variables to jointly explain the cross-country variation in the ICC’s ability to predict stock returns, the overall results do not change (see specifications 5 to 7). Yet, only the absolute consensus forecast error is significantly related to the ICC’s average forecast errors.

Panels B and C repeat the previous analysis, but decompose the MSE of each country in its two components, error variance (EV) and squared mean error (ME²). These two panels allow shedding more light on the role of market efficiency on the ICC forecast accuracy. Panel B shows that transaction costs—together with erroneous analyst forecasts—are the main drivers for cross-country differences in the ICC’s error variance. High transaction costs impede trade such that market prices cannot incorporate firm-specific information, therefore causing a low level of market efficiency at the firm level. As a result, the ICC is more prone to idiosyncratic forecast errors. In contrast, the market efficiency index is very good in explaining the level of systematic forecast errors of the ICC across countries, see panel C. In countries with a higher efficiency index (i.e., less efficient makers), the average forecast biases tend to be larger. This result can be explained by the nature of the Kristoufek and Vosvrda (2013) index. As
this index evaluates the time-series dynamics of the countries’ overall stock market indices, it is a measure of market-wide levels of market inefficiency, and thus captures systematic forecast errors. As before, analyst coverage is little related to both the ICC’s error variances and squared mean errors. And, not surprisingly, average analyst forecast errors are important determinants for both components of the ICC’s forecast errors.
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4.3 Panel regressions

The analysis presented in the previous section clearly underlines the role of market efficiency for the accuracy of ICC estimates to predict stock returns. Yet, it suffers from potential drawbacks. First the limited number of observations reduces the statistical power of the analysis. Second, the accuracy of the ICC to predict stock returns, as well as some of the explanatory variables, such as transaction costs, change over time. For example, Griffin et al. (2010) show that transaction costs have declined over the time period under consideration in many countries.

Against this backdrop, I form a panel data set that captures all variables for each of the 14 years separately (i.e., from 1995 to 2008). This allows incorporating the time-varying nature of market efficiency and analyst forecast quality into the analysis. The only exception is the market efficiency index by Kristoufek and Vosvrda (2013) for which there is only one observation per country for the sample period. 18 The regression specification for the panel data set is

\[ y_{j,t} = \alpha + \beta_1 EI_j + \beta_2 TC_{j,t} + \beta_3 \text{COVERAGE}_{j,t} + \beta_4 AFE_{j,t} + u_{j,t}, \]  

where \( j \) denotes the cross-sectional dimension (i.e., the country) and \( t \) the time-series dimension (i.e., the year). As before, \( y_{j,t} \) denotes the various ICC forecast error met-

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18 This panel data analysis excludes two countries, the United States and China. The U.S. is the largest equity market by far and therefore may be fundamentally different from all other countries. China has seen a tremendous transition over the last decades, which makes it less comparable to other countries analysed. However, the results do not change substantially when including the United States and China.
rics, and $u_{j,t}$ is the disturbance term. Equation (6) is estimated using the two-step Fama and MacBeth (1973) regression approach.19

Table 8 presents the results. Similar to the cross-country regressions (see Table 7), there is a strong relation between the ICC mean squared errors (MSE) and both the market efficiency index and transaction costs. Again, this means a higher the degree of market efficiency improves the reliability of the ICC as predictor of stock returns. Yet, as expected, the statistical significance is considerably higher when using panel data. Similar to the simple cross-country regressions, the relation between the ICC’s mean squared error and analyst coverage is not significant. Lower analyst forecast errors result in better ICC estimates, similar to the previous section.

The analyses of the ICC’s error variance (EV) and squared mean error (ME$^2$), see panels B and C, similarly confirm the previous results. There are however a few interesting new insights. First, transaction costs have the highest explanatory power for the ICC’s idiosyncratic forecast errors, as measured by the error variance. This means that idiosyncratic forecast errors of the ICC are largely due to firm-specific market inefficiencies, and not because of erroneous analyst forecasts. Second, variations in the ICC’s forecast bias (ME$^2$) are mainly explained by market-wide levels of market efficiency (as measured by the efficiency index) and analyst forecast errors.

Overall, the results of this section strengthen the perception that market efficiency is a crucial requirement for the reliability of the ICC to predict stock returns. While analyst forecasts—and the quality thereof—are an important element to obtain reliable ICC estimates, the analysis shows that market efficiency is equally an important prerequisite to obtain consistent ICC estimates. Only if market prices reflect fundamental values, the ICC is a reliable predictor of future stock returns, and hence a suitable proxy for expected stock returns.

5 Additional analyses

This section provides some additional analyses and robustness checks. First, I explore whether the main results of this study can be explained by some more fundamental legal and regulatory differences across capital markets. Section 5.2 examines whether the results are robust to using alternative models to estimate the firms’ ICC.

5.1 Institutional factors

The results of this study highlight the importance of efficient markets for the ICC to be a reliable predictor of stock returns. This implies that the more information is impounded in market prices, the better is a firm’s internal rate of return as estimate for expected stock returns.

Yet, the literature shows that cross-country differences in market efficiency and trading costs in turn may depend on more fundamental properties of the financial markets.

19 The results are qualitatively similar when using panel regression with standard errors clustered by country (cross-sectional dimension) and year (time-series dimension) following Rogers (1993), or when using country fixed-effects regressions.
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Table 8  Fama and MacBeth (1973) regressions

Panel A: Mean squared error (MSE)

| Specification       | (1)     | (2)     | (3)     | (4)     | (5)     |
|---------------------|---------|---------|---------|---------|---------|
| Market efficiency index | 0.006** | 0.003*  |         |         |         |
|                     | (2.82)  | (2.12)  |         |         |         |
| Transaction costs   | 0.002** | 0.001   |         |         |         |
|                     | (2.49)  | (1.38)  |         |         |         |
| Analyst coverage    | −0.00   | −0.00   |         |         |         |
|                     | (−0.63) | (−0.91) |         |         |         |
| Analyst forecast errors | 0.004*** | 0.003*** |         |         |         |
|                     | (3.19)  | (3.41)  |         |         |         |
| Average $R^2$       | 12.1%   | 6.1%    | 1.8%    | 21.1%   | 33.0%   |

Panel B: Error variance (EV)

| Specification       | (1)     | (2)     | (3)     | (4)     | (5)     |
|---------------------|---------|---------|---------|---------|---------|
| Market efficiency index | 0.003*  | 0.000   |         |         |         |
|                     | (2.50)  | (0.56)  |         |         |         |
| Transaction costs   | 0.001*** | 0.001*** |         |         |         |
|                     | (3.24)  | (3.31)  |         |         |         |
| Analyst coverage    | −0.00   | −0.00   |         |         |         |
|                     | (−0.56) | (−0.48) |         |         |         |
| Analyst forecast errors | 0.002*** | 0.002*** |         |         |         |
|                     | (3.05)  | (3.00)  |         |         |         |
| Average $R^2$       | 9.3%    | 10.1%   | 1.9%    | 18.3%   | 33.6%   |

Panel C: Squared mean error (ME$^2$)

| Specification       | (1)     | (2)     | (3)     | (4)     | (5)     |
|---------------------|---------|---------|---------|---------|---------|
| Market efficiency index | 0.004*** | 0.003** |         |         |         |
|                     | (2.91)  | (2.94)  |         |         |         |
| Transaction costs   | 0.000   | −0.000* |         |         |         |
|                     | (1.32)  | (−1.86) |         |         |         |
| Analyst coverage    | −0.00   | −0.00   |         |         |         |
|                     | (−0.56) | (−1.27) |         |         |         |
| Analyst forecast errors | 0.002*** | 0.002*** |         |         |         |
|                     | (3.22)  | (3.71)  |         |         |         |
| average $R^2$       | 15.7%   | 20.9%   | 2.4%    | 17.9%   | 35.2%   |

The table reports the results of Fama and MacBeth (1973) regressions of the average ICC mean squared error (MSE), error variance (EV), and squared mean error (ME$^2$) on the various measures of market efficiency and the absolute analyst consensus forecast error (AFE). The market efficiency index, transaction costs and analyst forecast errors are transformed in natural logarithms to reduce their skewness. The (unbalanced) panel data comprise 28 countries over 14 years (from 1995 to 2008). T-statistics are given in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Observations: 367
under consideration. For example, Eleswarapu and Venkataraman (2006) show that average transaction costs depend to a large extent on the legal and political institutions of a country. The better the regulatory environment of a country, the lower are average equity trading costs. More generally, La Porta et al. (1998) highlight the importance of legal and institutional factors on the quality and functioning of equity and debt markets around the globe. Finally, information gathering and information costs—and hence the informational efficiency of a financial market—might also depend on the country’s accounting standards. Only if basic accounting standards are in force, information provided by companies can be meaningfully interpreted by analysts and investors, and thus impounded in market prices (La Porta et al. 1998).

To control for such institutional factors, I include the measures of the “Efficiency of the judicial system” and the “Rule of law” by La Porta et al. (1998) in the regression analysis. In addition, I employ the “Financial disclosure index” of from the CIFAR, as used by DeFond et al. (2007), as additional measure of the availability of reliable information in each country. \(^{20}\)

The columns on the right of Table 6 give an overview on these three indicators. All indices are increasing in the quality of the legal or regulatory factor they are supposed to capture. Since not all indices are available for all countries, the analysis in this section can only be carried out for a smaller subset of 20 countries. According to these indicators, Finland and Switzerland have the best legal and regulatory framework, while the Philippines have the worst framework.

The lower part of panel B shows the correlation statistics for these indices. Not surprisingly, with correlations between 0.32 and 0.72, the three indicators are substantially related. More important in the context of this study is the observation that all indices are negatively related to the three measures of ICC accuracy. As conjectured, a better legal and regulatory framework directly translates into more accurate ICC estimates.

Table 9 presents the results when adding these three variables to the regression equation. Given the larger number of predictors, the panel data set as in Sect. 4.3 is used for this analysis.

The regression analysis confirms the negative relation between the various ICC forecast error metrics (MSE, EV, and ME\(^2\)) to the three indices of the correlation matrix. \(^{21}\) This indicates that the better the legal and institutional environment of a country, the more reliable are the firms’ ICC estimates to explain the cross section of stock returns, as conjectured. Both the coefficients of the rule of law and the financial disclosure indices are consistently significant. This underlines the importance of the availability of timely and accurate information, as well as the enforcement of such requirements for the accuracy of the ICC estimates.

Including these control variables does not significantly change the coefficient estimates of the various measures of market efficiency and analyst forecast quality. In comparison to Table 8, the market efficiency index loses its significance, presumably since the various institutional factors subsume some of its explanatory variance (there

\(^{20}\) Hail and Leuz (2006), Gianetti and Koskinen (2010) and Cao et al. (2017) use similar disclosure requirement indices.

\(^{21}\) The only exception is the association between squared mean error and the index of judicial efficiency. Yet, the coefficient is not significant.
Table 9  Fama and MacBeth (1973) regressions controlling for institutional factors

| Specification                  | (1) Mean squared error (MSE) | (2) Error variance (EV) | (3) Squared mean error (ME^2) |
|-------------------------------|-----------------------------|------------------------|-------------------------------|
| Market efficiency index       | 0.000                       | −0.001                 | 0.001                         |
|                               | (0.07)                      | (−1.26)                | (1.24)                        |
| Transaction costs             | 0.002**                     | 0.001***               | 0.000                         |
|                               | (2.83)                      | (4.63)                 | (0.27)                        |
| Analyst coverage              | 0.000                       | 0.000                  | 0.000                         |
|                               | (1.30)                      | (1.26)                 | (1.28)                        |
| Analyst forecast errors       | 0.002**                     | 0.001                  | 0.001**                       |
|                               | (2.43)                      | (1.69)                 | (2.92)                        |
| Rule of law                   | −0.001**                    | −0.000*                | −0.000**                      |
|                               | (−2.34)                     | (−2.15)                | (−2.24)                       |
| Judicial efficiency           | −0.000                      | −0.000                 | 0.000                         |
|                               | (−0.11)                     | (−0.40)                | (0.24)                        |
| Financial disclosure index    | −0.000**                    | −0.000**               | −0.000**                      |
|                               | (−2.88)                     | (−2.73)                | (−2.61)                       |
| Average R^2                   | 58.1%                       | 55.8%                  | 61.4%                         |

The table reports the results of Fama and MacBeth (1973) regressions of the average ICC mean squared error (MSE), error variance (EV), and squared mean error (ME^2) on the various measures of market efficiency, the absolute analyst consensus forecast error (AFE) and additional control variables. The Rule of law and the Judicial efficiency indices are taken from La Porta et al. (1998), the Financial disclosure index is taken from DeFond et al. (2007). The market efficiency index, transaction costs and analyst forecast errors are transformed in natural logarithms to reduce their skewness. The (unbalanced) panel data comprise 20 countries over 14 years (from 1995 to 2008). T-statistics are given in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Observations: 279

is only one observation for the entire sample period). Similarly, the absolute analyst consensus forecast error is less related to ICC accuracy once controlling for the countries’ institutional framework. In contrast, the role of transaction costs is even more pronounced in this specification.

Although these results draw on a smaller data set than Table 8, this robustness check confirms the role of market efficiency for the reliability of the ICC estimates.

5.2 Alternative ICC estimates

Besides the three-stage implementation of the RIM by Gebhardt et al. (2001), as presented in Sect. 2.1, there are many alternative versions of the RIM that can be used to estimate the firms’ ICC. This robustness check analyses whether the results are driven by the choice of the RIM to estimate the firms’ ICC, or whether they are robust to different approaches to estimate the ICC.

In addition to the three-stage model by Gebhardt et al. (2001), which has been most widely used in the accounting and finance literature, the two-stage model by Claus and Thomas (2001) has also received considerable attention. Most of all, Easton and
Monahan (2005) show that this model generates the best estimates of a firm’s expected return.

**Definition 3** *(Two-stage residual income valuation:)* Let \( E_0[e_t] \) denote the expected earnings per share. Then the price of a share is given by

\[
P_0 = b_0 + \sum_{t=1}^{5} \frac{E_0[e_t] - k(b_{t-1})}{(1+k)^t} + \frac{E_0[r(s)](1+g)}{(k-g)(1+k)^5}.
\]

(7)

Similar to the three-stage model by Gebhardt et al. (2001), the model combines earnings forecasts of analysts for the short horizon with assumptions on firm profitability in the long run. In the first three years, expected earnings are taken from equity analysts. After year 3, expected earnings are obtained by applying the IBES consensus long-term earnings growth rate to expected earnings in year 3. In the stable growth phase after year 5, residual incomes are presumed to grow at the expected inflation rate \( g \), which is calculated as the prevailing interest rate on 10-year treasury bonds less the assumed real-rate of three percent.

To assess the impact of using different valuation models to derive a firm’s ICC, I follow Hail and Leuz (2006) and create a synthetic ICC estimate. This synthetic ICC estimate is obtained by calculating the average ICC estimate obtained from the Claus and Thomas (2001) model and the Gebhardt et al. (2001) model. In case only one of the two estimates is available for a company, the synthetic ICC is simply given by the available ICC estimate. The pairwise correlations between the ICC obtained from the Gebhardt et al. (2001) and the Claus and Thomas (2001) models with the synthetic ICC reach 94% and 87%, respectively.

The panel regressions presented in Sect. 4.3 are then repeated using the synthetic ICC estimate. The results, presented in Table 10, are fairly similar to those of the main analysis (Table 8). Using various measures of market efficiency, the analysis confirms that the more efficient a capital market, the more reliable is the firms’ ICC as predictor for future stock returns. To conclude, the main results of this study are robust to using alternative models to estimate the firms’ ICC.

### 6 Concluding remarks

Empirical research in accounting and financial economics increasingly relies on the implied cost of capital (ICC) to estimate a firm’s cost of capital or, equivalently, a share’s expected rate of return. Yet, the implied cost of capital is only an unbiased

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22 Since Claus and Thomas (2001) require the IBES consensus long-term earnings growth rate, the sample of ICC estimates using the Claus and Thomas (2001) model is smaller in some countries. While forecasting the long-term earnings growth rate has a long tradition in the U.S., estimates for the long-term growth rate are less common in other countries.

23 Since the firms’ ICC estimates obtained from different ICC models tend to be highly correlated (Botosan and Plumlee 2005), including more ICC models is unlikely to change the results.
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Table 10  Fama and MacBeth (1973) regressions using synthetic ICC

| Dependent variable         | Mean squared error (MSE) | Error variance (EV) | Squared mean error (ME²) |
|----------------------------|--------------------------|---------------------|--------------------------|
| Market efficiency index    | 0.003*                   | 0.000               | 0.003**                  |
|                           | (2.13)                   | (0.58)              | (2.94)                   |
| Transaction costs          | 0.001                    | 0.001***            | −0.000*                  |
|                           | (1.37)                   | (3.29)              | (−1.87)                  |
| Analyst coverage           | −0.000                   | −0.000              | −0.000                   |
|                           | (−0.88)                  | (−0.46)             | (−1.24)                  |
| Absolute forecast error    | 0.004**                  | 0.002**             | 0.002***                 |
|                           | (3.38)                   | (2.97)              | (3.66)                   |
| Average R²                 | 32.7%                    | 33.4%               | 35.0%                    |

The table reports the results of Fama and MacBeth (1973) regressions of the average ICC mean squared error (MSE), error variance (EV), and squared mean error (ME²) on the various measures of market efficiency and the absolute analyst consensus forecast error (AFE) using the synthetic ICC measure (for a detailed description, see Sect. 5.2). The market efficiency index, transaction costs and analyst forecast errors are transformed in natural logarithms to reduce their skewness. The (unbalanced) panel data comprise 28 countries over 14 years (from 1995 to 2008). T-statistics are given in parenthesis. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Observations: 367

The study reveals large cross-country differences in the predictive power of the ICC for stock returns, and hence, the ICC’s ability to proxy for expected returns. Using various empirical measures of market efficiency, these differences can be explained by diverging levels of market efficiency across countries. In capital markets with higher degrees of market efficiency, the ICC is a better predictor of stock returns than in countries whose markets are less efficient. Taken together, this study underlines the importance of efficient markets when using a firm’s ICC to estimate expected stock returns.

The results of this study have a number of implications. First, the results suggest that using the ICC as estimate of the firms’ cost of equity capital is only appropriate in countries with efficient capital markets. This is especially important in view of the increasing research using the ICC as proxy for expected stock returns in many
countries around the globe. Empirical studies using data of countries with low degrees of market efficiency might come to incorrect conclusions.

Second, the findings suggest another channel by which a sound legal and regulatory environment can improve the functioning of capital markets, going beyond the aspects analysed in the literature so far. Especially a country’s disclosure requirements seem to have an important effect on the reliability of implied cost of capital estimates, which are increasingly important in many applications in accounting and finance.

Although the results of this study are obtained using a cross-country perspective, the findings may have some implications for firm-level ICC estimates as well. More specifically, this paper strengthens the view of Rusticus (2014), suggesting that firm-level ICC estimates are more accurate for companies whose equity shares have lower transaction costs and enjoy higher equity analyst coverage. ICC estimates should therefore not only be adjusted for predictable analyst forecast errors as proposed in the literature, but also for distortions caused by the mispricing of equity shares. Some recent studies (Asparouhova et al. 2013) have highlighted the impact of pricing errors when measuring realised returns, and have proposed solutions to reduce such measurement errors. In contrast, the literature on the ICC does not yet address this problem convincingly, with the exception of some early attempts by Gebhardt et al. (2001). This question is left for future research.

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Availability of data and material and Code availability The data used for this study are available upon request from the author. The software codes used for this study are available upon request from the author.

Compliance with ethical standards

Conflict of interest The author declares that there is no conflict of interest.

Appendix A: Implementation of the residual income model

This appendix describes the empirical implementation of the residual income model by Gebhardt et al. (2001).

In the first three years, the expected return on equity (\(roe\)) is derived from the median earnings forecast of equity analysts, provided by IBES. If no median earnings estimate for year 3 is available, an earnings estimate is generated by applying the long-term consensus earnings growth rate to expected earnings in year 2. If the last available explicit forecast is negative (i.e., either in year 2 or year 3), the observation is excluded.

The long-term industry \(roe\) (\(iroe\)) is the median \(roe\) of all companies belonging to the firm’s industry sector. This procedure aims to average out business cycle effects of industry profitability. Different from Gebhardt et al. (2001), this study resorts to the GICS industry sector classification since Bhojraj et al. (2003) show that the firms’ industry profitability have a higher correlation under GICS relative to other classifications. The industry \(roe\) is a rolling median industry sector \(roe\) using at least 5 years and up to 10 years of past data. To reduce the impact of outliers, the lowest and highest
centile of all realised roe are removed before calculating the industry sector roe. If the so-obtained industry roe is negative, it is replaced by the value of 0%.

Future expected book values of equity are calculated using the clean surplus relation:

\[ b_t = b_{t-1} + e_t (1 - p_t) \]

To that end, one has to make assumptions about future payout ratios, \( p_t \). In a slight variation of Gebhardt et al. (2001), this study does not keep payout ratios fixed at their current level until infinity, but fades them geometrically towards 50%. In case that the last reported payout ratio is negative, it is set to zero; in case that it is higher than one, it is set to one.

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