CAPE Ratios and Long-Term Returns

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Abstract

We demonstrate that 10-year equity market returns are considerably more predictable in relation to price–earnings ratios than previously thought. The traditional approach involves relating the current index price level, based on current index components, to the index earnings of previous years, calculated using those years' components. When we estimate the cyclically adjusted price–earnings (CAPE) ratio, ensuring that index component prices and earnings are aligned, and apply a superior regression approach, out-of-sample R^2 values are over 50%. The Component CAPE ratio weights individual stock CAPE ratios by their market capitalization, whereas the traditional CAPE ratio is more closely aligned with earnings weighting.

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1. Introduction

Despite the large increase in passive investment in recent decades, many investors continue to favor an active approach (e.g., Chinco and Sammon, 2024). Active investors form views on the expected returns of different assets and allocate their capital accordingly. Some use technical rules based on price information, particularly for shorter timeframes. However, most longer-term decisions are based on fundamental information, which is often compared to current prices via valuation ratios. The most popular ratio for forecasting long-term stock returns is the cyclically adjusted price–earnings (CAPE) ratio. Campbell and Shiller (1988) introduce the CAPE ratio and suggest calculating it by dividing an index, such as the S&P 500, by the total earnings of all component stocks. They note that recessions can temporarily depress earnings and distort analysis, so they average earnings over the previous 10 years. They document a strong negative relation between the CAPE ratio and future 10-year stock returns. The message is simple: when valuations are high, future expected returns are lower, and when valuations are low, future expected returns are higher. However, in recent times, the performance of the CAPE ratio has declined (e.g., Davis, Aliaga-Díaz, Ahluwalia, and Tolani, 2018), raising questions about its usefulness for active investment decision making going forward.

We make an intuitive modification to the CAPE ratio. The traditional CAPE ratio scales the current S&P 500 index by the average annual total index earnings reported over the previous 10 years. However, stocks are regularly added to and deleted from the S&P 500 index, resulting in a mismatch between the stocks in the numerator (current stocks) and those in the denominator (historically included stocks). We estimate the CAPE ratio by aligning stocks currently in the index with their historical earnings. This involves obtaining the historical reported earnings for each current component of the index each year and using these to calculate historical S&P 500 index earnings for the current components. We label this approach the Component CAPE ratio. This modification materially improves return predictions.[1]

Campbell and Shiller (1988) use a simple average of the last 10 years of earnings. However, there are also alternative approaches to measuring and combining earnings. We follow each of these. In every instance, we calculate the Component CAPE ratio and compare it to the equivalent traditional CAPE ratio. Campbell and Shiller (1988) note that their choice of a 10-year average is motivated by Graham and Dodd's (1934) observation that examining valuation ratios should average earnings over "not less than five years, preferably seven or ten years" (p. 452). Our second approach, therefore, is to take the simple average of earnings over the last five years. In our third approach, reflecting that smoothing earnings over a historical period is important but that more recent earnings can be more informative, we average over the last 10 years using an exponentially weighted moving average (EWMA).

Fourth, we employ the Total Return CAPE (TRCAPE) ratio proposed by Jivraj and Shiller (2017), which utilizes the total return price in the numerator to account for the increasing popularity of share buybacks over dividends in recent decades. Fifth, we utilize White and Haghani's (2024) payout-adjusted (P-CAPE) ratio, which adjusts earnings for the level of retained earnings, given that retained earnings are expected to increase earnings per share over time. Finally, following Hillenbrand and McCarthy (2024), we use "street earnings." These authors note that the earnings used by researchers such as Campbell and Shiller (1988) are based on those reported by companies. These include special items, whereas market participants (the "street") typically exclude them to focus on normal earnings unaffected by one-time items.

[1] As we outline in more detail below, differences between the CAPE ratios across the traditional and component approaches are driven more by subtle differences in the weighting of stocks than by a mismatch in the companies' part of the price numerator and the earnings denominator.

Long-term prediction analysis typically employs overlapping observations, which can introduce bias into in-sample techniques. We, therefore, conduct out-of-sample (OOS) analysis in the spirit of Campbell and Thompson (2008) and Goyal and Welch (2008) because, as Boudoukh, Israel, and Richardson (2022) note, this analysis is not affected by overlapping observation bias. There is an additional reason to focus on OOS analysis when evaluating CAPE ratios. Asness, Ilmanen, and Maloney (2017) note that CAPE ratio analysis may be subject to hindsight bias. This occurs when CAPE ratio valuations are compared to past and future CAPE ratios. For instance, CAPE ratios over time are often divided into quintiles, and the subsequent average 10-year returns to each quintile are calculated. However, an investor using CAPE ratios at historical points in time would not be able to place the current and historical CAPE ratios in the context of future CAPE ratios. We measure the performance of CAPE ratios using the OOS R^2. This involves comparing the mean squared error (MSE) of the 10-year return predicted by the CAPE ratio to the MSE of a historical mean forecast. Li, Li, Lyu, and Yu (2025) show that using a constant predictive slope coefficient can reduce bias and improve forecasts. We follow this approach.

Our results indicate that the Component CAPE ratios consistently generate more accurate return predictions than the traditional CAPE ratios. In our baseline tests, the average OOS R^2 from the Component CAPE ratio is 56%. The results are robust. Our baseline analysis begins with CAPE ratios calculated in 1964, using the 1964 index level and earnings dating back 10 years, to 1955. The OOS period starts in 1974. However, importantly, the result is evident in recent data. It is stronger in the second half of the OOS period, which starts in 1995. The result holds if we introduce a one-year lag between measuring the CAPE ratio and forecasting the 10-year return. This suggests that delays in the public release of earnings information are not driving the predictability. Our results also withstand adjustment for data mining. The chances of this are minimized by applying a Component CAPE approach that is easily understandable and well-motivated and by the inclusion of earnings measurement inputs into CAPE ratios that have already been discussed in the literature. Nonetheless, we formally account for data mining bias using both the Bonferroni correction and the Benjamini–Hochberg (1995) False Discovery Rate (FDR) procedure.

We also calculate the Mean Absolute Error (MAE) of the CAPE ratio forecasts and compare these to the MAE from the historical mean forecast. These results also confirm the superior performance of the Component CAPE ratio predictions. We calculate the certainty equivalence return (CER) for a risk-averse quadratic investor. We assume that an investor allocates between the stock market and T-bills based on signals from each CAPE ratio and the chosen implementation technique. We compare the CERs implied by CAPE-based forecasts with those from three benchmarks: i) forecasts based on the historical mean model, ii) a 60% equity market and a 40% T-bill portfolio, and iii) a 100% equity market portfolio. The results indicate that the Component CAPE ratio approach is superior.

We demonstrate that the traditional CAPE ratio differs from the Component CAPE ratio in several respects. First, whereas the Component CAPE ratio weights individual stock CAPE ratios by their market capitalizations, the traditional CAPE ratio is more closely aligned to an approach that weights individual stock CAPE ratios by the size of their earnings. This explains a large component of the difference between the traditional and Component CAPE ratios. Second, there is a mismatch between the stocks included in the index price in the numerator and average earnings in the denominator under the traditional CAPE ratio approach. Our results indicate that, on average, there is a 23-stock difference. However, this amounts to only an average of 2.5% of the market cap, suggesting it is not a material driver of the mismatch in CAPE ratios.

In addition to contributing to the literature on the CAPE ratio,[2] which we discussed earlier, our work contributes to the broader research on estimating equity returns. Many researchers focus on predicting monthly returns using variables such as investor sentiment (e.g., Huang, Jiang, Tu, and Zhou, 2015), technical indicators (e.g., Neely, Rapach, Tu, and Zhou, 2014), and short interest (e.g., Rapach, Ringgenberg, and Zhou, 2016). Goyal, Welch, and Zafirov (2024) examine the predictive ability of various variables for monthly returns and document their performance in predicting annual returns. Much less work focuses on estimating returns over five-year periods and longer.

However, important contributions have been made. Cochrane (2008) finds that dividend yields can assist in stock return forecasts over one- to 25-year horizons. Goyal and Welch (2008) find evidence of variables predicting five-year returns, although they note they are "hesitant to endorse them" (p. 1482) due to small sample sizes. Golez and Koudijs (2018) document that the dividend–price ratio predicts five-year returns across several markets and periods. Atanasov, Møller, and Priestley (2020) show that consumption variation can be used to predict five-year stock returns. Swinkels and Umlauft (2022) show that the "Buffett indicator," which scales stock market capitalization by the GDP, can predict long-horizon returns. Ma, Marshall, Nguyen, and Visaltanachoti (2024) consider a range of valuation ratios, including dividend yields, consumption, the Buffett indicator, and the CAPE ratio and suggest that the CAPE ratio is the most suitable.

We also build on Kelly and Pruitt's (2013) observation that aggregate quantities, such as the aggregate book-to-market ratio, understate the predictive ability of individual stock ratios aggregated up to the market level. The authors show considerable improvement in both in-sample and OOS predictive ability when stock-level information is used and aggregated to

[2] Our work is also related to an excellent research note by Commins, Hsu, and Kim (2025), who also investigate a CAPE ratio based on index constituent stocks. They show that this ratio generates stronger in-sample correlations with subsequent returns than Shiller's CAPE ratio.

predict monthly and annual stock returns. Our Component CAPE analysis is similar in spirit, but our paper focuses on the CAPE ratio and 10-year returns.

The remainder of this paper is organized as follows: Section 2 contains a discussion of the data, variable construction, and predictive performance models. The baseline results are shown in Section 3, with robustness checks in Section 4. Results relating to CAPE ratio differences and asset allocation are presented in Section 5. Section 6 concludes the paper.

2. Data, Variable Construction, and Predictive Performance Methods

2.1. Data and Variable Construction

We obtain the S&P 500 index and aggregate earnings data from Robert Shiller's website.[3] We calculate annual total returns by comparing the December price level in year t to the December price level in year $t - 1$ and then adding the dividends earned during year t. Shiller defines the December price as the average daily price in December.

We construct six CAPE ratios based on aggregate S&P 500 earnings. First, following Campbell and Shiller (1988), we compute *Aggregate 10-Year Earnings* by dividing the real price at the end of year t by the average of real aggregate earnings from years $t - 9$ to year t. Second, motivated by Graham and Dodd's (1934) observation that valuation ratios may use earnings over a period of "not less than five years" (p. 452), we define the *Aggregate 5-Year Earnings* CAPE ratio by dividing the real price at the end of year t by the average of real aggregate earnings from years $t - 4$ to t. Third, since more recent earnings may be more informative, we calculate the *Aggregate 10-Year Earnings EWMA* CAPE ratio by applying an EWMA to the past 10 years of real earnings (from the end of year $t - 9$ to year t), using a 10-year half-life to determine the rate of decay. Fourth, we use the total return CAPE ratio advocated by Jivraj and Shiller (2017), which assumes that dividends are reinvested into the

[3] See https://shillerdata.com/.

price index and is available on Robert Shiller's website. We refer to this measure as *Aggregate 10-Year Earnings TRCAPE*. Fifth, we calculate P-CAPE ratio proposed by White and Haghani (2024), who argue that retained earnings contribute to future earnings growth.[4] We refer to this ratio as *Aggregate 10-Year Earnings P-CAPE*. Finally, we use the street earnings CAPE constructed by Hillenbrand and McCarthy (2024), whose construction removes the transitory special items they identify. We refer to this measure as *Aggregate Street Earnings CAPE*.[5]

To calculate Component CAPE ratios, we obtain data on the components of the S&P 500 from Siblis, whose data start in 1970. Others who have used this database include Chinco and Sammon (2024). We supplement these data with the index constituents from Chen, Noronha, and Singal (2004), thereby extending our sample back to 1964, the first year for which we calculate CAPE ratios. Since the CAPE measure requires 10 years of earnings history, we retrieve data from Compustat beginning in 1955. We obtain data on company prices and shares outstanding from the Center for Research in Security Prices. We convert nominal prices and earnings to real prices and real earnings, respectively, using Consumer Price Index data from Robert Shiller's website. We then calculate each of the six CAPE ratios separately for each S&P 500 index stock. The final step is value-weighting these stock-level CAPEs based on stock market capitalization, to arrive at the following CAPE ratios: *Component 10-Year Earnings*, *Component 5-Year Earnings*, *Component 10-Year Earnings EWMA*, *Component 10-Year Earnings TRCAPE*, *Component 10-Year Earnings P-CAPE,* and *Component 10-Year Street Earnings*.[6]

Table 1, Panel A, reports summary statistics for both Aggregate and Component CAPE ratios, based on annual data from 1955 to 2024. They show that the mean of each Component

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[4] We thank Victor Haghani and James White for making their data available and for useful discussions.

[5] We thank Sebastian, Helen Brand, and Audran McCarthy for providing their data and for useful discussions.

[6] Robertson (2023) highlights that the index committee for the S&P 500 considers criteria other than market capitalization when constructing the index. This means that the weights we assign to each index component may differ from the actual weights. We run a robustness check that demonstrates any mismatch is not material. We winsorize to ensure outliers are not driving the result.

CAPE ratio is always higher than its aggregate counterpart. For instance, the mean of the *Component 10-Year Earnings* CAPE is 29.7, compared to 21.7 for the *Aggregate 10-Year Earnings* CAPE. The minimum values for the Component CAPE ratios are also higher, but the most notable differences are apparent in the maximum values, which are considerably larger for the Component CAPE ratios. For instance, the maximum of the *Component 10-Year Earnings* CAPE is 66.6, compared to 44.1 for its aggregate equivalent. There is also more variation in the Component CAPE ratios, as indicated by their standard deviations.

Panel B of Table 1 presents summary statistics for annualized 10-year log equity market returns over two sample periods. The first period starts in 1964, the earliest year for which 10-year returns are estimated. The second period spans 1973 to 2024, corresponding to the beginning of the OOS forecasting period. The average 10-year return over the first period is 9.8% with a minimum of -1.3%. However, the fifth percentile return is 1.1%, suggesting that losses over a 10-year horizon are uncommon. The maximum annualized return over a 10-year horizon is 17.1%. Return statistics are broadly similar for the more recent period, with a mean of 9.2% and a median of 9.1%.

[Please insert Table 1 about here]

2.2. Forecast Estimation

The traditional regression model, commonly used in the return predictability literature (e.g., Goyal and Welch, 2008), is specified as follows:

$$r_{t:t+h} = \alpha + \beta x_t + \varepsilon_{t:t+h} \text{ for } t = 1, \ldots, T - h \qquad (1)$$

where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$ is the average log return over a horizon of h = 10 years, r_t denotes the log return of the S&P 500 log return in year t, and x_t is one of the 10 CAPE ratio predictors. Since historical earnings data are available from 1955, we can construct the first 10-year CAPE ratio in 1964. We estimate Eq. (1) using an initial 15-year window of 1964–1978.[7] The estimated values of α and β from Eq. (1) and the CAPE ratio in 1988 are used to predict returns from 1989 to 1998. We then recursively expand the estimation window by one year and reestimate Eq. (1) to generate a rolling series of 10-year-ahead forecasts (e.g., Gao and Nardari, 2018).

While we conduct a preliminary analysis using this approach, our primary method is the constant slope approach proposed by Li, Li, Lyu, and Yu (2025), which replaces the estimated slope coefficient β with a fixed value. The authors demonstrate that using a constant predictive slope coefficient can enhance forecast accuracy by reducing estimation variance. Although this approach introduces bias when the predictor is informative, the reduction in variance yields a lower mean squared forecast error than using an estimated regression coefficient. Under the condition that the constant slope is between zero and the population coefficient, the resulting forecasts can theoretically and empirically stochastically dominate the historical mean benchmark in the first order. This implies that a strictly risk-averse investor would prefer the constant slope forecast over the historical mean forecast, the current standard for forecasting equity risk premium, as shown by Goyal and Welch (2008) and Goyal, Welch, and Zafirov (2024).

Valuation theory suggests that the predictive slope should be negative. Following Li, Li, Lyu, and Yu (2025), we adopt a constant slope of magnitude 0.02 (i.e., 1/50) and set β = -0.02. For instance, in our data, regressing standardized returns on standardized Component

[7] For the CAPE value in 1978, the corresponding average log return in Eq. (1) is computed over the 10 years from 1979 to 1988.

CAPE ratios (*Component 10-Year Earnings*, as an illustrative case) yields a slope estimate of -0.6237 (s.e. = 0.1967), implying a 95% upper confidence bound of -0.2381. This bound corresponds to an implied slope magnitude well above 0.02 (equivalently, an implied *A* well below 50), which would yield an overly aggressive return-forecasting rule. We therefore report our main results using the benchmark *A* = 50 and apply β = -0.02 uniformly to each of the 12 CAPE ratios.[8]

2.3. Predictive Performance Evaluation

We compare the forecast performance of CAPE ratios using OOS R^2, a widely used measure in the return predictability literature (e.g., Goyal and Welch, 2008; Rapach, Ringenberg, and Zhou, 2010).

The OOS R^2 is based on the mean squared error (MSE of the forecasts, calculated as follows:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2 \quad (2)$$

$$R^2_{OOS} = 1 - \frac{MSE_{CAPE}}{MSE_{HM}} \quad (3)$$

where MSE_{CAPE} is the MSE of the CAPE-based forecast, and MSE_{HM} is the MSE of a benchmark forecast based on the historical mean return. A positive OOS R^2 indicates that the CAPE model outperforms the historical mean benchmark in terms of forecast accuracy.

To assess the statistical significance of the difference between each CAPE model's OOS R^2 value and that of the historical mean benchmark, we use a moving block bootstrap to account for autocorrelation in the return series. We resample squared forecast errors and

[8] We present results for A = 100 and β = -0.01 in Appendix Table A1 and show the results are robust.

construct bootstrapped samples of length equal to that of the original series. The optimal block length is determined following Patton, Politis, and White (2009). We generate 10,000 bootstrap resamples for each CAPE model and report the one-sided *p*-value, defined as the proportion of bootstrap samples in which the CAPE model's OOS R^2 is below zero. We apply the same moving block bootstrap procedure to the MAE metric. Specifically, we resample absolute forecast errors for each CAPE model and for the historical mean model. We then report the one-sided bootstrap *p*-value equal to the proportion of 10,000 bootstrap samples in which the CAPE model's MAE exceeds that of the historical mean model, thereby testing the null hypothesis that the CAPE-based forecast does not outperform the historical mean model.

3. Baseline Results

We begin our empirical analysis with OOS results for Component CAPE ratios and traditional CAPE ratios, with forecasting conducted using both the traditional regression approach and the constant slope regression approach. The first CAPE ratio is in 1964, and we apply an initial 15-year in-sample period, which expands over time. Therefore, the CAPE ratios in the in-sample period run from 1964 to 1978, and the 10-year return forecasts in the in-sample period run from 1979 to 1988. The OOS period starts with the 1988 CAPE ratio being used to predict returns from 1989 to 1998. We employ Campbell and Shiller's (1988) approach, which involves averaging 10-year historical earnings in each instance.

The results in Table 2 demonstrate that the Aggregate CAPE ratio has no predictive ability when forecasts are generated using a traditional regression approach. This is consistent with the literature (e.g., Davis, Aliaga-Díaz, Ahluwalia, and Tolani, 2018). The results indicate that the constant slope regression approach is more effective than the traditional regression approach and, more importantly, that the Component CAPE ratio generates superior forecasts to the Aggregate CAPE ratio. The difference between the OOS R^2 values for the Component versus Aggregate CAPE ratios is 0.1282 when estimated with the constant slope approach, and 0.7441 when estimated using the traditional regression approach. We test the statistical significance of these differences using a bootstrap approach. We bootstrap years with their corresponding squared errors for each CAPE model, generating 10,000 bootstrap samples. For each bootstrap replication, we sum the squared errors over the full sample period. We then compute the ratio of the lower sum for the Component CAPE model to the higher sum for the Aggregate CAPE model. The *p*-value is defined as the proportion of bootstrap replications in which this ratio exceeds one. The results indicate that the differences are highly statistically significant.

[Please insert Table 2 about here]

In Table 3, we focus on the constant slope estimation technique and compare each of the six Component CAPE ratios with its equivalent Aggregate CAPE ratio. We can focus on the 42-year (1974–2015) OOS period because the constant slope estimation approach does not require in-sample observations, unlike the traditional regression approach. The results indicate that each of the six approaches to estimating earnings results in a larger OOS R^2 for the Component CAPE ratio than for its Aggregate CAPE ratio equivalent. We consider whether these differences are statistically different from zero by using the bootstrapped approach outlined previously. The differences range from 0.1374 for CAPE ratios computed using five years of earnings to 0.0405 for CAPE ratios estimated following the P-CAPE approach. The results indicate that we can strongly reject the null hypothesis that the differences are not zero in five of the six earnings estimation approaches. The exception is when earnings are estimated using the P-CAPE approach.[9]

[Please insert Table 3 about here]

4. Robustness Checks

As a robustness check, we also calculate the Mean Absolute Error (MAE. The MAE, as defined in the following equation, is a straightforward and intuitive measure of the average magnitude of the forecast errors:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|A_i - P_i| \quad (4)$$

where A_i is the actual 10-year return and P_i is the predicted 10-year return using a CAPE ratio. The MAE for a historical mean forecast is similarly calculated by replacing P_i with the historical mean value.

In Table 4, we present MAEs for the six Component CAPE ratios and six Aggregate CAPE ratios. Each of these is compared to the MAE from historical mean model predictions. Each of the Component CAPE models' MAEs is lower than that of the historical mean model. For instance, the MAE for the Component CAPE ratio model, based on a simple average of 10 years of earnings, is 0.0312, compared to 0.0478 for the historical mean model. This represents a 35% improvement. The null hypothesis of no difference in predictability between the

[9] In untabulated results, we consider whether the average OOS R^2 across the six Component CAPE ratios is statistically different from the average from the six Aggregate CAPE ratios. We determine this using a bootstrap procedure similar to that employed for our baseline results. We bootstrap years with their corresponding squared errors for each CAPE model, generating 10,000 bootstrap samples. For each bootstrap replication, we compute the cross-sectional average squared error across the six Aggregate CAPE models for each year and similarly compute the average squared error across the six Component CAPE models. For both groups, we then sum these annual averages over the full sample period. Next, we compute the ratio of the lower sum for the Component CAPE models to the higher sum for the Aggregate CAPE models. The *p*-value is defined as the proportion of bootstrap replications in which this ratio exceeds one. The results indicate that we can reject the null hypothesis that this difference is zero.

Component CAPE ratio models and the historical mean model can be rejected at the 1% level under the bootstrap procedures described in Section 2.3, which resamples absolute forecast errors. We are also able to reject the null hypothesis that there is no difference between the Component CAPE ratio MAE and the equivalent Aggregate CAPE ratio MAE on average[10] and for five of the six approaches to estimated earnings. The exception is for the CAPE ratio estimated using the P-CAPE approach. Moreover, we can reject the null hypothesis that the difference between the historical mean model and the MAE from each of the Aggregate CAPE ratio models is zero, using our bootstrap procedure described in Section 2.3.

[Please insert Table 4 about here]

It is important to consider the potential impact of data mining bias on the results. We do this in several ways. First, we suggest that the approach we take to calculating each Component CAPE ratio is intuitive. We simply compare each firm's current price to its historical earnings, and then value-weight each firm's individual CAPE ratio to arrive at the Component CAPE ratio for the market. This approach should reassure the reader that the Component CAPE ratio is not the result of extensive fishing through the data to determine what works best. Second, the six approaches we take to calculating average historical earnings are not unique to this paper. Rather, they have all been used in previous work that has documented reasonable justification for their development and application. Our contribution is using them

[10] We determine this using a bootstrap procedure similar to that employed for our baseline results. We bootstrap years with their corresponding absolute forecast errors for each CAPE model and generate 10,000 bootstrap samples. For each bootstrap replication, we compute the cross-sectional average absolute error across the six Aggregate CAPE models for each year and similarly compute the average absolute error across the six Component CAPE models. For both groups, we then average these annual mean values over the full sample period. Next, we compute the ratio of the lower average for the Component CAPE models to the higher average for the Aggregate CAPE models. The *p*-value is defined as the proportion of bootstrap replications in which this ratio exceeds one.

at the individual stock level and, in many instances, recent data that were not available when the models were developed.

Nonetheless, we do examine a total of 12 prediction approaches. We therefore take the conservative step of formally adjusting the results for data mining bias. We do this in two ways. First, we apply a Bonferroni adjustment. As Harvey and Liu (2020) note, this is the simplest approach. To implement this, we multiply the raw *p*-value by 12. As the results in Table 5 show, each of the Component CAPE ratio results remains statistically significant at the 5% level following this adjustment. In contrast, three of the six Aggregate CAPE ratio results are no longer statistically significantly different from zero after this data mining adjustment. Second, we apply the Benjamini–Hochberg (1995) False Discovery Rate (FDR approach (e.g., see Chordia, Goyal, and Saretto, 2020**)**. These results indicate we can reject the null hypothesis that the predictive ability of each of the CAPE ratio models is due to data mining.

[Please insert Table 5 about here]

The Shiller CAPE data, widely used by researchers in this area, are based on quarterly earnings from S&P.[11] Shiller calculates annual earnings at each quarter-end date by summing the current quarter's earnings and the earnings from the previous three quarters. The author then linearly interpolates the quarterly figures to generate monthly estimates of annual earnings. Shiller's year-end CAPE ratio is calculated by dividing the December price by the average monthly earnings over the past 120 months, starting in November. The issue here is that researchers wanting to make real-time return forecasts for the 10 years from December would not have access to the November CAPE ratio. This is because the November CAPE ratio is linearly interpolated from the September and December CAPE ratios and December

[11] See https://www.spglobal.com/spdji/en/documents/additional-material/sp-500-eps-est.xlsx.

company earnings and not released until the following year. We follow convention in our baseline tests and assume that the December CAPE ratio was available in time to make forecasts for the next 10 years. However, we note that this approach is subject to a look-ahead bias. We do not believe this will be a significant factor, given return forecasts are for 10 years, and the CAPE ratio does not normally materially change over short-term periods.

Nevertheless, we run robustness tests under the conservative assumption that the CAPE ratio from December of one year cannot be used to predict returns for the following year; rather, there is a one-year delay in return forecasts. These results are presented in Table 6. These indicate that the average OOS R^2 from the Component CAPE ratio approach is 0.5538, compared to 0.5565 in the baseline tests.

We also conduct robustness tests around the time period of the OOS period, given the evidence that the Aggregate CAPE ratio performance has declined over time (e.g., Davis, Aliaga-Díaz, Ahluwalia, and Tolani, 2018). We divide the baseline OOS period into two parts: the first is from 1974 to 1994, and the second is from 1995 to 2015. The results indicate stronger performance in the more recent time period. The average OOS R^2 from the six Component CAPE approaches is 0.6339 in the more recent period, compared to 0.4728 in the earlier period. The Component CAPE approach outperforms the Aggregate CAPE approach across all six measures in the earlier subperiod and for five of the six measures in the later subperiod.

[Please insert Table 6 about here]

5. CAPE Ratio Differences and Asset Allocation

5.1. CAPE Ratio Differences

We commence this section by discussing the differences between the Aggregate and Component CAPE ratio approaches. As noted by the S&P (2024), the total market value of stocks in the S&P 500 is scaled by a divisor to arrive at an index level. This ensures that the index level does not change when stocks are added or removed from the index. This is shown as

$$\mathbb{I}_t = \frac{\sum_i P_{i,t}}{\mathbb{D}_t} \tag{5}$$

where $P_{i,t}$ is the dollar total market value of firm *i* in year *t* and $\mathbb{D}_t$ is a divisor in year *t*, which is a scaling factor that equates adjacent-period estimates of S&P 500 total market capitalization.

Similarly, the total earnings of all stocks in the S&P 500 are divided by the same divisor (e.g., Petrick, 2001). This is shown as

$$\mathbb{E}_t = \frac{\sum_i E_{i,t}}{\mathbb{D}_t} \tag{6}$$

The average S&P 500 index earnings in the past 10 years ($\mathbb{E}_t^{10}$) is given by

$$\mathbb{E}_t^{10} = \sum_t^{t-9} \left(\frac{\sum_i E_{i,t}}{\mathbb{D}_t}\right) / 10 \tag{7}$$

The Aggregate CAPE at year *t* ($\text{CAPE}_{Agg,t}$) is therefore

$$\text{CAPE}_{Agg,t} = \frac{\text{Index Level}_t}{\text{Average 10 Year Index Earning}_t} = \frac{\mathbb{I}_t}{\mathbb{E}_t^{10}} \tag{8}$$

If we assume *D* is constant over a consecutive 10-year period,[12] drop the subscript *t*, and substitute the value of the index level and index earnings, we get

$$\text{CAPE}_{Agg} = \frac{\sum_i P_i / D}{\sum_i E_i^{10} / D} \tag{9}$$

[12] We obtain S&P 500 divisor data from LSEG and calculate annual changes. The mean of these over the sample period used in this study is just 1.1%.

where E_i^{10} is the average earning of firm i in the past 10 years. The Aggregate CAPE (CAPE_{Agg}) is therefore

$$\text{CAPE}_{Agg} = \frac{\sum_i P_i}{\sum_i E_i^{10}} \tag{10}$$

For the numerator, we multiply and divide the average 10-year earnings of the corresponding firm:

$$\text{CAPE}_{Agg} = \frac{\frac{E_1^{10}}{E_1^{10}} \cdot P_1 + \frac{E_2^{10}}{E_2^{10}} \cdot P_2 + \dots}{\sum_i E_i^{10}} \tag{11}$$

The individual CAPE for firm i (CAPE_i) is

$$\text{CAPE}_i = \frac{P_i}{E_i^{10}} \tag{12}$$

Therefore,

$$\text{CAPE}_{Agg} = \frac{E_1^{10} \cdot \text{CAPE}_1 + E_2^{10} \cdot \text{CAPE}_2 + \dots}{\sum_i E_i^{10}} \tag{13}$$

$$\text{CAPE}_{Agg} = W_1^E \cdot \text{CAPE}_1 + W_2^E \cdot \text{CAPE}_2 + \cdots \tag{14}$$

$$\text{CAPE}_{Agg} = \sum_i W_i^E \cdot \text{CAPE}_i \tag{15}$$

where $W_i^E = \frac{E_i^{10}}{\sum_i E_i^{10}}$ is the earnings weight and $\text{CAPE}_i = \frac{P_i}{E_i^{10}}$ is the CAPE of firm *i*.

This shows that CAPE_{Agg} is the earnings-weighted average of each firm's CAPE_i when the divisor is constant. We also demonstrate this numerically in the Appendix Table A2 results.

However, in reality, the divisor is not constant. We obtain these data from LSEG and calculate annual changes. The mean of these values over the sample period used in this study is just 1.1%. We therefore expect the Aggregate CAPE ratio to be very similar to the earnings-weighted Component CAPE ratio. However, this is ultimately an empirical question, and we present the results in Table 7.

These results are consistent with the equations. We compare Component CAPE ratios to Aggregate CAPE ratios and Component CAPE ratios calculated using earnings weighting. We test mean differences using *t*-tests, median differences using Wilcoxon rank sum tests on median differences, and F-tests to examine differences in variances. The results in Table 7 indicate that we can reject the null hypothesis that the mean Component CAPE ratio based on value weighting is the same as the mean Aggregate CAPE ratio for the 10-year earnings, EWMA earnings, and street earnings. We can also reject the null hypothesis that the median CAPE ratio and CAPE ratio variances are the same for the equivalent Component CAPE ratio based on value-weighting the Aggregate CAPE ratio for the earnings-weighted Component CAPE ratios.

We cannot reject the null hypothesis that the mean (median) Aggregate CAPE ratio equals the mean (median) Component CAPE ratio under earnings weighting for each approach except for the TRCAPE one. Further, we cannot reject the null hypothesis that the Aggregate CAPE ratio variance equals the Component CAPE ratio variance under earnings weighting for any of the six CAPE ratio estimation approaches.

Finally, the results indicate that we can reject the null hypothesis that the mean Component CAPE ratio based on value weighting equals the mean Component CAPE ratio based on earnings weighting for each of the six CAPE estimation ratios. We can also reject the null hypothesis that the median CAPE ratio and the variance of the CAPE ratios are equal under value and equal weighting. Overall, we conclude that the Aggregate CAPE approach is very similar to an earnings-weighted Component CAPE approach and that both differ from a value-weighted Component CAPE approach.[13]

[Please insert Table 7 about here]

5.2. Asset Allocation

In this section, we examine the asset allocation value of the CAPE predictors. We follow the approach developed by Campbell and Thompson (2008). We consider a quadratic risk-averse investor with a coefficient of relative risk aversion $\gamma = 5$ who uses a CAPE-based forecast of the 10-year market excess return, $\widehat{E_t}[R]$ and assumes the 10-year excess return variance observed in the estimation window, $V_t(R)$, will continue in the future. Under these assumptions, the optimal stock market weight is given as

$$w_t = \frac{1}{\gamma}\frac{\widehat{E_t}[R]}{V_t(R)} \quad (16)$$

and the residual weight $1 - w_t$ is allocated to the Treasury bill. Rapach, Ringgenberg, and Zhou (2016) allow leveraged and short positions in the equity market. We take a more conservative approach. In one set of results, we impose the bounds $0 \leq w_t \leq 1$, while, in the other, we allow a maximum of 50% of leverage and the bounds $0 \leq w_t \leq 1.5$. An investor who follows Eq. (16) achieves an average utility or Certainty Equivalent Return (CER) as in the following equation, where the CER is the risk-free return the investor would give up to hold the risky portfolio:

[13] In untabulated results, we generate pooled results across all six CAPE ratio estimation techniques. They show that the mean Component CAPE ratio (based on market capitalization weighting) across all six measures is 26.18. The pooled mean Aggregate CAPE ratio across all six measures is 20.81. The pooled mean earnings weighted Component CAPE ratio across all six measures is 20.69. We can strongly reject the null hypothesis that the mean Component CAPE ratio is the same as either the mean Aggregate CAPE ratio or the mean earnings-weighted CAPE ratio. However, we cannot reject the null hypothesis that the means of the Aggregate and earnings-weighted Component CAPE ratios are the same.

$$CER_{Mdl} = \hat{\mu}_{Mdl} - \frac{\gamma}{2}\hat{\sigma}^2_{Mdl} \tag{17}$$

We benchmark each CAPE strategy against three alternatives: 1) a risk-averse investor who assumes the expected return on the stock market equals its historical mean, 2) an investor who follows a static allocation of 60% stocks and 40% T-bills, and 3) an investor who invests 100% in equities. We calculate the incremental utility relative to each unconditional benchmark, denoted with the subscript *Unc*:

$$\Delta CER = \left(\hat{\mu}_{Mdl} - \frac{\gamma}{2}\hat{\sigma}^2_{Mdl}\right) - \left(\hat{\mu}_{Unc} - \frac{\gamma}{2}\hat{\sigma}^2_{Unc}\right) \tag{18}$$

The results presented in Table 8, Panel A, indicate CERs above 5% for each of the CAPE rules, and the Component CAPE CERs are greater than those from the historical mean forecasts, the 60/40 equity strategy, and the 100% equity strategy. The Aggregate CAPE CERs exceed those from the historical mean forecast and the 100% equity strategy. However, four of the six Aggregate CAPE ratio rules are not greater than for the 60/40 strategy. CERs are greater for the Component CAPE ratios than for the Aggregate CAPE ratios. However, the differences are not large. The results in Panel B are not materially different from those in Panel A. This indicates that allowing leverage does not have a big impact on the outcomes.[14] Overall, we conclude that Component CAPE ratios add value from an asset allocation perspective, although the gains are not large.

[Please insert Table 8 about here]

[14] In Appendix Table A3 we present results for $\gamma = 3$. These are qualitatively similar.

6. Conclusions

We show that price–earnings ratios are much more effective at forecasting long-term equity returns than previously thought. We focus on the widely used CAPE ratio, which smooths earnings over a historical period to account for cyclical variation. The traditional and widely used approach divides the current index price level, based on the current components of the S&P 500, by the aggregate index earnings reported over the previous 10 years. However, because stocks are added to and removed from the S&P 500 index on an annual basis, there is a mismatch between the stocks used to calculate the price level and those from which historical earnings are derived. We estimate the CAPE ratio by ensuring index alignment between the component stocks in the price numerator and earnings denominator. Our results indicate that the OOS R^2 achieved by this approach exceeds 50%.

Further analysis reveals that, while mismatches in the index components in traditional CAPE ratio analysis contribute to the outperformance of the approach we outline, the main driver is the value weighting of our individual stock CAPE ratios. In contrast, the traditional approach is more closely aligned with an earnings-weighted measure of individual stock CAPE ratios. Our results are robust to a myriad of checks.

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Table 1: Summary Statistics

	N	Mean	Std Dev	Min	P5	P25	Median	P75	P95	Max
Panel A: Aggregate and Component CAPE Ratios										
Aggregate 10-Year Earnings	61	21.65	8.95	7.83	8.75	14.70	21.24	27.28	37.71	44.20
Aggregate EWMA Earnings	61	20.82	8.16	7.71	8.57	14.68	20.65	25.89	35.24	40.64
Aggregate 5-Year Earnings	61	19.71	7.07	7.43	8.43	14.68	20.25	24.23	31.67	34.56
Aggregate 10-Year Earnings TRCAPE	61	24.41	9.23	9.79	10.78	17.74	24.75	29.52	40.54	48.11
Aggregate 10-Year Earnings P-CAPE	61	19.38	8.57	5.96	7.14	12.25	19.74	25.15	34.54	40.27
Aggregate 10-Year Street Earnings	61	18.88	7.27	7.41	8.22	13.42	18.49	22.72	31.45	37.71
Component 10-Year Earnings	61	29.74	12.59	11.34	12.76	19.90	29.23	35.17	55.39	66.61
Component EWMA Earnings	61	29.04	12.45	10.83	12.31	19.57	29.12	33.47	53.80	69.58
Component 5-Year Earnings	61	24.48	9.80	9.40	11.08	17.67	24.53	28.83	44.36	54.29
Component 10-Year Earnings TRCAPE	61	26.56	11.00	10.45	11.87	18.53	26.07	31.29	49.02	57.18
Component 10-Year Earnings P-CAPE	61	22.13	10.04	6.85	8.33	12.68	20.54	29.60	39.01	43.64
Component 10-Year Street Earnings	61	25.12	11.16	7.77	9.46	17.27	24.72	29.42	47.90	56.04
Panel B: Annualized 10-Year Log Returns										
1964–2024	51	0.098	0.049	-0.013	0.011	0.066	0.113	0.138	0.164	0.171
1973–2024	42	0.109	0.046	-0.013	0.012	0.080	0.126	0.139	0.164	0.171
1988–2024	27	0.092	0.049	-0.013	-0.007	0.067	0.091	0.127	0.164	0.171

This table reports summary statistics for various CAPE measures and annualized 10-year market returns. The CAPE ratios start in 1961 and end in 2024. The five Aggregate CAPE ratios are constructed using the S&P 500's real prices and real cap-weighted earnings over either 10-year or 5-year horizons. The CAPE ratio based on an exponentially weighted moving average EWMA places greater weight on more recent earnings, using a 10-year half-life to determine the rate of decay. The TRCAPE ratio uses a total return index that accounts for dividend reinvestment, while the P-CAPE ratio adjusts for the dividend payout ratio. Component CAPE ratios are computed by first estimating the CAPE ratio for each S&P 500 constituent and then aggregating them using cap-weighted averaging.

Table 2: Constant Slope versus Regression Approaches

	OOS R^2	BS *p*-Value
Panel A: Constant Slope Approach		
(1) *Component 10-Year Earnings*	0.5449	0.0033
(2) *Aggregate 10-Year Earnings*	0.4166	0.0565
Panel B: Regression Approach		
(3) *Component 10-Year Earnings*	0.2407	0.0741
(4) *Aggregate 10-Year Earnings*	-0.5034	0.9094
Panel C: Comparisons		
(1) – (2)	0.1282	0.0000
(3) – (4)	0.7441	0.0000
(1) – (3)	0.3041	0.0147
(2) – (4)	0.9200	0.0000

This table reports the OOS R^2 values (OOS R^2) for Campbell and Shiller's (1988) Aggregate 10-Year Earnings CAPE and for our Component 10-Year Earnings CAPE ratios, estimated using both the traditional regression approach and the constant slope approach that assumes a constant slope coefficient β = -1/50. The *p*-values assessing the statistical significance of the OOS R^2 are computed using 10,000 bootstrap samples (BS *p*-values). The OOS period starts in 1988 since the regression approach requires an in-sample estimation window.

Table 3: OOS R^2 Comparisons		
	OOS R^2	BS p-Value
(1) *Component 10-Year Earnings*	0.5752	0.0000
(2) *Component EWMA Earnings*	0.5680	0.0000
(3) *Component 5-Year Earnings*	0.5505	0.0001
(4) *Component 10-Year Earnings TRCAPE*	0.5492	0.0026
(5) *Component 10-Year Earnings P-CAPE*	0.5475	0.0000
(6) *Component 10-Year Street Earnings*	0.5486	0.0000
(7) *Aggregate 10-Year Earnings*	0.4667	0.0078
(8) *Aggregate EWMA Earnings*	0.4555	0.0129
(9) *Aggregate 5-Year Earnings*	0.4132	0.0288
(10) *Aggregate 10-Year Earnings TRCAPE*	0.4448	0.0123
(11) *Aggregate 10-Year Earnings P-CAPE*	0.5069	0.0016
(12) *Aggregate 10-Year Street Earnings*	0.4942	0.0009
(1) – (7)	0.1085	0.0000
(2) – (8)	0.1125	0.0000
(3) – (9)	0.1374	0.0000
(4) – (10)	0.1044	0.0000
(5) – (11)	0.0405	0.1939
(6) – (12)	0.0544	0.0013

This table reports the OOS R^2 values (OOS R^2) for the Aggregate and Component CAPE ratios estimated using the constant slope approach that assumes a constant slope coefficient β = -1/50. The p-values assessing the statistical significance of the OOS R^2 are computed using 10,000 bootstrap samples (BS p-values). The OOS period begins in 1974 since the constant slope approach does not require an in-sample estimation window.

Table 4: MAE Comparisons				
	MAE	HR MAE	MAE DIFF	BS *p*-Value
(1) *Component 10-Year Earnings*	0.0312	0.0478	-0.0166	0.0000
(2) *Component EWMA Earnings*	0.0317	0.0478	-0.0161	0.0000
(3) *Component 5-Year Earnings*	0.0319	0.0478	-0.0159	0.0000
(4) *Component 10-Year Earnings TRCAPE*	0.0325	0.0478	-0.0153	0.0025
(5) *Component 10-Year Earnings P-CAPE*	0.0321	0.0478	-0.0157	0.0000
(6) *Component 10-Year Street Earnings*	0.0322	0.0478	-0.0156	0.0000
(7) *Aggregate 10-Year Earnings*	0.0354	0.0478	-0.0124	0.0091
(8) *Aggregate EWMA Earnings*	0.0357	0.0478	-0.0121	0.0137
(9) *Aggregate 5-Year Earnings*	0.0365	0.0478	-0.0113	0.0275
(10) *Aggregate 10-Year Earnings TRCAPE*	0.0363	0.0478	-0.0115	0.0129
(11) *Aggregate 10-Year Earnings P-CAPE*	0.0338	0.0478	-0.0139	0.0028
(12) *Aggregate 10-Year Street Earnings*	0.0340	0.0478	-0.0138	0.0005
(1) – (7)			-0.0042	0.0000
(2) – (8)			-0.0040	0.0002
(3) – (9)			-0.0046	0.0002
(4) – (10)			-0.0038	0.0000
(5) – (11)			-0.0018	0.1558
(6) – (12)			-0.0018	0.0103

This table reports the mean absolute error (MAEs for the Aggregate and Component CAPE ratios estimated using the constant slope approach that assumes a constant slope coefficient β = -1/50. Here, HR MAE refers to the MAE from the historical mean prediction model. The statistical significance of the MAE differences is evaluated using 10,000 bootstrap samples (BS *p*-values). The OOS period begins in 1974 since the constant slope approach does not require an in-sample estimation window.

Table 5: Data Snooping and Look-Ahead Bias

Panel A: Data Snooping Robustness

	OOS R^2	Bonferroni p-Value	FDR test
(1) *Component 10-Year Earnings*	0.5752	0.0000	Reject Null
(2) *Component EWMA Earnings*	0.5680	0.0000	Reject Null
(3) *Component 5-Year Earnings*	0.5505	0.0012	Reject Null
(4) *Component 10-Year Earnings TRCAPE*	0.5492	0.0312	Reject Null
(5) *Component 10-Year Earnings P-CAPE*	0.5475	0.0000	Reject Null
(6) *Component 10-Year Street Earnings*	0.5486	0.0000	Reject Null
(7) *Aggregate 10-Year Earnings*	0.4667	0.0936	Reject Null
(8) *Aggregate EWMA Earnings*	0.4555	0.1548	Reject Null
(9) *Aggregate 5-Year Earnings*	0.4132	0.3456	Reject Null
(10) *Aggregate 10-Year Earnings TRCAPE*	0.4448	0.1476	Reject Null
(11) *Aggregate 10-Year Earnings P-CAPE*	0.5069	0.0192	Reject Null
(12) *Aggregate 10-Year Street Earnings*	0.4942	0.0108	Reject Null

Panel B: Look-Ahead Bias

	OOS R^2	BS p-Value
(1) *Component 10-Year Earnings*	0.5784	0.0000
(2) *Component EWMA Earnings*	0.5703	0.0000
(3) *Component 5-Year Earnings*	0.5466	0.0000
(4) *Component 10-Year Earnings TRCAPE*	0.5302	0.0000
(5) *Component 10-Year Earnings P-CAPE*	0.5377	0.0000
(6) *Component 10-Year Street Earnings*	0.5599	0.0000
(7) *Aggregate 10-Year Earnings*	0.5089	0.0036
(8) *Aggregate EWMA Earnings*	0.4934	0.0066
(9) *Aggregate 5-Year Earnings*	0.4416	0.0173
(10) *Aggregate 10-Year Earnings TRCAPE*	0.4887	0.0059
(11) *Aggregate 10-Year Earnings P-CAPE*	0.5469	0.0007
(12) *Aggregate 10-Year Street Earnings*	0.5205	0.0000
(1) – (7)	0.0696	0.0055
(2) – (8)	0.0769	0.0045
(3) – (9)	0.1050	0.0002
(4) – (10)	0.0414	0.1494
(5) – (11)	-0.0092	0.5343
(6) – (12)	0.0394	0.0235

This table reports the OOS R^2 values (OOS R^2) for the Aggregate and Component CAPE ratios estimated using the constant slope approach that assumes a constant slope coefficient β = -1/50. The p-values assessing the statistical significance of the OOS R^2 are computed using 10,000 bootstrap samples (BS p-values). The Bonferroni p-value is obtained by multiplying the BS p-value by 12. The FDR test is based on Benjamini and Hochberg's (1995) False Discovery Rate FDR procedure, where the null hypothesis is that the predictive ability of each of the CAPE-based models arises from data mining. In Panel B, we use the lagged one-year CAPE ratios in the prediction model to avoid potential look-ahead bias.The OOS period begins in 1974

Table 6: Subsample Periods				
	1974–1994		1995–2015	
	OOS R^2	BS *p*-Value	OOS R^2	BS *p*-Value
(1) *Component 10-Year Earnings*	0.4828	0.0000	0.6606	0.0001
(2) *Component EWMA Earnings*	0.4719	0.0000	0.6568	0.0001
(3) *Component 5-Year Earnings*	0.4484	0.0001	0.6449	0.0001
(4) *Component 10-Year Earnings TRCAPE*	0.4166	0.0020	0.6718	0.0007
(5) *Component 10-Year Earnings P-CAPE*	0.5739	0.0000	0.5230	0.0000
(6) *Component 10-Year Street Earnings*	0.4429	0.0000	0.6464	0.0001
(7) *Aggregate 10-Year Earnings*	0.3491	0.0063	0.5755	0.0070
(8) *Aggregate EWMA Earnings*	0.3246	0.0144	0.5765	0.0108
(9) *Aggregate 5-Year Earnings*	0.2835	0.0345	0.5331	0.0263
(10) *Aggregate 10-Year Earnings TRCAPE*	0.3172	0.0136	0.5628	0.0103
(11) *Aggregate 10-Year Earnings P-CAPE*	0.4327	0.0001	0.5756	0.0012
(12) *Aggregate 10-Year Street Earnings*	0.4079	0.0003	0.5740	0.0002
(1) – (7)	0.1338	0.0000	0.0851	0.0018
(2) – (8)	0.1474	0.0000	0.0803	0.0055
(3) – (9)	0.1649	0.0000	0.1119	0.0059
(4) – (10)	0.0993	0.0018	0.1090	0.0000
(5) – (11)	0.1412	0.0001	-0.0526	0.7498
(6) – (12)	0.0350	0.0642	0.0724	0.0047

This table reports the OOS R^2 values (OOS R^2) for the Aggregate and Component CAPE ratios estimated using the constant slope approach that assumes a constant slope coefficient β = -1/50. The *p*-values assessing the statistical significance of the OOS R^2 are computed using 10,000 bootstrap samples (BS *p*-values). The results are for two subsample periods: 1974–1994 and 1995–2015.

Table 7: Effects of Weighting

		10-Year Earnings	EWMA Earnings	5-Year Earnings	10-Year Earnings TRCAPE	10-Year Earnings P-CAPE	10-Year Street Earnings
(1) Component CAPE Ratio (MV Weighted)	Mean	29.74	29.04	24.48	26.56	22.13	25.12
	Median	29.23	29.12	24.53	26.07	20.54	24.72
	Max	66.61	69.58	54.29	57.18	43.64	56.04
	Min	11.34	10.83	9.40	10.45	6.85	7.77
	Std Dev	12.59	12.45	9.80	11.00	10.04	11.16
(2) Aggregate CAPE Ratio	Mean	21.65	20.82	19.71	24.41	19.38	18.88
	Median	21.24	20.65	20.25	24.75	19.74	18.49
	Max	44.20	40.64	34.56	48.11	40.27	37.71
	Min	7.83	7.71	7.43	9.79	5.96	7.41
	Std Dev	8.95	8.16	7.07	9.23	8.57	7.27
(3) Component CAPE Ratio (Earnings Weighted)	Mean	23.42	22.68	19.31	21.37	17.94	19.44
	Median	23.11	22.60	19.81	20.26	18.19	19.74
	Max	46.86	45.97	35.38	41.34	33.58	39.36
	Min	9.35	8.93	7.90	8.76	5.67	6.09
	Std Dev	9.05	8.58	6.72	8.16	7.51	8.12
Difference in Means							
(1) – (2)	*p*-value	0.0001	0.0000	0.0026	0.2437	0.1059	0.0004
(2) – (3)	*p*-value	0.2796	0.2234	0.7493	0.0567	0.3266	0.6889
(1) – (3)	*p*-value	0.0019	0.0014	0.0009	0.0038	0.0103	0.0017
Difference in Medians							
(1) – (2)	*p*-value	0.0002	0.0000	0.0082	0.4244	0.1459	0.0009
(2) – (3)	*p*-value	0.2986	0.2556	0.6523	0.0529	0.4126	0.8217
(1) – (3)	*p*-value	0.0024	0.0019	0.0018	0.0060	0.0163	0.0028
Difference in Variances							

(1) – (2)	*p*-value	0.0090	0.0013	0.0127	0.1771	0.2221	0.0011
(2) – (3)	*p*-value	0.9302	0.6954	0.6974	0.3426	0.3098	0.3912
(1) – (3)	*p*-value	0.0115	0.0045	0.0041	0.0222	0.0261	0.0150

This table reports the differences in the means, medians, and variances between the Aggregate CAPE, Component MV-weighted CAPE (as in previous tables), and Component earnings-weighted CAPE ratios. The *p*-values are obtained from parametric tests for differences in means, Wilcoxon rank sum tests for differences in medians, and *F*-tests for differences in variances.

Table 8: Asset Allocation with Gamma = 5				
		CER Difference from		
	CER Level	Historical Mean	60% Equity	100% Equity
Panel A: No Leverage and No Short Sale Constraints				
(1) *Component 10-Year Earnings*	0.0581	0.0072	0.0030	0.0255
(2) *Component EWMA Earnings*	0.0571	0.0062	0.0020	0.0246
(3) *Component 5-Year Earnings*	0.0576	0.0067	0.0025	0.0251
(4) *Component 10-Year Earnings TRCAPE*	0.0597	0.0088	0.0046	0.0272
(5) *Component 10-Year Earnings P-CAPE*	0.0566	0.0057	0.0015	0.0241
(6) *Component 10-Year Street Earnings*	0.0554	0.0045	0.0003	0.0229
(7) *Aggregate 10-Year Earnings*	0.0547	0.0038	-0.0004	0.0222
(8) *Aggregate EWMA Earnings*	0.0546	0.0038	-0.0005	0.0221
(9) *Aggregate 5-Year Earnings*	0.0537	0.0028	-0.0014	0.0212
(10) *Aggregate 10-Year Earnings TRCAPE*	0.0540	0.0031	-0.0012	0.0214
(11) *Aggregate 10-Year Earnings P-CAPE*	0.0556	0.0047	0.0005	0.0231
(12) *Aggregate 10-Year Street Earnings*	0.0566	0.0058	0.0015	0.0241
Panel B: Leverage and No Short Sale Constraints				
(1) *Component 10-Year Earnings*	0.0579	0.0078	0.0028	0.0254
(2) *Component EWMA Earnings*	0.0570	0.0069	0.0019	0.0245
(3) *Component 5-Year Earnings*	0.0574	0.0074	0.0023	0.0249
(4) *Component 10-Year Earnings TRCAPE*	0.0597	0.0096	0.0046	0.0272
(5) *Component 10-Year Earnings P-CAPE*	0.0562	0.0062	0.0011	0.0237
(6) *Component 10-Year Street Earnings*	0.0552	0.0051	0.0001	0.0227
(7) *Aggregate 10-Year Earnings*	0.0547	0.0047	-0.0004	0.0222
(8) *Aggregate EWMA Earnings*	0.0546	0.0046	-0.0005	0.0221
(9) *Aggregate 5-Year Earnings*	0.0537	0.0036	-0.0014	0.0212
(10) *Aggregate 10-Year Earnings TRCAPE*	0.0540	0.0039	-0.0012	0.0214
(11) *Aggregate 10-Year Earnings P-CAPE*	0.0556	0.0055	0.0005	0.0231

(12) *Aggregate 10-Year Street Earnings*	0.0566	0.0065	0.0015	0.0241

This table reports the Certainty Equivalent Returns (CERs for the CAPE-based strategy, assuming no short sale constraints and evaluating performance both with and without leverage. The historical mean refers to the historical mean return benchmark method, and 60% (100%) equity denotes an asset allocation strategy consisting of 60% (100%) equity and 40% (0%) Treasury bills. Predicted returns are estimated using a regression that assumes a constant slope coefficient β = -1/50. The term γ is the coefficient of relative risk aversion. The start date is 1974.

Table A1: Constant Slope of -1/100

	OOS R^2	BS p-Value
(1) *Component 10-Year Earnings*	0.3411	0.0000
(2) *Component EWMA Earnings*	0.3381	0.0000
(3) *Component 5-Year Earnings*	0.3269	0.0000
(4) *Component 10-Year Earnings TRCAPE*	0.3330	0.0009
(5) *Component 10-Year Earnings P-CAPE*	0.3118	0.0000
(6) *Component 10-Year Street Earnings*	0.3251	0.0000
(7) *Aggregate 10-Year Earnings*	0.2896	0.0033
(8) *Aggregate EWMA Earnings*	0.2831	0.0062
(9) *Aggregate 5-Year Earnings*	0.2600	0.0137
(10) *Aggregate 10-Year Earnings TRCAPE*	0.2750	0.0064
(11) *Aggregate 10-Year Earnings P-CAPE*	0.3105	0.0007
(12) *Aggregate 10-Year Street Earnings*	0.2917	0.0005
(1) – (7)	0.0515	0.0000
(2) – (8)	0.0551	0.0000
(3) – (9)	0.0669	0.0001
(4) – (10)	0.0581	0.0000
(5) – (11)	0.0013	0.4631
(6) – (12)	0.0334	0.0015

This table reports the OOS R^2 values (OOS R^2) for the Aggregate and Component CAPE ratios estimated using the constant slope approach that assumes a constant slope coefficient β = -1/100. The p-values assessing the statistical significance of the OOS R^2 are computed using 10,000 bootstrap samples (BS p-values). The OOS period begins in 1974 since the constant slope approach does not require an in-sample estimation window.

Table A2: Component vs. Aggregate CAPE Computations

	Time	Stocks					Market
		A	B	C	D	E	
Earnings	*t*	1,000	1,000	4,000	2,000	3,000	11,000
	t - 1	1,030	1,040	3,960	2,000	3,030	11,060
	t - 2	1,061	1,082	3,920	2,000	3,060	11,123
	t - 3	1,093	1,125	3,881	2,000	3,091	11,190
	t - 4	1,126	1,170	3,842	2,000	3,122	11,260
	t - 5	1,159	1,217	3,804	2,000	3,153	11,333
	t - 6	1,194	1,265	3,766	2,000	3,185	11,410
	t - 7	1,230	1,316	3,728	2,000	3,216	11,490
	t - 8	1,267	1,369	3,691	2,000	3,249	11,575
	t - 9	1,305	1,423	3,654	2,000	3,281	11,663
	Average	1,146	1,201	3,825	2,000	3,139	11,310
Market Cap	*t*	10,000	20,000	30,000	40,000	50,000	150,000
Aggregate CAPE	*t*						13.26
Individual CAPEs	*t*	8.72	16.66	7.84	20.00	15.93	
Earnings-Weighted Component CAPE	*t*						13.26
Market Cap-Weighted Component CAPE	*t*						15.01

This table illustrates the computation of stock-level and market-level CAPEs in a market consisting of five stocks. The Aggregate CAPE is computed following Campbell and Shiller (1988). Stock-level CAPEs are calculated analogously and then aggregated to the market level using two alternative weighting schemes: earnings weights and market-capitalization weights.

Table A2: Asset Allocation with Gamma = 3

	CER Level	CER Difference from		
		Historical Mean	60% Equity	100% Equity
Panel A: No Leverage and No Short Sale Constraints				
(1) *Component 10-Year Earnings*	0.0657	0.0085	-0.0001	0.0045
(2) *Component EWMA Earnings*	0.0641	0.0069	-0.0017	0.0029
(3) *Component 5-Year Earnings*	0.0651	0.0079	-0.0007	0.0039
(4) *Component 10-Year Earnings TRCAPE*	0.0692	0.0120	0.0034	0.0080
(5) *Component 10-Year Earnings P-CAPE*	0.0615	0.0043	-0.0044	0.0002
(6) *Component 10-Year Street Earnings*	0.0616	0.0044	-0.0042	0.0004
(7) *Aggregate 10-Year Earnings*	0.0604	0.0032	-0.0054	-0.0008
(8) *Aggregate EWMA Earnings*	0.0604	0.0032	-0.0054	-0.0008
(9) *Aggregate 5-Year Earnings*	0.0589	0.0017	-0.0069	-0.0023
(10) *Aggregate 10-Year Earnings TRCAPE*	0.0592	0.0020	-0.0066	-0.0020
(11) *Aggregate 10-Year Earnings P-CAPE*	0.0615	0.0043	-0.0044	0.0002
(12) *Aggregate 10-Year Street Earnings*	0.0630	0.0058	-0.0028	0.0018
Panel B: Leverage and No Short Sale Constraints				
(1) *Component 10-Year Earnings*	0.0665	0.0113	0.0007	0.0053
(2) *Component EWMA Earnings*	0.0649	0.0097	-0.0009	0.0037
(3) *Component 5-Year Earnings*	0.0658	0.0105	0.0000	0.0046
(4) *Component 10-Year Earnings TRCAPE*	0.0696	0.0144	0.0038	0.0084
(5) *Component 10-Year Earnings P-CAPE*	0.0641	0.0088	-0.0017	0.0029
(6) *Component 10-Year Street Earnings*	0.0623	0.0070	-0.0036	0.0010
(7) *Aggregate 10-Year Earnings*	0.0608	0.0056	-0.0050	-0.0004
(8) *Aggregate EWMA Earnings*	0.0607	0.0055	-0.0051	-0.0005
(9) *Aggregate 5-Year Earnings*	0.0592	0.0039	-0.0066	-0.0020
(10) *Aggregate 10-Year Earnings TRCAPE*	0.0595	0.0043	-0.0063	-0.0017
(11) *Aggregate 10-Year Earnings P-CAPE*	0.0623	0.0071	-0.0035	0.0011

(12) *Aggregate 10-Year Street Earnings*	0.0641	0.0088	-0.0018	0.0028

This table reports the Certainty Equivalent Return (CER for the CAPE-based strategy, assuming no short sale constraints and evaluating performance both with and without leverage. The historical mean refers to the historical mean return benchmark method, and 60% (100%) equity denotes an asset allocation strategy consisting of 60% (100%) equity and 40% (0%) Treasury bills. Predicted returns are estimated using a regression that assumes a constant slope coefficient β = -1/50. The term γ is the coefficient of relative risk aversion. The start date is 1974.