A modified Shiller's cyclically adjusted price-to-earnings (CAPE) ratio for stock market index valuation in a zero-interest rate environment

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Abstract

The cyclically adjusted price-earnings ratio (CAPE) is a tool that has become widely used to predict market returns. However, recently, deterioration in its forecast strength has surfaced. At the same time, global long-term interest rates have declined and are expected to remain at record lows, which the CAPE fails to consider, and which represents a gap in knowledge. This study uses a modified CAPE to account for interest rates, known as the excess CAPE yield (ECY), to offer an alternative – and potentially improved – model for predicting global stock market returns. We find that CAPEs peak when real interest rates are between 3% and 5%, while the ECY fails to improve on the predictive abilities of the CAPE.

Keywords: CAPE ratio; excess CAPE yield; interest rates; market returns; capital allocation

Introduction

There is a collection of well-known financial ratios and tools which are used to measure the relative value of equity (Algaba & Boudt, 2017). Among the collection of these financial models and ratios is the price-earnings ratio (PER), price-dividend ratio or dividend yield, price-earnings to growth ratio (PEG), price-to-book ratio, price-to-sales ratio, and free cash flow amongst others (Algaba & Boudt, 2017, p. 245). The PER is the most widely used valuation metric employed to predict stock returns and assess relative value (Algaba & Boudt, 2017, p. 245; McMillan, 2019, p. 333; Davis, Aliaga-Diaz, Ahluwalia, & Tolani, 2018, p. 43). However, the PER is a relatively static measure in that it provides a valuation based on the preceding years' earnings and is thus sensitive to price volatility, market fluctuations, economic and business cycles (Bunn et al., 2014, p. 16). As a result, the PER can be volatile and its value may change frequently reducing its robustness and reliability as a forecasting tool(Evgenidis & Malliaris, 2020, p. 1959). In addition, Siegel (2016, p. 45) details situations in which the PER offers a negative value based on losses from the previous year which is not a logical valuation metric. Beyond this, including companies that make large once-off losses and carry negative PERs can distort valuations and present a valuation that understates the true value of a company, portfolio or index (Siegel, 2016). As such, the PER’s popularity and simplicity has been overshadowed by its deficiencies. Therefore, the cyclically adjusted price-to-earnings ratio (CAPE) was developed by Campbell and Shiller in 1988 as a superior alternative, to overcome the PER's shortcomings and provide a more stable metric that incorporated average earnings over ten years (Bunn et al., 2014). Since then, the CAPE has demonstrated strong explanatory power for predicting stock market returns across markets which is why this study has focused on this valuation tool.

It is a commonly accepted notion that lower interest rates result in higher stock market valuations and thus, should result in higher CAPEs (Shiller et al., 2020; Evgenidis & Malliaris, 2020, p. 1968). The recent elevation of CAPEs and the deterioration of stock-return estimates have given rise to a renewed interest in the CAPE-based valuation measure (Davis et al., 2018, p. 43). According to Stolyarov & Tesar (2020, p. 2), since the 1980s, advanced economies have experienced declining interest rates and, more recently, global markets have been subjected to very low and sometimes negative interest rates given the unique global economic circumstances. This unique macroeconomic environment, where long-term interest rates are expected to remain at low rates, is expected to remain in place for longer (Stolyarov & Tesar, 2020, p. 5). However, the CAPE fails to consider interest rates as a macroeconomic condition and only considers inflation in its valuation process (Shiller et al., 2020). As such, this is a problem that has become increasingly relevant because of the anticipated global low interest macroeconomic environment which is being experienced and that is expected to endure. This unique macroeconomic climate necessitates the need to construct a CAPE valuation measure to enhance the predictability of stock market returns by considering interest rates. Siegel (2016, p. 42) and Davis et al. (2018, p. 43) cite low interest rates as a possible factor in driving CAPEs higher. In addition, Shiller et al. (2020), by his own admission, hypothesises that the low interest rate environment may be the reason for elevated CAPEs in stock markets. As a result, there is a clear motivation to investigate how interest rates affect the CAPE and whether adjusting the CAPE may result in enhanced stock market return predictions.

Philips & Ural (2016, p. 123) describe several enhancements which have been proposed to improve its ability to better predict returns. However, none of those appear to have made any substantial improvements. As a result, the excess CAPE yield (ECY) was introduced by Shiller, Black, & Jivraj (2020) as a means to account for the interaction between equity valuation and interest rate levels. The ECY is calculated by inverting the CAPE and subtracting the ten-year real interest rate (Shiller et al., 2020). When the ECY is elevated compared to historical levels, it suggests that equities are more attractive than bonds.

The CAPE, in particular, is prominently used by market practitioners to make capital asset allocation decisions and time their entry into the market through the establishment of relative market valuations and prediction of future market returns (McMillan, 2019, p. 333; Jivraj & Shiller, 2017, p. 4). Therefore, within this economic context, market practitioners may benefit from this research by generating excess returns through optimal asset allocation decisions based on this research to improve their portfolio returns for clients or themselves (Pfau, 2012, p. 1344). In addition, market practitioners can take advantage of this research which will offer them an enhanced ability to cycle their investments to alternate classes or markets in anticipation of market crashes, changes in earnings cycles or recessions (Seibert, 2015, p. 68).

While there is extant research to evaluate and compare the various valuation metrics with the CAPE in determining future stock returns, there is limited research on the effects that interest rates have on CAPEs and whether the ECY improves forecasts of stock market returns. Therefore, this study sought to offer a greater understanding of the relationship between interest rates and the CAPE, and then to compare and evaluate the performance of the CAPE and ECY in predicting stock market returns across twenty market indices. We provide insightful evidence of the relationship between interest rates and the CAPE which suggest a tent-shaped pattern. In addition, we use the traditional CAPE and the ECY to predict stock market returns and find surprising, and interesting, results.

This study presents three main contributions to literature. The first provides a greater understanding of the relationship and effects that macroeconomic indicators such as the interest rates and inflation, may have on the CAPE-based valuation measure in international indices. The second contribution offers a comparison of the linear correlation between the CAPE and ECY across the international indices. Our final contribution presents a detailed comparison of the predictive abilities and accuracy between CAPEs and the interest rate-adjusted ECY over several time horizons.

This paper has the following structure. The upcoming section presents an assessment of the relevant literature, followed thereafter by an overview of the data and methodology used to present the results. The section after that presents the results of the study, followed by the last section which concludes the paper.

Literature Review

Analysts and market practitioners have sought to predict prospective stock market returns accurately and reliably ever since the inception of stock markets. While there are many models and ratios used for valuing equity and predicting stock markets returns, Li, Li, Singh, & Shi (2020) noted that there is evidence to suggest that predicting stock market returns is possible to a reasonable degree of accuracy and reliability. However, Li et al. (2020) posits that traditional financial tools appear to have reached the ambit of their abilities in valuing equity and predicting stock market returns and as a result, market practitioners have shifted their efforts to find models and predictors which could enhance the accuracy of their valuation and in addition, improve the accuracy of their predictions.

Campbell & Shiller (1998) introduced the CAPE which adjusts the last 10 years of earnings by inflation to establish the real earnings and then takes the average of those 10 years to arrive at its value (Bunn et al., 2014, p. 16). The idea of extending the earnings over ten years is to dampen earnings volatility which may be due to the common economic cycle (Bunn et al., 2014, p. 17).

CAPE Applications

The traditional application for the CAPE ratio is the prediction of equity returns, but more recently for relative valuation of different assets and asset allocations (Jivraj & Shiller, 2017). Bunn et al. (2014, p. 16) developed a CAPE-based measure to evaluate the relative valuations of difference USA and European sectors and present a sector rotation strategy that achieves 4% of annualised performance above the S&P500 total return index. Warren Buffet's market value to the gross national product (MV/GNP) and CAPE ratio was used to estimate their relative value. Warren Buffet's MV/GNP was also found to be an indicator of the relative valuation of the USA stock market, however, underperformed when compared with the predictive ability of the CAPE ratio.

Extant research focuses heavily on the USA market and therefore, international research using the CAPE ratio has been left somewhat neglected. Radha (2018) used the inverse CAPE ratio metric, CY-M, commonly known as the medium-term country yield, to forecast stock market returns in 46 countries including the USA and used a cyclically adjusted real exchange rate to augment the model and enhance performance. The author found strong evidence to suggest that the CY-M metric correlated with stock market returns and proposed using this metric to forecast six-year stock market returns in his sample markets and allocate capital accordingly.

Another application of the CAPE ratio resides in predicting market crashes. Greenwood, Shleifer, & You (2019) found that the CAPE ratio has a significant ability to predict equity market returns but also, among other measures, provides a strong indicator for an impending market crash in the USA and other international equity markets. In addition, Lleo & Ziemba (2018) tested the capability of the CAPE ratio and other tools, to predict the likelihood of market crashes in Chinese markets. The CAPE ratio was shown to be a statistically significant and robust tool to predict stock market crashes over the period for both Chinese exchanges. (Lleo & Ziemba, 2018, p. 132).

Interestingly, the CAPE ratio has also found some application in the retirement planning research field. Clare, Seaton, Smith, & Thomas (2017) found evidence that the CAPE ratio may be used to improve withdrawal rates for pensioners during retirement and that there is a relationship between the CAPE ratio and withdrawal rates in the USA. Significantly higher withdrawal rates can be achieved by measuring the CAPE ratio each year at its beginning and using its predictive abilities to make decisions regarding withdrawal rates.

The CAPE ratio has also been used in asset allocation strategies and as an indicator for market timing. Dimitrov & Jain (2018, p. 742) found that it is difficult to time the market using the CAPE ratio when switching between equity and bonds unless the CAPE ratio is extremely elevated. The CAPE ratio has also been used by Luskin (2017) to determine when dollar-cost averaging could produce superior returns than lump-sum investments in the S&P500 over a 15-year time horizon. Pfau (2012) used the CAPE ratio to indicate optimal asset allocation inflection points which occurred every 5 or 6 years and entailed the complete switch of equity-based investments into cash and *vice versa* over a period from 1871 to 2009. Peterson (2018) combined the CAPE ratio with the spot gold price to construct a model which is an indicator of an impending bull or bear market, and signal to investors when they should reconsider their asset allocation. Peterson (2018) tested the model using the S&P500 index and found only a slight improvement when compared to the traditional CAPE model.

CAPE Valuation Ability

The ability of the CAPE ratio to value and predict stock market returns has been thrown into question most recently with various authors finding poor results. In response, some authors have offered reasons for the recent poor valuation ability of CAPE and offered some interesting research to enhance its predictive ability.

Siegel (2016, p. 47) found that the CAPE ratio has been skewed upwards and thus, predicted subdued real returns from the stock market because of changes in the GAAP accounting standards. Dimitrov & Jain (2018, p. 761) describe how the results show that using the CAPE ratio can be a frustrating experience for market practitioners because the CAPE ratio should revert to its mean but in some cases, the CAPE may remain in outlying valuations for some time before mean-reverting. For this reason, says Dimitrov & Jain (2018, p. 761), market practitioners may be disappointed at the results when using the traditional CAPE ratio to predict stock market returns. This drawback relates to the debate regarding whether the CAPE ratio is mean-reverting or whether the long-term mean should be altered in some form. Either way, the CAPE faces some challenges in producing predictions.

An interesting study by Davis et al. (2018, p. 43) discusses how the predictions of stock market returns using CAPE have been poor from 1995 onwards. The average out-of-sample predicted errors of the predicted returns from 1995 have been larger than the trailing long-term average. Davis et al. (2018) estimate a vector autoregression model to improve the accuracy of the predicted S&P500 returns and use the average forecast error (RMSE) to illustrate an improved result. Philips & Ural (2016, p. 109) have also noted that the CAPE ratio has attracted some criticism regarding its predictive ability. The authors describe how the CAPE ratio has indicated that the stock market appears undervalued in only 16 months between the period from January 1987 through to August 2016. This is consistent with studies by Siegel (2016) and Davis et al. (2018) who describe how the CAPE ratio has consistently remained at elevated levels and as a result, predicted lower stock market returns. Philips & Ural (2016, p. 109) constructed alternative weighting enhancements to construct the CAPE ratio using revenue, gross domestic product (GDP) and sector composition weights.

Philips & Kobor (2020) compared the CAPE ratio to an adjusted CAPE which used three quarters of the best earnings in a single year and a sales-to-price metric to predict the 10-year returns of the S&P500. They found that the sales-to-price metric and their composite model improved their prediction of 10-year stock returns in the S&P500

and resulted in a correlation between out-of-sample forecasts and actual returns of 0.87 and significantly reduced the standard deviation of the forecast error. Kenourgios, Papathanasiou, & Bampili (2021) published a study on the predictive ability of the CAPE ratio in the Greek stock market, using both five and ten years of trailing real earnings for the Athens Stock Exchange Large Cap Index. The authors found that the CAPE ratio appeared to be the best predictor of stock market returns only for long-term returns, and its ability to predict returns diminished as the return's horizon shortened.

The Role of Interest Rates

The role that interest rates play in pushing up asset valuations is a commonly accepted notion. When interest rates fall, the discount rates follow suit and push the asset valuations up, resulting in elevated valuation metrics (Shiller et al., 2020). For this reason, CAPE ratios may be fundamentally linked to interest rates and could potentially be justified at elevated levels when interest rates are very low. Evgenidis & Malliaris (2020, p. 1968) found that with the introduction of quantitative easing, borrowing costs are very low and this expansionary monetary policy has resulted in increased CAPE ratios.

Recent and increasingly likely low interest rate environments globally over the long term warrant the exploration of the role that interest rates play in elevating CAPE ratios and the ability for CAPE to predict future stock market returns. There is limited research regarding the role interest rates have on CAPE ratios. According to Shiller et al. (2020), market observers have highlighted the existence and possible role that low interest rates have on elevated CAPE ratios. In addition, Shiller et al. (2020) also admitted to the possibility that interest rates are a factor in elevated CAPE ratios and hypothesised that the low interest rate environment may be the reason for elevated CAPE ratios in stock markets.

Davis et al. (2018, p. 43) referred to two well-known authors, both of which cited that low interest rates could potentially be a factor in justifying elevated CAPE ratios. The authors used interest rates and other factors to adjust the CAPE mean reversion instead of keeping it constant. Davis et al. (2018, p. 44) conclude that in their improved two-step method using a vector autoregressive model, lower real bond yields imply higher CAPE ratios while nominal yields do not matter. Arnott, Chaves, & Chow (2016, p. 55) conducted research on the optimal rate of inflation and interest rates for stock prices in the USA and several other developed markets and found that the CAPE ratio varies with inflation and real interest rates. The results show that when real yields and inflation are between 3% and 4%, CAPE ratios peak, suggesting the very low or very high macroeconomic conditions stifle stock prices.

The relative valuation of equity and bonds seems increasingly more relevant in the current context, with authors citing that given low interest rates, the returns of bonds need to be considered. Jivraj & Shiller (2017, p. 12) conclude their study by noting that the CAPE ratio can no longer be evaluated in isolation, given the low level of interest rates and that the relative valuation of stocks and bonds are now increasingly relevant. Furthermore, Philips & Ural (2016, p. 123) cautions when using the CAPE ratio due to the markets ability to rise or fall and stagnate in extreme levels of valuation. As such, the authors recommend comparing equities with other asset classes such as bonds and inflation-linked savings vehicles. Sorge, Montagna, & Amendola (2021) found that CAPE was a powerful predictor of stock market returns given its unique ability to adjust for inflation. However, given the low inflation and low interest rate setting that has dominated markets since 2009, the CAPE ratio evidently is less powerful than it once was. Therefore, Sorge et al. (2021) proposed an adjusted CAPE ratio that does not adjust for inflation but rather, it adjusts the earnings using Bloomberg's 10-year treasury bond index.

Data and methodology

Initially, the top twenty largest stock markets by capitalisation were selected from our population of global stock exchanges. We set a criterion of a minimum of 20 years of data history. Since the CAPE requires 10 years of earnings data, a complete set of data of at least 30 years was required. Once the stock market and macroeconomic data had been collected, we removed several markets which were found to have data which were missing, or which did not meet the minimum period of data criterion we set. We then added seven additional established major stock markets and several established stock market indices. In instances where there was a total market index and an established index that represented a limited number of constituents in that market, the instrument that had the largest number of data points was chosen.

The data were obtained at monthly intervals as far back as possible, to August 2021, through the *Refinitiv Datastream* database. The market data and macroeconomic data span various time horizons for each jurisdiction, given the differing availability of data. Appendix A Table 1 sets out the start date for each index data set.

We use 10-year sovereign bonds as the benchmark for nominal interest rates and obtain the inflation index in the residing jurisdiction. The following data were collected for each of the samples:

- Nominal price index (NPI).
- Price-earnings ratio (PER).
- Nominal total return index or the dividend yield, whichever was available.

- Consumer price inflation index (CPI).
- 10-year long-term sovereign interest rates (10IR).

We perform a calculation of several key variables required in the analysis. The CPI was scaled to calculate the monthly real price index (RP) and used again in conjunction with the PER to calculate monthly real earnings (RE). The monthly real total return price index (RTR) was calculated using the nominal total return index and scaling CPI. If only a dividend yield was available, we first calculate the real dividend (RD) and then calculate the MRTR as follows, where *n* denotes a particular month:

$$RTR_n = RTR_{n-1} \times ((RP_n + \left(\frac{RD_n}{12}\right) / RP_{n-1})$$

The real long-term interest rate (3RIR) was calculated using a three-year trailing CPI, consistent with the methodology employed by Arnott et al (2016, p. 58). Next, the CAPE was calculated using the average trailing 10-year RE. The ECY is then calculated by inverting the CAPE and subtracting the real long-term interest rate (10RIR) using a trailing ten-year annualised inflation rate. The monthly total bond returns (TBR) were calculated as follows:

$$TBR_n = \frac{10IR_n}{10IR_{n+1}} + \frac{10IR_n}{1200} + \left(1 + \frac{10IR_{n+1}}{1200^{-119}}\right) \times \left(1 - \frac{10IR_n}{10IR_{n+1}}\right)$$

The real monthly total bond returns (RTBR) were then calculated using CPI as before but scaling for each consecutive month. Using the RTBR, the 10-year annualised real bond return (10RBR) was calculated. Similarly, the 10-year annualised real stock return (10RSR) was also calculated. Finally, the 10-year annualised real excess return (10RER) was calculated by subtracting the 10RBR from the 10RSR. Using the RTBR, we also calculate two additional forecast periods for the real stock returns and the real excess stock returns, namely the three-year real stock and excess stock returns (3RSR)

(3RER) and five-year real stock and excess stock returns (5RSR) (5RER respectively.

Once all the variables had been calculated for each sample, 3RIR and corresponding CAPEs were imported into *MATLAB R2017a* to group all CAPEs into nine pre-defined real interest rate intervals starting with real interest rates below 1% and ending with real interest rates above 6%. A table was compiled and converted into a heatmap to show the median CAPE for each sample and the overall mean and median CAPE at each real interest rate interval. In addition, we employed *IBM SPSS Statistics* to produce two-tailed independent t-tests using Levene's test for equality of variances with a 95% confidence interval to compare the means between the CAPEs in the real interest rate interval which had the highest median CAPE and the left and right outermost intervals. These tests were performed to evaluate whether there was a significant difference between the resulting CAPEs based on the varying real interest rates. The median was chosen to eliminate the influence of outliers, consistent with the methodology used by Arnott et al (2016, p. 67). As is customary, all variables were summarized with descriptive statistics using *IBM SPSS Statistics*.

The CAPE, ECY, 10RSR and 10RER data were subjected to inferential statistical analysis to determine the relationship between these variables. In particular, the comparison between the strength of the correlations between the CAPE and ECY was of particular interest. This analysis was conducted by establishing the Pearson's coefficient for these variables and the results thereof, tabled for discussion in the form of a heatmap again. Several other authors use correlations to test the relationships between similar variables, including Kenourgios et al. (2021), Jivraj & Shiller (2017) and Algaba & Boudt (2017).

Finally, to determine whether the ECY achieved enhanced accuracy of predicted stock market returns when compared to the traditional CAPE, the CAPE and the ECY were regressed using an in-sample ordinary least squares (OLS) linear regression. Several studies raise concerns regarding the reliability of long-term predictability regressions of time-series data (Baek & Lee, 2018, p. 119; Kenourgios et al., 2021; Jivraj & Shiller, 2017; Cejnek & Randl, 2020, p. 1240; Dimitrov & Jain, 2018, p. 755; Zakamulin, 2017). Of particular concern is heteroskedasticity and autocorrelation (serial correlation) which is prevalent in time-series data and is caused by overlapping data (Philips & Ural, 2016, p. 117). These two phenomena render long-term linear regression predictability less reliable and as result, the OLS regressions need to be corrected, so several authors use the Newey-West method which corrects the standard errors using the heteroskedasticity and autocorrelation consistent (HAC) estimators (Newey & West, 1987; Arnott et al., 2016, p. 58; Baek & Lee, 2018, p. 119; Antell & Vaihekoski, 2019; Kenourgios et al., 2021; McMillan, 2017). This method corrects the biased standard errors upwards, which results in reduced values for the t-statistics. We conduct an Augmented Dickey-Fuller (ADF) test to confirm stationarity in our data. This test will check if the data has seasonal or trending behaviours which reduce the reliability of forecasts. The OLS regressions are then performed, simultaneously checking for autocorrelation using the Durbin-Watson test. Finally, the Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent) method is adopted to correct for autocorrelation and heteroskedasticity and improve the long-term reliability of the regressions. As such, OLS regressions are reported with the corrected t-statistics. We used three different forecast periods for the real stock returns and the real excess stock returns, which were selected based on the recent study completed by Kenourgios et al. (2021). In addition, to test the forecast accuracy of the two models, the root mean square error (RMSE) statistical metric was used, consistent with other authors who compared accuracies of models such as McMillan (2017, p. 368), Davis et al. (2018)

and Avdis & Watchter (2017). The resulting adjusted coefficients of determinations (R^2) and RMSE values and their resulting means are tabled in the form of a heat map for ease of comparison and pattern identification.

Results

Relationship between real interest rates and CAPE

We determine the univariate relationship between the real interest rates for each index in our sample data and the CAPE for their respective market. Refer to Appendix B Table 2 for the summary of the descriptive statistics for the real interest rates and CAPE. Real interest rates were calculated using a trailing three-year inflation rate, 3RIR, consistent with the method by Arnott et al (2016). We find that CAPEs are at their highest when real interest rates are between 3% and 4% but fall significantly outside of this narrow interval. Generally, CAPEs fall as real interest rates approach -1% and beyond, and when real interest rates reach over 6%. The outcome of this analysis is consistent with preceding studies by Arnott et al. (2016) and Leibowitz & Bova (2007) who found that the CAPE and PER in the USA peak when real interest rates are between 3% and 4% and 2% and 3% respectively. This study extends this analysis to several other international indices. Table 3 shows the median CAPE for each real interest rate yield across all indices in our sample data.

INSERT TABLE 3 ABOUT HERE

This tent-shaped pattern is visually confirmed by producing the median and mean CAPE for all sample data in each of the real interest rate intervals. Both the median and the mean CAPE also peak when real interest rates are between 3% and 4%. Interestingly, however, we find several indices that exhibit peak median CAPEs again when real interest rates are negative including all three USA stock exchange indices, namely the Nasdaq Composite index, Dow Jones index and the S&P500 index, as well as the market index for the USA, France, and Switzerland. This is in contrast to the findings in the USA by Arnott et al. (2016) who found a continued decline in the CAPE at lower real interest rate intervals. However, a significant proportion of the data collected in this study which had very low or even negative real interest rates were found to be dated post-2016, the year in which Arnott et al. (2016) completed their study. For instance, the Nasdaq Composite index had 37 negative interest rate data points throughout the sample of which, 14 were pre-2016 and had an average CAPE of 26.68. Post-2016 there were 23 data points, with an average CAPE of 44.94. This study also has a far shorter timeframe of data for the USA in comparison with Arnott et al. (2016) who collected data from 1880. Switzerland is unique in that, not only does it exhibit peak median CAPEs when real interest rates are negative, but as real interest rates approach the range of 3% to 5%, its median CAPE is at its lowest. India and South Africa also exhibit unique data patterns as their median CAPEs remain relatively flat across the real interest rate interval range and those markets have no CAPE data in the lower real interest rate intervals.

We ran independent samples t-tests to test whether there is a significant difference between the CAPE data in the real interest rate interval where the median CAPE is at its peak and the CAPE data in the two outermost real interest rate intervals. Most indices were found to have significant differences in the CAPEs between both outermost intervals except for India which showed no statistically significant difference. Switzerland, Taiwan, the S&P500 index, and the Dow Jones index had significant differences with only one of the outermost intervals.

We conclude that, broadly speaking, there is a relationship between real interest rates and the CAPE, broadly disguised as a tent-like pattern, given that indices experience peak CAPEs when real interest rates are between 3% and 5% and CAPEs reduce significantly as real interest rates move further away from this interval.

Relationship between CAPE and market returns

We performed a Pearson's correlation analysis for the CAPE and ECY, between the 10RSR and the 10RER for our sample data. Appendix C Table 4 sets out the summary of the descriptive statistics for all the variables. The CAPEs generally had a moderate to strong negative statistically significant correlation with both the 10RSR and the 10RER. The mean correlation coefficient between the CAPE and each stock return metric was 0.71 and 0.61. Furthermore, the ECY was found to have a moderate but positive, statistically significant correlation with both the 10RSR and the 10RER. The mean correlation coefficient between the ECY and both stock return metrics was 0.50 which suggests that the CAPE is more strongly correlated with the stock return metrics when compared to the ECY. Table 5 details the Pearson's correlation coefficient for the CAPE and ECY, between 10RSR and the 10RER for our sample data.

INSERT TABLE 5 ABOUT HERE

We find that eleven of the nineteen (58%) samples exhibit higher correlations between the CAPE and the 10RSR, while six (32%) exhibit higher correlations between the CAPE and the 10RER. The remaining markets were Hong Kong, which had its highest correlation between ECY and 10RSR, India and Taiwan which had their highest correlation between ECY and 10RER. South Africa, Canada, Belgium, Australia, and Spain had the weakest set of correlations among the samples while Taiwan, India, the S&P500, Switzerland, Japan and the United Kingdom had the strongest set of correlations among the samples when all four of their correlations were considered. In addition, South Africa, Canada, Belgium, Australia, and Hong Kong had at least one correlation which was not statistically significant.

Interestingly, while the ECY was expected to be more strongly correlated than the CAPE, given that it accounts for interest rates, the evidence suggests that few cases exist where ECY has more explanatory power than the CAPE. The results confirm that the CAPE or ECY is a particularly useful tool for predicting stock market returns across all metrics in Taiwan, India, the S&P500 index, Switzerland, Japan, the United Kingdom, and Sweden. On the opposite side of the spectrum, these tools are weak in South Africa and Canada. Lastly, CAPE and ECY are useful for predicting the 10RSR in Australia, while only the CAPE is useful for predicting the 10RSR and 10RER for Belgium's BE20 index.

We conclude that the traditional CAPE is strongly correlated with stock market returns across all sample data and it appears to be the most strongly correlated variable compared to the ECY. It is more strongly correlated with the traditional 10RSR than with the 10RER. The ECY has an average Pearson's correlation of 0.5 which is moderately strong but is only more correlated to CAPE, and useful, in limited markets and indices.

ECY prediction accuracy

Notwithstanding the results thus far, we determine whether the ECY achieves enhanced accuracy of predicted stock market returns when compared to the traditional CAPE. This is achieved by determining the adjusted R^2 value using an in-sample ordinary least squares (OLS) linear regression over three-year, five-year and ten-year real stock returns and real excess stock returns. Variables were tested for normality using the Shapiro-Wilk test and most do not follow a normal distribution. The ADF test for stationarity resulted in only two variables being stationary. However, the ADF test was repeated on the first differences and all variables were found to be stationary. We then proceed with our OLS regression where the test for autocorrelation using the Durbin-Watson test demonstrates that our variables are positively autocorrelated as expected. The OLS regressions are then revised using the Newey-West HAC (Heteroskedasticity and Autocorrelation Covariance) estimators where we obtain corrected t-statistics.

In general, we find that the CAPE has the highest mean adjusted R^2 of 0.55 when predicting 10RSR, followed by a mean adjusted R^2 when predicting the 10RER, with a value of 0.45. The adjusted R^2 values for the ECY when predicting RSR and RER over the 10-year periods are the same, achieving a value of 0.32. The heatmap of adjusted R^2 values is biased toward the CAPE when predicting stock market returns, while ECY has some isolated instances where it demonstrates high adjusted R^2 values. Table 6 shows the adjusted R^2 values for the CAPE and ECY, for all stock return metrics in our sample data in heatmap form. Overall, Table 6 demonstrates that the CAPE has greater adjusted R^2 values when compared to the ECY for each respective return metric and in general, adjusted R^2 values are greater for greater stock return metric periods. Appendix D Table 7 and Table 8 set out the OLS regression coefficients and probability values respectively.

INSERT TABLE 6 ABOUT HERE

In addition, to evaluate the forecast accuracy of the two models, the RMSE statistical metric was used. Generally, the RMSE values are lowest for the CAPE and ECY when predicting ten-year returns, with values of 2.70 and 3.45 respectively, and RMSE values increasing significantly, as expected, as the period of the stock market predictions reduce to five years and again, to three years. Furthermore, the RMSE value is lowest when CAPE predicts RSR (2.70), followed by RER (2.78), followed by the

RMSE value when ECY predicts the RER (3.15) and then RSR (3.25). This is confirmed by the increase in the mean RMSE in each of the stock return predictor tools, i.e., CAPE and ECY, and across the spectrum within each time horizon, ten-, five- and three-year periods. Table 9 shows the RMSE values for the CAPE and ECY, for all stock return metrics in our sample data. It demonstrates, generally, that forecast accuracy is greater for the CAPE when compared to the ECY for each stock return metric, and forecast accuracy is enhanced for greater stock return metric periods.

INSERT TABLE 9 ABOUT HERE

Overall, the results suggest that CAPE is a more useful tool in predicting stock market returns by any measure, while predicting returns over 10 years is far more accurate when compared to five- and three-year periods. This is an interesting finding which confirms that the ECY, while still possessing some explanatory power, lags the traditional CAPE in almost all respects.

Conclusion

This study aims to provide an enhanced understanding of the association between interest rates and the CAPE, and then to assess the performance of the CAPE and ECY in predicting stock market returns across international markets. First, the results suggest that CAPE are at the peak when real interest rates are between the narrow band of 3% to 5%, but outside this interval, they fall significantly in each direction, exhibiting a tent-like pattern. However, several indices exhibit a peak in CAPE values as real interest rates approach negative values, including the USA. The study then finds that the traditional CAPE is more strongly correlated with stock market returns across all markets when compared to the ECY. Correlations for CAPE are also stronger when predicting real stock market returns versus real excess stock market returns, while the

ECY has no real difference in correlations (0.5** for both returns metrics). Lastly, we use CAPE and ECY to predict stock market returns and find compelling evidence to suggest that the traditional CAPE is a far more useful tool when predicting stock market returns across several time horizons. While the ECY has enhanced performance in limited markets.

The results of this study offer some important implications for market practitioners. There exists a general real interest rate “sweet spot” of 3% to 4% across market indices where CAPE appear to peak which may result in lower stock market returns. During these periods, market practitioners may want to reconsider their asset allocations to maximise their investment returns. There exists limited index and forecast return periods where the ECY out-performs the CAPE. Therefore, while market practitioners would do well to use the ECY to predict long-term stock market returns given its moderate correlation and relative forecast accuracy with such returns, the CAPE appears to have a stronger correlation and enhanced predictive ability when compared to the ECY.

From these findings, we conclude that the traditional CAPE is a more powerful tool for use by market practitioners than the ECY to make capital asset allocation decisions and time their entry into the market. We recognise the limitations of using linear regressions to produce these results. Given that these results are somewhat surprising, efforts in investigating alternative constructions in the ECY and its performance in developing markets is an avenue for future research.

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Appendices

Appendix A

INSERT TABLE 1 ABOUT HERE

Appendix B

INSERT TABLE 2 ABOUT HERE

Appendix C

INSERT TABLE 4 ABOUT HERE

Appendix D

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***Table 1**: Sample data index list*

Country	Index	Data Start Date
USA	USA Top 999 DS Index	02 / 1983
Japan	Japan Top 1000 DS Index	01 / 1983
United Kingdom	United Kingdom Top 548 DS Index	02 / 1979
France	France Top 249 DS Index	01 / 1984
Canada	Canada Top 249 DS Index	02 / 1983
India	India Top 200 DS Index	01 / 2000
South Korea	South Korea Top 100 DS Index	12 / 2000
Switzerland	Switzerland Top 150 DS Index	03 / 1984
Taiwan	Taiwan Top 70 DS Index	05 / 1999
Australia	Australia Top 159 DS Index	01 / 1983
South Africa	South Africa Top 70 DS Index	01 / 1983
Spain	Spain Top 120 DS Index	03 / 1997
Netherlands	Netherlands Top 119 DS Index	01 / 1983
Sweden	Sweden Top 69 DS Index	02 / 1992
USA	S&P500 Index	02 / 1973
USA	Dow Jones Index	03 / 1978
USA	Nasdaq Composite Index	02 / 1973
Hong Kong	Hang Seng 60 Index	11 / 1996
Germany	DAX 40 Index	01 / 1973
Belgium	BE 20 Index	07 / 1989

DS = Datastream

Table 2: *Summary of the descriptive statistics for the real interest rates and CAPE.*

Stock Market	Variable	N	Mean	Median	Std. Deviation	Min	Max	Std. Error Mean
USA Top 999 DS Index	CAPE	463	22.8	22.7	7.5	9.2	43.4	0.3
	3RIR	463	3.3	2.8	2.6	-1.2	11.5	0.1
Japan Top 1000 DS Index	CAPE	463	39.2	37.9	16.8	15.9	86.8	0.8
	3RIR	463	1.8	2.1	1.9	-1.7	6.2	0.1
United Kingdom Top 548 DS Index	CAPE	510	16.3	16.0	4.5	7.6	29.4	0.2
	3RIR	510	4.2	3.5	3.5	-1.6	11.7	0.2
France Top 249 DS Index	CAPE	451	17.8	17.0	5.4	8.6	38.6	0.3
	3RIR	451	3.2	2.7	2.9	-2.0	9.9	0.1
Canada Top 249 DS Index	CAPE	462	19.5	18.5	6.4	8.4	44.4	0.3
	3RIR	462	4.0	3.6	3.0	-0.8	11.1	0.1
India Top 200 DS Index	CAPE	259	21.8	21.1	6.1	11.8	48.3	0.4
	3RIR	259	4.9	4.8	1.2	2.4	8.7	0.1
South Korea Top 100 DS Index	CAPE	249	16.0	15.5	2.9	10.5	26.6	0.2
	3RIR	249	2.1	1.9	1.5	-0.2	6.1	0.1
Switzerland Top 150 DS Index	CAPE	450	21.1	19.8	7.0	9.7	44.4	0.3
	3RIR	450	1.7	1.8	1.3	-2.2	4.4	0.1
Taiwan Top 70 DS Index	CAPE	268	19.6	18.3	6.3	9.8	47.6	0.4
	3RIR	268	0.7	0.1	1.6	-0.9	5.2	0.1
Australia Top 159 DS Index	CAPE	462	18.1	16.9	5.2	7.4	30.9	0.2
	3RIR	462	4.9	3.9	3.5	-1.0	12.3	0.2
South Africa Top 70 DS Index	CAPE	464	16.4	16.8	4.1	6.9	28.0	0.2
	3RIR	464	8.9	8.3	3.1	3.5	15.6	0.1
Spain Top 120 DS Index	CAPE	294	17.6	14.9	6.3	6.9	32.4	0.4
	3RIR	294	1.9	2.2	9.5	-1.5	5.0	0.1
Netherlands Top 119 DS Index	CAPE	464	15.6	13.4	7.3	5.7	39.5	0.3
	3RIR	464	2.7	2.7	2.7	-2.4	7.6	0.1
Sweden Top 69 DS Index	CAPE	355	22.3	19.6	8.6	10.0	61.7	0.5
	3RIR	355	2.5	2.4	2.7	-2.2	9.5	0.1
S&P500 Index	CAPE	463	21.9	21.6	7.3	9.7	42.6	0.3
	3RIR	463	3.3	2.8	2.6	-1.2	11.5	0.1
Dow Jones Index	CAPE	715	19.7	20.8	7.7	5.3	41.7	0.3
	3RIR	715	3.8	3.6	2.6	-1.2	12.4	0.1
Nasdaq Composite Index	CAPE	463	36.4	33.8	11.5	15.5	105.0	0.5
	3RIR	463	3.3	2.8	2.6	-1.2	11.5	0.1
Hang Seng 60 Index	CAPE	297	16.8	15.5	4.8	9.6	35.2	0.3
	3RIR	297	2.5	0.8	3.3	-1.7	9.4	0.2
DAX 40 Index	CAPE	464	19.9	18.5	6.1	9.2	45.9	0.3
	3RIR	464	2.6	2.7	2.5	-2.4	7.1	0.1
BE 20 Index	CAPE	386	16.4	15.9	4.7	7.3	30.9	0.2
	3RIR	386	2.5	2.4	2.7	-2.1	8.8	0.1

Table 3: *Median CAPE for each real interest rate interval*

Stock Market	Below 1%	-1% to 0%	0% to 1%	1% to 2%	2% to 3%	3% to 4%	4% to 5%	5% to 6%	Above 6%	t-test: Peak to left most	t-test: Peak to right most
USA Top 999 DS Index	27.9	27.8	24.3	20.3	25.3	31.3	26.3	17.6	12.1	1.4	15.2**
Japan Top 1000 DS Index	22.8	23.7	37.0	38.2	43.5	56.3	38.6	27.4	42.7	15.1**	5.3** #
United Kingdom Top 548 DS Index	14.8	15.1	13.5	13.6	18.5	21.2	21.8	18.9	15.4	8.3**	8.6**
France Top 249 DS Index	22.5	18.3	13.7	12.7	17.2	25.0	16.5	15.2	15.4	3.6**	11.2**
Canada Top 249 DS Index	-	18.9	18.5	18.5	25.5	25.8	30.1	18.5	12.9	12.4** ^	17.4**
India Top 200 DS Index	-	-	-	-	21.6	20.0	21.4	21.7	20.3	-1.4 ^	1.1
South Korea Top 100 DS Index	-	13.3	13.9	15.2	16.5	19.0	14.6	16.0	13.6	9.1** ^	2.7** #
Switzerland Top 150 DS Index	24.0	22.1	19.2	20.7	18.0	18.1	14.9	-	-	- %	19.4** ^
Taiwan Top 70 DS Index	-	16.6	18.2	19.9	19.0	24.0	39.7	35.3	-	14.9** ^	- ^#%
Australia Top 159 DS Index	14.9	19.1	16.4	15.5	15.8	23.9	23.9	19.5	13.6	10.2** #	20.1**
South Africa Top 70 DS Index	-	-	-	-	-	17.7	17.1	17.9	16.2	2.8** ^	8.1**
Spain Top 120 DS Index	14.4	13.7	13.9	19.5	16.9	22.2	10.7	16.8	-	5.4**	2.7** ^#
Netherlands Top 119 DS Index	17.6	11.9	9.2	10.3	16.8	31.1	12.4	11.2	11.5	9.7**	15.9**
Sweden Top 69 DS Index	19.4	17.7	16.5	17.3	22.1	26.8	38.7	24.9	20.8	11.9**	12.4**
S&P500 Index	27.5	27.5	23.2	19.2	24.1	31.1	24.4	17.1	12.3	0.9	13.8**
Dow Jones Index	22.7	23.8	23.0	21.5	23.1	21.2	15.3	17.2	8.5	1.3	19.3**
Nasdaq Composite Index	42.4	35.8	31.3	28.3	33.0	43.6	44.3	36.5	31.4	3.1**	8.2**
Hang Seng 60 Index	13.9	12.8	18.5	23.8	24.0	21.1	21.4	18.1	16.8	12.0**	6.1**
DAX 40 Index	18.9	18.5	15.2	16.2	17.6	30.5	20.0	16.7	18.4	10.9**	9.4**
BE 20 Index	17.6	16.8	11.5	11.1	14.7	23.1	15.7	13.8	14.1	9.9**	11.4**
Sample Median	19.1	17.0	18.6	18.6	22.0	24.6	22.2	18.0	14.5	15.9**	29.0**
Sample Mean	19.9	18.4	20.2	20.1	23.6	27.4	25.7	19.7	15.2		
Standard Deviation	5.1	6.7	7.5	8.4	10.1	12.5	13.6	8.0	5.6		

Only one data point available in the outermost interval, therefore a t-test is done with the next outermost interval.
^ No CAPE ratio data available, next interval containing data used.
% Outermost interval is the peak value dataset; no comparison can be made.
** Statistically significant observations for a significance level α = 0.05

***Table 4**: Summary of the descriptive statistics for ECY, 10RSR and 10RER.*

Stock Market	Variable	N	Mean	Median	Std. Deviation	Min	Max	Std. Error Mean
USA Top 999 DS Index	ECY	343	2.8	2.3	2.1	-1.4	8.5	0.1
	10RSR	343	8.3	8.3	5.1	-5.4	17.2	0.3
	10RER	343	3.9	3.7	4.6	-9.5	14.2	0.2
Japan Top 1000 DS Index	ECY	344	0.8	0.9	1.7	-4.0	5.2	0.1
	10RSR	344	1.2	1.0	4.3	-7.2	10.5	0.2
	10RER	344	-2.4	-2.2	5.4	-13.7	9.7	0.3
United Kingdom Top 548 DS Index	ECY	391	4.6	3.0	3.6	-0.7	13.8	0.2
	10RSR	391	7.5	6.6	4.4	-2.9	16.5	0.2
	10RER	391	2.0	2.0	3.2	-6.7	10.0	0.2
France Top 249 DS Index	ECY	332	3.5	3.1	2.4	-1.1	9.8	0.1
	10RSR	332	7.8	8.1	4.7	-3.1	18.1	0.2
	10RER	332	2.1	2.4	3.6	-7.6	9.3	0.2
Canada Top 249 DS Index	ECY	343	2.5	2.2	2.3	-1.6	9.2	0.0
	10RSR	343	7.4	6.7	3.2	1.8	16.4	0.2
	10RER	343	1.4	1.6	3.6	-4.8	7.1	0.1
India Top 200 DS Index	ECY	140	3.4	2.9	2.5	-0.8	9.5	0.2
	10RSR	140	5.7	5.2	4.7	-2.5	14.3	0.4
	10RER	140	5.3	5.6	5.2	-4.3	14.0	0.4
South Korea Top 100 DS Index	ECY	129	4.2	4.2	1.4	1.2	7.9	0.1
	10RSR	129	5.9	4.9	3.3	0.4	13.8	0.3
	10RER	129	1.9	1.4	3.5	-4.3	10.2	0.3
Switzerland Top 150 DS Index	ECY	330	3.7	3.2	1.9	0.5	9.6	0.1
	10RSR	330	8.4	8.7	5.0	-2.3	19.7	0.3
	10RER	330	4.9	4.6	4.9	-4.9	16.4	0.3
Taiwan Top 70 DS Index	ECY	148	3.7	3.8	2.3	-1.2	9.5	0.2
	10RSR	148	5.2	5.3	3.1	-3.0	11.4	0.3
	10RER	148	3.0	3.6	4.4	-8.7	10.5	0.4
Australia Top 159 DS Index	ECY	344	2.6	2.1	2.1	-1.3	11.6	0.1
	10RSR	344	7.5	7.7	3.1	1.0	13.3	0.2
	10RER	344	1.2	1.1	2.4	-5.5	8.1	0.1
South Africa Top 70 DS Index	ECY	344	4.4	3.6	3.2	-0.7	14.4	0.2
	10RSR	344	8.7	9.1	3.0	1.4	15.9	0.2
	10RER	344	2.7	2.5	3.8	-5.8	10.5	0.2
Spain Top 120 DS Index	ECY	174	4.0	3.9	1.5	1.3	8.3	0.1
	10RSR	174	2.9	2.8	2.7	-2.6	11.5	0.2
	10RER	174	-0.4	-0.6	2.8	-4.8	7.5	0.2
Netherlands Top 119 DS Index	ECY	344	4.5	3.9	3.5	-0.7	16.6	0.2
	10RSR	344	7.1	6.5	7.0	-0.3	20.5	0.4
	10RER	344	2.4	2.1	6.0	-10.4	14.3	0.3
Sweden Top 69 DS Index	ECY	235	1.9	1.5	2.0	-1.8	8.2	0.1
	10RSR	235	9.0	10.3	4.0	-2.0	16.7	0.3
	10RER	235	3.6	4.1	3.7	-7.0	12.1	0.2

Continued…

Index	Variable	N	Mean	Median	Std. Deviation	Min	Max	Std. Error Mean
S&P500 Index	ECY	343	3.0	2.6	2.0	-1.4	9.2	0.1
	10RSR	343	7.5	7.8	5.0	-6.3	16.1	0.3
	10RER	343	3.1	2.9	4.7	-10.4	14.5	0.3
Dow Jones Index	ECY	402	3,98	2.6	3.7	-1.3	13.9	0.2
	10RSR	402	8.9	10.0	4.5	-3.6	16.1	0.2
	10RER	402	4.0	4.1	3.8	-7.7	14.6	0.2
Nasdaq Composite Index	ECY	343	0.5	0.3	1.5	-2.7	6.2	0.1
	10RSR	343	8.3	8.2	6.4	-8.7	24.9	0.3
	10RER	343	3.9	3.7	6.4	-12.8	19.6	0.3
Hang Seng 60 Index	ECY	178	3.1	3.0	2.3	-2.0	8.2	0.2
	10RSR	178	6.1	6.4	3.4	-0.5	15.8	0.3
	10RER	178	2.3	2.4	3.0	-4.0	10.3	0.2
DAX 40 Index	ECY	344	2.2	1.8	2.0	-2.0	9.5	0.1
	10RSR	344	6.0	6.4	4.0	-4.5	15.0	0.2
	10RER	344	1.2	1.8	3.6	-9.0	8.9	0.2
BE 20 Index	ECY	266	3.2	2.3	2.5	-0.4	11.8	0.2
	10RSR	266	4.9	5.0	3.8	-4.8	12.6	0.2
	10RER	266	0.3	0.5	2.8	-7.2	6.2	0.2

Note: Descriptive statistics for CAPE detailed in Table 2

Note: The number of observations differ from Table 2, depending on the availability of data for all variables.

***Table 5**: Pearson's correlation coefficient for the CAPE and ECY of sample data.*

Stock Market	CAPE		ECY	
	10RSR	10RER	10RSR	10RER
USA Top 999 DS Index	-0.91**	-0.80**	0.69**	0.66**
Japan Top 1000 DS Index	-0.77**	-0.74**	0.68**	0.76**
United Kingdom Top 548 DS Index	-0.75**	-0.83**	0.62**	0.74**
France Top 249 DS Index	-0.73**	-0.75**	0.50**	0.46**
Canada Top 249 DS Index	-0.52**	0.02	0.07	-0.39**
India Top 200 DS Index	-0.81**	-0.81**	0.71**	0.83**
South Korea Top 100 DS Index	-0.70**	-0.69**	0.59**	0.64**
Switzerland Top 150 DS Index	-0.80**	-0.79**	0.67**	0.76**
Taiwan Top 70 DS Index	-0.91**	-0.94**	0.91**	0.94**
Australia Top 159 DS Index	-0.84**	-0.10	0.59**	0.12*
South Africa Top 70 DS Index	-0.25**	-0.23**	0.02	0.18**
Spain Top 120 DS Index	-0.61**	-0.39**	0.52**	0.31**
Netherlands Top 119 DS Index	-0.75**	-0.77**	0.39**	0.43**
Sweden Top 69 DS Index	-0.84**	-0.80**	0.53**	0.72**
S&P500 Index	-0.91**	-0.78**	0.71**	0.68**
Dow Jones Index	-0.79**	-0.53**	0.53**	0.29**
Nasdaq Composite Index	-0.73**	-0.72**	0.39**	0.55**
Hang Seng 60 Index	-0.62**	-0.55**	0.76**	0.09
DAX 40 Index	-0.69**	-0.71**	0.17**	0.37**
BE 20 Index	-0.52**	-0.52**	-0.05	0.16**
Mean	-0.71	-0.61	0.50	0.50

** Correlation is statistically significant for a significance level $\alpha = 0.01$ (2 tailed).

* Correlation is statistically significant for a significance level $\alpha = 0.05$ (2 tailed).

***Table 6**: Adjusted R^2 for CAPE and ECY, for stock return metrics in our sample data.*

Stock Market	CAPE						ECY					
	10RSR	5RSR	3RSR	10RER	5RER	3RER	10RSR	5RSR	3RSR	10RER	5RER	3RER
USA Top 999 DS Index	0.82	0.48	0.34	0.64	0.36	0.21	0.48	0.20	0.14	0.43	0.16	0.09
Japan Top 1000 DS Index	0.60	0.50	0.31	0.55	0.48	0.23	0.47	0.39	0.25	0.58	0.52	0.31
United Kingdom Top 548 DS Index	0.56	0.60	0.45	0.70	0.64	0.43	0.39	0.36	0.21	0.55	0.41	0.24
France Top 249 DS Index	0.54	0.46	0.41	0.56	0.41	0.33	0.25	0.17	0.16	0.21	0.16	0.16
Canada Top 249 DS Index	0.27	0.08	0.08	0.00	0.00	0.00	0.00	0.02	0.00	0.15	0.09	0.04
India Top 200 DS Index	0.65	0.67	0.49	0.65	0.65	0.34	0.51	0.72	0.66	0.68	0.77	0.58
South Korea Top 100 DS Index	0.49	0.44	0.55	0.47	0.40	0.38	0.35	0.32	0.64	0.40	0.38	0.61
Switzerland Top 150 DS Index	0.64	0.43	0.25	0.62	0.53	0.26	0.44	0.17	0.12	0.58	0.32	0.19
Taiwan Top 70 DS Index	0.83	0.61	0.64	0.89	0.77	0.78	0.84	0.59	0.51	0.88	0.77	0.66
Australia Top 159 DS Index	0.70	0.36	0.29	0.00	0.02	0.04	0.35	0.24	0.24	0.01	0.08	0.14
South Africa Top 70 DS Index	0.06	0.16	0.27	0.04	0.29	0.34	0.00	0.02	0.12	0.03	0.25	0.37
Spain Top 120 DS Index	0.38	0.46	0.30	0.15	0.30	0.31	0.27	0.30	0.15	0.09	0.19	0.22
Netherlands Top 119 DS Index	0.57	0.39	0.26	0.60	0.38	0.21	0.15	0.03	0.03	0.19	0.03	0.03
Sweden Top 69 DS Index	0.71	0.49	0.40	0.64	0.62	0.44	0.28	0.10	0.07	0.52	0.20	0.17
S&P500 Index	0.82	0.48	0.34	0.61	0.36	0.22	0.51	0.22	0.15	0.46	0.20	0.12
Dow Jones Index	0.63	0.25	0.10	0.31	0.11	0.05	0.28	0.09	0.01	0.08	0.02	0.01
Nasdaq Composite Index	0.53	0.25	0.21	0.52	0.25	0.21	0.15	0.02	0.01	0.31	0.07	0.05
Hang Seng 60 Index	0.38	0.62	0.44	0.29	0.39	0.26	0.58	0.16	0.18	0.00	0.00	0.04
DAX 40 Index	0.48	0.50	0.39	0.50	0.52	0.36	0.03	0.08	0.13	0.14	0.14	0.17
BE 20 Index	0.26	0.45	0.34	0.27	0.43	0.29	0.00	0.05	0.04	0.02	0.12	0.10
Mean	0.55	0.43	0.34	0.45	0.40	0.28	0.32	0.21	0.19	0.32	0.24	0.22

***Table 7**: Coefficients for OLS regressions.*

Stock Market	CAPE						ECY					
	10RSR	5RSR	3RSR	10RER	5RER	3RER	10RSR	5RSR	3RSR	10RER	5RER	3RER
USA Top 999 DS Index	-0.56	-0.67	-0.76	-0.45	-0.57	-0.61	168.40	169.96	195.16	143.92	152.58	161.83
Japan Top 1000 DS Index	-0.21	-0.48	-0.55	-0.26	-0.48	-0.48	179.42	397.25	463.20	247.15	471.76	509.96
United Kingdom Top 548 DS Index	-0.68	-1.16	-1.34	-0.54	-0.99	-1.13	77.00	121.94	125.79	66.19	109.29	115.60
France Top 249 DS Index	-0.60	-1.06	-1.48	-0.46	-0.91	-1.27	100.71	159.56	228.11	69.23	138.32	216.13
Canada Top 249 DS Index	-0.22	-0.24	-0.33	0.00	-0.02	-0.05	10.53	-41.54	-29.75	-45.54	-78.20	-71.13
India Top 200 DS Index	-0.51	-1.57	-1.82	-0.57	-1.47	-1.65	134.53	478.34	626.77	172.39	473.20	633.31
South Korea Top 100 DS Index	-0.71	-1.44	-2.35	-0.74	-1.56	-2.18	140.27	282.16	586.97	158.54	352.04	637.83
Switzerland Top 150 DS Index	-0.50	-0.72	-0.75	-0.48	-0.77	-0.75	176.63	194.52	221.19	198.11	253.60	270.04
Taiwan Top 70 DS Index	-0.37	-0.62	-1.03	-0.54	-0.95	-1.56	127.29	207.61	316.37	185.10	321.86	488.97
Australia Top 159 DS Index	-0.44	-0.54	-0.79	-0.41	-0.16	-0.32	87.17	122.94	197.55	14.64	76.19	162.32
South Africa Top 70 DS Index	-0.15	-0.51	-1.10	-0.18	-0.85	-1.40	2.81	27.52	106.12	21.35	114.86	212.94
Spain Top 120 DS Index	-0.28	-0.89	-1.17	-0.18	-0.69	-1.20	91.61	277.62	325.50	57.30	215.29	393.63
Netherlands Top 119 DS Index	-0.65	-0.83	-0.90	-0.57	-0.75	-0.78	78.08	55.16	71.19	74.89	53.77	67.32
Sweden Top 69 DS Index	-0.34	-0.86	-1.07	-0.30	-0.79	-0.98	105.31	190.86	218.10	133.18	219.31	296.55
S&P500 Index	-0.58	-0.71	-0.80	-0.46	-0.60	-0.65	175.81	187.28	209.21	156.37	176.00	186.39
Dow Jones Index	-0.40	-0.40	-0.32	-0.24	-0.24	-0.23	65.56	61.25	35.41	30.52	29.33	27.86
Nasdaq Composite Index	-0.36	-0.40	-0.50	-0.36	-0.41	-0.52	163.44	98.87	89.77	233.56	190.79	224.43
Hang Seng 60 Index	-0.48	-1.35	-1.62	-0.37	-1.34	-1.54	110.20	129.65	196.58	10.84	25.00	114.09
DAX 40 Index	-0.39	-0.93	-1.21	-0.36	-0.91	-1.14	33.93	129.15	241.60	65.87	163.13	270.55
BE 20 Index	-0.38	-1.17	-1.56	-0.28	-1.02	-1.38	-8.81	85.44	115.97	19.09	114.34	175.70

Table 8: *OLS regression statistical significance (p-value).*

Stock Market	CAPE						ECY					
	10RSR	5RSR	3RSR	10RER	5RER	3RER	10RSR	5RSR	3RSR	10RER	5RER	3RER
USA Top 999 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00**	0.00***	0.00***	0.01*
Japan Top 1000 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
United Kingdom Top 548 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
France Top 249 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Canada Top 249 DS Index	0.00***	0.00**	0.01*	0.855	0.778	0.748	0.482	0.133	0.545	0.00**	0.00**	0.105
India Top 200 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
South Korea Top 100 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Switzerland Top 150 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Taiwan Top 70 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Australia Top 159 DS Index	0.00***	0.00***	0.00***	0.379	0.213	0.075	0.00***	0.00***	0.00***	0.217	0.00**	0.00***
South Africa Top 70 DS Index	0.02*	0.00***	0.00***	0.02*	0.00***	0.00***	0.779	0.200	0.00***	0.110	0.00***	0.00***
Spain Top 120 DS Index	0.00***	0.00***	0.00***	0.00**	0.00***	0.00***	0.00***	0.00***	0.00**	0.01*	0.00***	0.00**
Netherlands Top 119 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.094	0.169	0.00***	0.071	0.154
Sweden Top 69 DS Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.02*	0.070	0.00***	0.00**	0.00**
S&P500 Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00**
Dow Jones Index	0.00***	0.00***	0.00**	0.00***	0.00***	0.04*	0.00***	0.00**	0.245	0.00**	0.106	0.271
Nasdaq Composite Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.263	0.483	0.00***	0.02*	0.074
Hang Seng 60 Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00**	0.00***	0.564	0.704	0.04*
DAX 40 Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.203	0.00**	0.00**	0.00**	0.00***	0.00***
BE 20 Index	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.588	0.00**	0.04*	0.113	0.00***	0.00**

Note: *, ** and *** statistically significant observations for a significance level α-0.05, α-0.01 and α-0.001, respectively, using the Newey-West (1987) adjusted t-statistics.

***Table 9**: Root Mean Squared Error (RMSE) for forecast accuracy of the CAPE and ECY.*

Stock Market	CAPE						ECY					
	10RSR	5RSR	3RSR	10RER	5RER	3RER	10RSR	5RSR	3RSR	10RER	5RER	3RER
USA Top 999 DS Index	2.11	5.69	8.62	2.73	6.25	9.53	3.65	7.09	9.87	3.45	7.13	10.21
Japan Top 1000 DS Index	2.71	7.36	12.63	3.59	7.81	13.27	3.12	8.16	13.21	3.49	7.47	12.62
United Kingdom Top 548 DS Index	2.92	4.58	7.19	1.75	3.66	6.37	3.46	5.84	8.64	2.13	4.67	7.35
France Top 249 DS Index	3.21	6.67	10.30	2.36	6.28	10.43	4.10	8.27	12.27	3.18	7.52	11.70
Canada Top 249 DS Index	2.72	6.02	8.29	2.58	5.66	7.85	3.19	6.22	8.62	2.37	5.38	7.69
India Top 200 DS Index	2.74	7.92	13.60	3.03	7.91	16.60	3.26	7.38	10.97	2.89	6.34	13.22
South Korea Top 100 DS Index	2.39	5.30	6.99	2.57	6.31	9.16	2.69	5.87	6.21	2.73	6.41	7.24
Switzerland Top 150 DS Index	2.99	6.57	10.26	3.01	5.72	9.97	3.72	7.90	11.10	3.17	6.90	10.46
Taiwan Top 70 DS Index	1.29	3.78	5.97	1.45	3.90	6.27	1.25	3.90	6.93	1.49	3.96	7.90
Australia Top 159 DS Index	1.66	4.11	7.08	2.42	5.51	8.74	2.46	4.49	7.34	2.41	5.35	8.26
South Africa Top 70 DS Index	2.90	5.32	8.40	3.71	6.18	9.14	2.99	5.77	9.26	3.74	6.38	8.94
Spain Top 120 DS Index	2.09	5.62	10.49	2.60	6.20	10.47	2.28	6.41	11.53	2.69	6.67	11.15
Netherlands Top 119 DS Index	4.58	8.46	12.38	3.80	7.77	12.01	6.47	10.66	14.18	5.42	9.69	13.36
Sweden Top 69 DS Index	2.14	8.56	12.95	2.24	6.09	10.88	3.36	11.36	16.11	2.58	8.85	13.26
S&P500 Index	2.06	5.72	8.61	2.88	6.30	9.56	3.48	7.03	9.79	3.42	7.05	10.17
Dow Jones Index	2.71	6.26	8.78	3.19	6.24	8.59	3.81	6.89	9.17	3.68	6.53	8.78
Nasdaq Composite Index	4.3	8.9	12.2	4.5	9.1	12.8	5.9	10.1	13.7	5.4	10.1	14.0
Hang Seng 60 Index	2.66	4.58	7.88	2.49	7.25	11.22	2.20	6.88	9.57	2.96	9.32	12.83
DAX 40 Index	2.87	6.41	10.57	2.52	6.02	10.57	3.93	8.73	12.61	3.33	8.09	12.03
BE 20 Index	3.24	6.65	11.17	2.40	6.11	11.03	3.78	8.78	13.50	2.78	7.59	12.43
Mean	2.72	6.22	9.72	2.79	6.31	10.22	3.45	7.39	10.73	3.16	7.07	10.68