Uncloaking CAPE: A New Look at an Old Valuation Ratio

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This version 2/8/2016

Abstract

Professor Robert Shiller's Cyclically Adjusted Price-Earnings (CAPE) Ratio has proven to be a powerful descriptor, as well as a useful predictor, of long-term equity returns in the United States and some global markets. In recent years, though, it has been criticized for being overly pessimistic about the prospects for equity returns, its lack of robustness to distortions in corporate earnings, and for overstating the predictability of returns at long horizons on account of overlapping observations and endogeneity, particularly when estimated using Ordinary Least Squares (OLS).

In this paper, we explore various definitions of CAPE, present new construction techniques that make it robust to a wide range of accounting and index construction biases as well as to changing fundamentals in equity markets, and evaluate its forecasts using econometric methods that account for endogeneity and overlapping observations. We show that most of these enhancements have a minimal impact on CAPE for the US equity market, but can prove useful in smaller markets and in markets that have experienced significant dislocations. We also show that certain accounting flow variables such as cash flow and revenues can be useful supplements to earnings and cyclically adjusted earnings.

Introduction and Overview

Since its publication in Campbell and Shiller (1998), CAPE (an acronym for Cyclically Adjusted P/E), which is defined to be the ratio of an equity index's price level to the ten-year average of its real (i.e. inflation adjusted) earnings, has become a popular measure of equity market valuation. CAPE is not a new idea: it has its roots in Graham and Dodd's *Security Analysis* (1934), in which the authors urge investors not to focus on a company's current earnings, but instead to average its earnings over a business cycle of seven to ten years. But their suggestion did not become standard practice, and Campbell and Shiller's (1988) application of the averaging step to the entire equity market was novel, as was their introduction of an inflation adjustment to make earnings more comparable over a decade.

It was but a short step from using CAPE to forecast long horizon returns to using it as a market timing tool, and CAPE soon attracted criticism. If periods of overvaluation are identified by their elevated level of CAPE relative to its long term average from January 1881 to the end of the prior month, the market has appeared undervalued in only 16 out of the 336 months from January 1987 to December 2014. Furthermore, these periods of undervaluation were concentrated in two clusters: one after the crash of 1987 (9 out of 13 months following October 1987) and the other following the collapse of Lehman Brothers in September 2008 (7 consecutive months starting in November 2008).

A variety of enhancements have been proposed to rectify CAPE's shortcomings. Siegel (2013) suggests the use of per-share NIPA earnings in place of as-reported earnings, which can be distorted by one-time write-downs, and correcting for trend changes in per-share earnings growth. In an interview with Alan Abelson (1998), John Hussman proposes using the ratio of price to ten-year peak earnings. Asness (2012) explores the use of the median in place of the mean to make CAPE robust to outliers. Unfortunately, none of these modifications has proven to substantially improve upon the ability of the basic CAPE methodology to describe and forecast returns, which begs the question of whether CAPE can be improved upon at all. We believe it can, and in this article, we constructively show how, by addressing the following three questions:

1. **Why does CAPE predict equity market returns?** Is there a theoretical relationship between CAPE and the prospective return of equities?

2. **How should CAPE be constructed?** Should its denominator be the average of reported earnings, operating earnings, per-share NIPA earnings or some other measure of corporate activity such as operating cash flow, dividends or revenues? Should a robust measure of location be used in place of the sample mean? Should past earnings be scaled by CPI, GDP or revenues? How should we account for changes in index composition - should we average the past earnings of the index or instead aggregate and average the historical earnings of its current constituents? Should we take into account the secular decline in corporate tax rates and the increased rate of earnings growth?

3. **How should it be used, and how should its efficacy be evaluated?** Should CAPE be used to forecast real or nominal returns, and how should the significance of its estimates be evaluated? Should it be used as an estimator of long horizon returns or as a market timing tool? Can it be used for cross-country or cross-sector comparisons?

The remainder of this article is organized as follows. We first construct a simple model that illuminates the relationship between CAPE and the expected return of the market, show how it can be adapted to use variables other than earnings, and how its parameters can be estimated using Ordinary Least Squares (OLS). Following this, we describe our datasets and explore various construction methods and weighting schemes, and show how they impact CAPE in the U.S. and in Iceland. We then determine the ability of CAPE and its variants to forecast real and nominal returns in the U.S. over different periods, evaluate the significance of our results using a scaled *t*-test and simulations, and identify those changes to its definition and construction that most enhance its predictive power and robustness. Next, we repeat a subset of these tests using our more limited international dataset, and conclude by estimating the current 10 year forward return of the S&P 500, and by making concrete recommendations for CAPE's construction and use.

Why Does CAPE Predict Equity Market Returns?

We start our discussion of CAPE with Williams (1938) Dividend Discount Model (DDM), which asserts that the current price of a security (or the market), P_t, is the present value of its expected future per-share dividends $E[D_{t+i}], i > 0$, discounted at its expected return $E[r]$:

$$P_t = \sum_{i>0} \frac{E[D_{t+i}]}{(1+E[r])^i}. \tag{1}$$

If we have estimates of future dividends, we can solve equation (1) and (in principle at least) obtain an expression for $E[r]$, but it proves profitable to first restate the DDM in terms of future earnings (E_{t+i}) and book values (B_{t+i}) using the clean surplus relationship, which asserts that the change in book value from one period to the next equals retained earnings, i.e.

$$B_{t+1} - B_t = E_{t+1} - D_{t+1}. \tag{2}$$

Frankel and Lee (1998) show that the clean surplus relationship is almost always satisfied under GAAP accounting, and they, along with Claus and Thomas (2001), substitute equation (2) into equation (1) and rearrange terms to get

$$P_t = B_t + \sum_{i>0} \frac{E[(ROE_{t+i} - E[r]) \times B_{t+i-1}]}{(1+E[r])^i}, \tag{3}$$

where $ROE_{t+i} = \frac{E_{t+i}}{B_{t+i-1}}$ is the return on equity in period $t+i$. Equation (3) appears less tractable than equation (1), but holds several advantages in practice:

1. Its inputs are more readily available, as analysts more commonly forecast earnings than dividends,
2. It is insensitive to the division of shareholder returns between dividends and share buybacks,
3. It makes it easy to enforce standard economic conditions such as the eventual convergence of the return on capital (ROE) to the cost of capital ($E[r]$), and
4. It can be manipulated to give a simple closed form expression for $E[r]$ in terms of the Earnings Yield.

Philips (1999, 2003) assumes that ROE is time invariant, that per-share earnings grow at a constant rate g, and that all profits in excess of what is needed to sustain earnings growth are returned to investors, and, starting with equation (3), derives the following closed form expression for $E[r]$:

$$E[r] \quad = \quad E[g] \times \left(1 - \frac{B_t}{P_t}\right) + \frac{E[E_{t+1}]}{P_t}. \tag{4}$$

Equation (4) has an intuitive explanation: In the absence of growth ($E[g] = 0$), the security behaves like a perpetual bond, and its expected return equals its earnings yield. On the other hand, if the firm's earnings grow, the expected return increases as well, but not in direct proportion to growth, as a fraction $\left(1 - \frac{B_t}{P_t}\right)$ of the growth must be reinvested in assets that are required to support this growth. Unfortunately, earnings estimates are not available in the U.S. prior to 1976, and in order to allow studies of the stock market going back to 1881, Campbell and Shiller (1998) proxy the expected prospective earnings of the S&P 500 by averaging its real (i.e. inflation adjusted) earnings for the past ten years, i.e.,

$$E[E_{t+1}] \quad = \quad \beta_t \times \frac{1}{10} \times \sum_{0 \le i < 10} \frac{CPI_t}{CPI_{t-i}} E_{t-i}. \tag{5}$$

where CPI_t is the consumer price index at time *t*, and the constant β_t ensures that the equality holds at all times. Substituting equation (5) into equation (4) gives

$$\begin{aligned} E[r] \quad &= \quad E[g] \times \left(1 - \frac{B_t}{P_t}\right) + \beta_t \times \frac{\frac{1}{10} \times \sum_{0 \le i < 10} \frac{CPI_t}{CPI_{t-i}} E_{t-i}}{P_t} \\ &= \quad E[g] \times \left(1 - \frac{B_t}{P_t}\right) + \beta_t \times \frac{1}{CAPE_t} \end{aligned} \tag{6}$$

where

$$\frac{1}{CAPE_t} \quad = \quad \frac{\frac{1}{10} \times \sum_{0 \le i < 10} \frac{CPI_t}{CPI_{t-i}} E_{t-i}}{P_t}. \tag{7}$$

Equation (6) makes clear the linear relationship between 1/CAPE and expected return. If we assume that expected returns translate to realized returns with some additive noise, we can estimate equation (6) using OLS. If we had access to historical estimates of long term earnings growth and book value measured at replacement cost, we could estimate equation

(6) using a bivariate regression. Unfortunately, we know of no source for this data, and therefore estimate it using a univariate regression. To do so, we map the first term $E[g] \times \left(1 - \frac{B_t}{P_t}\right)$ to a constant α, replace the time varying multiplier β_t by a constant β, and write:

$$r_{t,t+1} = \alpha + \beta \times \frac{1}{CAPE_t} + \varepsilon_{t,t+1}, \; t = 0,1,2, \cdots T-1, \tag{8}$$

which generalizes naturally to multiple periods as:

$$r_{t,t+q} = \alpha + \beta \times \frac{1}{CAPE_t} + \varepsilon_{t,t+q}, \; t = 0,1,2, \cdots T-q-1. \tag{9}$$

where $r_{t,t+q}$ is the *annualized* return from *t* to *t*+*q*, and $\varepsilon_{t,t+q}$ is a noise term. Stambaugh (1986, 1999) further allows the predictor to evolve in accordance with its own evolution equation:

$$\frac{1}{CAPE_{t+1}} = \mu + \rho \times \frac{1}{CAPE_t} + \delta_{t,t+1}. \; t = 0,1,2, \cdots T-1. \tag{10}$$

Equation (7) is the ratio of a flow (Cyclically Adjusted Earnings) to a stock (Price), and we could, in principle, replace the numerator with a suitably scaled multiple of some other flow that proxies the equity holder's share of corporate income (e.g. operating earnings, per-share NIPA earnings, cash flow, revenues or dividends), and the denominator with some other stock (e.g. book value of equity, enterprise value) that proxies the value of the assets used to generate the chosen flow.

Campbell and Shiller's use of price as the stock is logical, as the forward return of an asset is inversely proportional to its purchase price, and we so follow their practice, but we test a variety of flows for use in the numerator. To do so, we need only replace $\frac{1}{CAPE_t}$ in equations (8) – (10) with $\frac{F_t}{P_t}$, where F_t is the value of the candidate flow during period *t*, and P_t is the price at the end period *t*. Unfortunately, analysts do not produce forward estimates for most flows, but competition exerts a powerful restraining force on profitability, and it is likely that the future value of many flows will be similar to their recent historical averages.

Data Sets

Our longest data set is for the U.S. Equity market, and is obtained from Professor Robert Shiller's website at http://www.econ.yale.edu/~shiller/data.htm. It covers the period 1925 to 2014 for the S&P 500 and its predecessors, and provides prices, dividends, earnings and CPI levels. We obtain annual returns for the S&P 500 from Professor Aswath Damodaran's website at http://pages.stern.nyu.edu/~adamodar/New_Home_Page/datacurrent.html. In addition, we have a shorter data set from a paper copy of the S&P Capital IQ Analyst's Handbook, as well as from Dow Jones S&P Indices' website. This data set includes:

1. Annual as-reported earnings and dividends per share as well as high, low, and closing prices for the S&P 500 from 1967 to 2014.
2. Annual operating earnings per share for the S&P 500 from 1988 to 2014.
3. Annual cash flow per share for the S&P 500 from 1977 to 2014.
4. Annual revenues per share for the S&P 500 from 1992 to 2014.
5. Quarterly returns for the S&P 500 from 1936 to 1969 and monthly returns thereafter.
6. Annual revenues, operating earnings, as-reported earnings, dividends per share as well as high and low prices for the S&P 425 Industrials from 1946 to 1966.
7. Annual revenues, operating earnings, as-reported earnings and dividends per share as well as high and low prices for the S&P 400 Industrials from 1957 to 1987.
8. Annual revenues, operating earnings, as-reported earnings and dividends per share as well as high, low, and closing prices for the S&P Industrials from 1967 to 2007.
9. Annual cash flow per share for the S&P Industrials from 1977 to 2007.

Some data items have a longer history than others. Cash flow is reported starting in 1977 for all indices, but operating earnings and revenues are reported over different time periods for different indices. We found that we could quite accurately extend the history of revenues for the S&P 500 back to 1946 using the following insight: The S&P Industrials constitute a significant portion of the S&P 500, and the year-end Price to Sales ratio of the S&P 500 would likely have been similar to that of the S&P 425 Industrials Index (from 1946 to 1966), and to that of the S&P Industrials Index (from 1967 to 1991).

We therefore divide the price level of the S&P 500 Index by the Price to Sales ratio of one of these two Industrials indices to obtain an estimate of its per share revenues. From 1967 to 1991, this procedure is straightforward, as we have both the per-share revenues and the closing price of the S&P Industrials. From 1946 to 1966, we have the per-share revenues, but only the high and low prices in each year, of the S&P 425 industrials. We therefore estimate the per-share revenues of the S&P 500 as follows:

1. In each year, determine the high (P_H), low (P_L) and closing price (P_C) of the S&P 500, and the relative position $\left(\frac{P_H - P_C}{P_H - P_L}\right)$ of the closing price within this range.
2. Assume that the closing price of the S&P 425 Industrials lies at the same percentile of its range as the S&P 500.
3. Estimate the per-share revenues of the S&P 500 using the formula

$$\text{Per} - \text{Share Revenues (S\&P 500)} \approx \text{Per} - \text{Share Revenues (S\&P 425 Industrials)} \times \frac{\text{Closing Price } (S\&P\ 500)}{\text{Estimated Closing Price } (S\&P\ 425\ Industrials)} \quad (11)$$

From 1967 to 2007, over which period we have high, low and closing prices for both indices, our approximation estimates the per-share cash flow of the S&P 500 with a mean error of -3.9% and a standard deviation of 3.5%, and its per-share revenues with a mean error of 2.3% and a standard deviation of 3.9%. It proves far less successful at estimating operating earnings – the mean error is 151.6% with a standard deviation of 41.4%. As cash flow data for both indices goes back only to 1977, we cannot extend our history of cash flow using this method, but we can, and do, use it to extend the history of per-share revenues back to 1946.

This gives us two sets of data for the S&P 500 – one official, with data going back to 1988 (for operating earnings), to 1977 (for cash flow), to 1967 (for earnings and dividends), to 1946 (for revenues) and to 1936 (for prices and returns) – and the other going back to 1925, with data on earnings, dividends, prices and returns from Professors Shiller's and Damodaran's web sites. We also obtain a history of U.S. Nominal GDP from the BEA. In addition, we have access to Compustat data from 1979 onwards for U.S. companies, and use this data to analyse a variety of alternative constructions for CAPE. We measure earnings using Compustat item IB (Income Before Extraordinary Items). As we do not have access to a history of the constituents of the S&P500, we proxy it when required by the largest 500 companies ranked by their market capitalization at the start of each year.

We also have access to a limited set of country level earnings and price data from MSCI for thirteen countries from 1985 to 2014, and to an extremely limited dataset with only the historical earnings, market values, and revenues of the constituents of OMX Iceland 15 Index as of December 31, 2007 and December 31, 2008.

Constructing CAPE: Enhanced Construction Methods

1. Alternative Flows

We start our exploration of CAPE by listing a set of flows that can be used in conjunction with the various construction techniques next to create variables for use on the right hand side of equations (8) – (10). Our flows include:

1. Most recent year's as-reported earnings (from 1925 to 2014): E_t
2. Most recent year's dividends (from 1925 to 2014): D_t
3. Most recent year's revenues (from 1946 to 2014): S_t
4. Most recent year's cash flow (from 1977 to 2014): CF_t
5. Most recent year's operating earnings (from 1988 to 2014): OE_t

We later explore the ability of each of these flows to predict the forward returns of the S&P 500 over a range of forecast horizons and over various periods of time determined by the availability of data.

2. Robust Measures of Location

Over longest period for which we have data for each our chosen variables, the volatilities of the fractional annual change in as-reported earnings, dividends, revenues, cash flow and operating earnings (i.e. the standard deviations of $\frac{E_t - E_{t-1}}{E_{t-1}}$, $\frac{D_t - D_{t-1}}{D_{t-1}}$, $\frac{S_t - S_{t-1}}{S_{t-1}}$, $\frac{CF_t - CF_{t-1}}{CF_{t-1}}$ and $\frac{OE_t - OE_{t-1}}{CF_{t-1}}$) are 33.8%, 11.2%, 7.7%, 15.5% and 17.7% respectively. As-reported earnings are significantly more volatile than dividends, revenues, cash flow and operating earnings, but their volatility can be tamed by averaging, and this is, in effect, what Campbell and Shiller achieve with their computation of CAPE.

The volatility of non-overlapping 10 year fractional changes in as-reported earnings ranges from 7.5% to 15.4% (depending on the starting year), with an average of 10.2%, a reduction by approximately a factor of $\sqrt{10}$ from its one-year volatility of 33.8%. That said, while the sample mean has an efficiency[1] of 1, it has a breakdown point[2] of 0 – even a single outlier can cause an arbitrarily large error in its estimate of the true mean. We therefore test two alternative measures of location that make different trade-offs between robustness and efficiency.

1. **The 10-year median**. The median is exceptionally robust, and has a breakdown point of 50% in large samples. In a sample of size 10, it is robust to 4 outliers. Against this, its asymptotic efficiency is 0.64 for normally distributed data, and it can be slow to respond to changes in the mean that are not reflected in the central observations.

2. **The 10-year Hodges–Lehmann mean**[3]. The Hodges–Lehmann mean (Hodges and Lehmann (1963)) has a breakdown point of 29.3% in large samples, which is lower than that of the median, but which is still adequate for many purposes. In a sample of size 10, it is robust to 2 outliers. Its efficiency is 0.95 for normally distributed random variables, and it does not get stuck at the central observations as does the median.

We test the impact of our three proposed measures of location (the mean, the median, and the Hodges–Lehmann mean) by computing CAPE for the S&P 500 over the period 1935-2014, and the results are plotted in Figure 1. The three estimators of location work about equally well, though the median and the Hodges–Lehmann mean reject the sharp drop in earnings in

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[1] The efficiency is the minimum possible variance for an unbiased estimator divided by its actual variance, and is bounded above by 1.

[2] The breakdown point of an estimator is the maximum proportion of arbitrarily large errors that it can tolerate in its inputs without causing the error in its output to become unbounded.

[3] The Hodges–Lehmann estimate of the mean of a sequence $\{x_i\}$ is given by $median\{(x_i + x_j)/2\}$.

2008 better than the mean. We recommend the routine use of the Hodges–Lehmann mean on account of its high efficiency and its reasonable protection against outliers.

3. Alternative Weighting Schemes for Historical Flows

Next, we consider three weighting schemes that can be used when averaging past flows. While we describe them in terms of the ten-year mean applied to earnings, they can just as well be specified in terms of any measure of location, and can be applied to any flow.

1. **CPI Weights**. When computing a ratio at time *t*, earnings at time $t - \tau$ is weighted by $\frac{CPI_t}{CPI_{t-\tau}}$, where CPI_t is the level of the Consumer Price Index at time *t*. While this scaling does make past earnings more commensurable with current earnings by accounting for inflation, earnings tend to grow faster than consumer prices over time, and CPI weights do not automatically adapt to changes in the growth rate of earnings. Formally, we write:

$$\begin{aligned} \text{CPI Weighted Earnings}_t &= \frac{1}{10} \times \sum_{\tau=0}^{9} E_{t-\tau} \times \frac{CPI_t}{CPI_{t-\tau}} \\ &= \frac{CPI_t}{10} \times \sum_{\tau=0}^{9} \frac{E_{t-\tau}}{CPI_{t-\tau}} \ . \end{aligned} \tag{12}$$

2. **Revenue Weights**. In a competitive economy we expect margins to be relatively stable over the long term, and hence for earnings to grow more in line with revenues than with CPI. Revenue weighted earnings should, therefore, be more comparable across time than CPI weighted earnings, and we therefore write:

$$\begin{aligned} \text{Revenue Weighted Earnings}_t &= \frac{1}{10} \times \sum_{\tau=0}^{9} E_{t-\tau} \times \frac{S_t}{S_{t-\tau}} \\ &= \frac{S_t}{10} \times \sum_{\tau=0}^{9} \frac{E_{t-\tau}}{S_{t-\tau}} \ , \end{aligned} \tag{13}$$

   where S_t is the per-share revenues of the index at time *t*.

   Revenue weighting is robust to changes in earnings growth rates driven by changes in productivity growth and dividend policy, both of which should induce corresponding changes in earnings growth. Equation (13) admits an alternative interpretation: Revenue weighted earnings are the product of current per-share revenues and the average of past profit margins. If profit margins are mean reverting (Figure 2, which displays the growth rate of earnings relative to CPI, revenues, and GDP, suggests that they are), the average of past margins should be a good estimator of future margins.

3. **GDP Weights**. In the event that information on revenues is not available, we can proxy revenues by nominal GDP, with the assumption that growth in corporate revenues mirror growth in Nominal GDP (though the 1939–1944 period provides a striking counterexample), and therefore write:

$$\text{GDP Weighted Earnings}_t = \frac{1}{10} \times \sum_{\tau=0}^{9} E_{t-\tau} \times \frac{GDP_t}{GDP_{t-\tau}} . \tag{14}$$

Ideally, the long-term growth rate of the weighting variable will be identical to that of earnings, but without most of its short-term fluctuations, so that all ten years' earnings are about equally weighted. Figure 2 displays the evolution of $\left\{\frac{E_t}{CPI_t}\right\}$, $\left\{\frac{E_t}{S_t}\right\}$ and $\left\{\frac{E_t}{GDP_t}\right\}$ over time, with each sequence scaled to an initial value of 1 to facilitate comparisons with each other.

From 1925 – 2014, earnings grew faster than CPI (by 2.1% per annum) and slower than GDP (by 0.9% per annum). From 1946 – 2014, the per-share earnings of the S&P 500 grew faster than CPI (by 3.3% per annum), Nominal GDP (by 0.3% per annum) and per-share revenues (by 0.8% per annum). A large part of the drift relative to GDP occurs from 1939 – 1944, when nominal GDP grew by 144% on account of the vast increase in government expenditure during World War II, while corporate earnings rose only by 7%. This illustrates the dilution effect that Arnott and Bernstein (2003) describe – many enterprises created during World War II were not new private enterprises, but defence industries owned by the government, and whose earnings and revenues were not reflected in those of the S&P 500.

We recommend that flows, in general, and earnings, in particular, be weighted by revenues whenever possible, as they are more likely to grow in line with revenues than with CPI. If revenues are unavailable, we recommend the use of GDP weights, provided that the growth rate of GDP is not markedly different from that of earnings. From a practical perspective, the impact of modifying the weighting scheme in the U.S. is small. Figure 3 displays the value of CAPE computed using each of these three weighting schemes, and with the mean as the measure of location. It is striking how similar the three lines are, particularly after 1955, when revenue weighted CAPE first becomes available.

4. Addressing Time Variation in Index Composition

Another enhancement we test is a method by which to account for the changing composition of the stock market. Figure 4 displays the sector weights of our S&P 500 proxy, as defined by its Global Industry Classification Standard (GICS) Level 1 sectors, from 1980 to 2014. Sector weights exhibit substantial time variation: in 1980, the Energy sector was two and a half times as large as the Information Technology Sector. Nineteen years later, it had shrunk to one-eighth the size of the Information Technology Sector.

We might expect the Technology sector to exhibit a higher CAPE than the Energy sector on account of the high expectations of growth embedded in its price (see Ural, Lazanas, Zhuang and Staal (2012) for different ways in which to normalize CAPE across sectors to make them more comparable), and can account for this by constructing a hypothetical earnings series for the stock market with its *current* sector composition. Our construction is general: it is not restricted to sectors, but can be applied to any decomposition of an index, up to and including its individual constituents. When computing a sector adjusted CAPE at time *t*, we define the sector-adjusted earnings for the market at time *t-i* to be

$$E_{t-i}^{sector\ adjusted} = \sum_j \frac{w_t^j}{w_{t-i}^j} \times E_{t-i}^j, \qquad (15)$$

where E_{t-i}^j and w_{t-i}^j are the earnings and the weight respectively of the j^{th} sector at time *t-i*, and w_t^j is the *current* weight of sector *j*. Once we have computed the adjusted historical earnings of the index, we can weight and average them over time using any weighting scheme and any measure of location.

For the purposes of illustration, we use CPI weights and the arithmetic mean as our measure of location, and display in Figure 5 the impact of this enhancement on CAPE for our S&P 500 proxy using Compustat data from 1989 to 2014. Even though this enhancement makes intuitive sense, it, like the last two enhancements described, does not have a significant impact on either the level or the evolution of CAPE in the U.S., as sectors are high-level financial instruments (the US stock market has only 10 sectors), and the set of sectors does not change over the period of our analysis.

For highly concentrated indices though, many sectors can be thinly populated or even non-existent, and, in addition, the sector composition of the index can exhibit significant time variation. In such cases, it makes sense to focus on individual stocks instead of sectors, and we so cyclically adjust the earnings of each *current* index constituent separately, and then aggregate all these cyclically adjusted earnings to obtain a bottom-up estimate of the cyclically adjusted earnings of the index. We start by writing the identity:

$$E_t = \sum_j E_t^j, \tag{16}$$

where E_t^j is the earnings of the j^{th} index constituent in period t. If we cyclically adjust the earnings of each index constituent using, say, revenue weights and the sample mean, and then aggregate over all index constituents, we get

$$\text{Cyclically Adjusted Bottom} - \text{up Index Earnings}_t = \sum_j \frac{1}{10} \times \sum_{\tau=0}^{9} E_{t-\tau}^j \times \frac{S_t^j}{S_{t-\tau}^j} \tag{17}$$

where S_t^j represents the revenues of the j^{th} index constituent in period t. In essence, we construct a robust estimate of the earnings of the current index from the historical earnings of its constituents, and can now compute a bottom-up CAPE using the identity:

$$\text{Bottom} - \text{up CAPE}_t = \frac{\text{Aggregate Market Value}_t}{\text{Cyclically Adjusted Bottom}-\text{up Index Earnings}_t}. \tag{18}$$

We will later use equations (16) – (18) in our analysis of the Icelandic stock market.

5. Addressing Changes in Effective Tax Rates

Some critics of CAPE argue that a decline in effective corporate tax rates has led to abnormal earnings growth, and to a permanent increase in the profitability of companies. To test this hypothesis, we compute the effective tax rate by taking the ratio of income taxes paid to pre-tax income for the 500 largest public companies in the U.S. using Compustat data. With two exceptions, it is clear from Figure 6 that the effective tax rate has steadily declined over the past 25 years as corporations have lowered their taxes by moving their operations and their registrations to tax havens, by astute transfer pricing, and by better managing their global tax liabilities. The exceptions follow the bursting of the technology bubble in 2000 and the 2008 financial crisis. In both cases, aggregate earnings declined much more than taxes paid, leading to a transitory spike in effective tax rate.

We reconstruct the ten-year historical post-tax earnings of our 500 stock proxy for the S&P 500 at each point in time using the most recent effective tax rate, and then aggregate and average these tax-equalized earnings to create a tax adjusted CAPE (i.e. when computing CAPE in 2010, we apply the tax rate that prevailed in 2010 to corporate earnings from 2001 to 2010 to compute a tax equalized series of earnings). As with our earlier enhancements, Figure 7 shows that tax-rate equalization has a minimal impact on CAPE in the U.S.

6. Addressing Outsized Accounting Losses and Aggregation Bias

Following FAS Ruling 115 in 1993, and Rulings 142 and 144 in 2001, firms are required to write down the value of assets which decline in value, regardless of whether or not they are sold. They are not, however, allowed to write up assets which increase in value until they are sold, creating an asymmetry in the treatment of shocks to earnings, a downward bias in reported company and index earnings, and an upward bias in CAPE.

The 2008 financial crisis graphically illustrates the impact of these rulings: Siegel (2013) reports that the unprecedented $23.25 loss in reported earnings for the S&P 500 firms in the fourth quarter of 2008 was driven overwhelmingly by the write downs of just three firms that did not make up a large percentage of the S&P 500: AIG, Bank of America, and Citigroup. One way in which to account for this bias is to limit the accounting losses of a firm in each year to be no greater than its beginning of year market value, which is equivalent to restricting earnings yields to be bounded below by -100%.

We apply this limit to the reported earnings of each company in our 500 stock proxy for the S&P 500 using Compustat data and then use this time series of adjusted earnings to re-compute CAPE. The impact of our aggregation bias adjustment is minimal in the U.S., even during the 2008 crisis, and we do not therefore display it.

7. Dynamic Business Cycle Adjustments

The duration of business cycles as defined by the NBER ranges from less than two years to more than ten years. Campbell and Shiller (1998) follow Graham and Dodd (1934) and use a ten-year average in their construction of CAPE to ensure that they cover at least one full business cycle. But a given ten-year period need not contain an integral number of business cycles – it may, for example, cover two recessions but only one expansion. One way in which to overcome such a bias is to identify the point in the last business cycle that corresponds most closely to where we are in the current business cycle, and to average earnings over this period instead of using a fixed ten-year window. Unfortunately, identifying business cycles in real time is exceptionally difficult, and we therefore stay with the simple and intuitive ten-year average and its robust alternatives.

Case Study: The Icelandic Stock Market

Each of these enhancements to CAPE is well motivated by economic intuition, but has only a modest impact on its level in the U.S., even during the 2008 crisis. We can, however, illustrate the value of revenue weighting and the Hodges–Lehmann mean, as well as that of our bottom-up construction, by computing CAPE for the OMX Iceland 15 Stock Index.

The Icelandic stock market was young, but grew rapidly, and when the 2008 crisis struck, Iceland's over-extended banking sector collapsed. The OMX Iceland 15 Stock Index lost 73% of its market value over three days in October 2008 as its three biggest constituents – Glitnir, Kaupthing Bank and Landsbanski Islands – were revalued at 0 and deleted, and we can get a meaningful perspective on its valuation immediately after the crisis only by using the past earnings of its then current constituents to compute CAPE.

Computing the earnings for the OMX Iceland 15 Index is tedious. Financial statements for Icelandic companies are not readily available, and the majority of Icelandic companies have at some point been acquired, taken private, nationalized or gone bankrupt. Our data, which is sourced from Bloomberg and Worldscope, as well as from individual financial statements obtained from company websites and OMX Nasdaq's website, is missing a number of items in each year, and Table 1 displays the number of companies that are missing one or more data items in each year from 1989 to 2008. We test our alternative methodology by computing CAPE for the OMX Iceland 15 Index using equations (16) – (18) at two discrete points in time: December 31, 2007 and December 31, 2008.

Data quality is particularly bad in 2000, when the technology bubble burst, and in 2008, when the majority of the companies in the index merged or went bankrupt. A number of firms did not publish financial statements for 2008, including Kaupthing, Landsbanki Islands, and Exista HF (which was Kaupthing's single largest shareholder with just under 25% of its shares). We estimate their earnings by comparison with Glitnir Bank, which suffered losses of ISK 458 bn in that year, which is approximately 2.3 times its beginning of year market value of ISK 240 bn and 2.7 times its beginning of year common equity of ISK 169 bn. We conservatively estimate 2008 losses of financial firms for which we have no data to be the average of their beginning of year common equity and their beginning of year market value.

Table 2 displays index and CPI levels, as well as per-share index earnings and revenues for each year from 1998 to 2008The impact of a robust measure of location is immediately evident from the four bottom rows of the table. The time series of index earnings is so dominated by the losses experienced in 2008 that its average over the entire period is negative, while both its median and its Hodges–Lehmann mean are positive. Figure 8 displays the growth of earnings, revenues, index levels and consumer prices in Iceland from 1998 to 2007. It is evident from the figure that earnings grow roughly in line with revenues and index levels, and much faster than both nominal GDP and consumer prices. Table 3 summarizes the value of CAPE computed using three different weighting schemes for past earnings – CPI, revenues and GDP, along with three different measures of location as well as a bottom-up computation using revenue weights and the three measures of location.

At year-end 2007, CAPE computed using revenue weighted index earnings is comparable to the bottom-up CAPE computed using equations (16) – (18). At year-end 2008, however, Table 3 starkly illustrates the failings of the basic CAPE methodology. In particular:

1. The sample mean proves worthless, as the index's losses in 2008 dwarf its earnings all prior years combined, clearly illustrating the value of a robust measure of location.

2. The 95% drop in the index level renders the ratio of index price to any average of past index earnings meaningless

3. The bottom-up measures of CAPE are the most realistic– they are positive, and range from 2.6 (using the median) to 9.3 (using the mean). The truth probably lies somewhere in between: we expect CAPE to be low, but positive, in early 2009.

While we believe that the bottom-up construction method provides the most realistic estimate of the prospective earning power of an index, its data requirements are significant, and we feel confident in saying that it will prove relevant primarily when a market experiences a significant dislocation, and therefore recommend that it be used at the discretion of the user.

This case study illustrates the significant impact that some of our proposed enhancements can have on the level of CAPE in distressed markets. Unfortunately, we do not have access to the extensive firm level data required to prove the superiority of these enhanced metrics using statistical analysis, but must rely instead on economic intuition and simple calculations to demonstrate how they can, in some circumstances, result in more plausible values for CAPE.

Tests of Statistical and Economic Significance

In this section, we explore the ability of various valuation ratios to forecast real and nominal equity market returns using OLS regressions corrected overlapping observations, as well as with a simulation framework to account for endogeneity. As previously formulated in equation (9), we regress q-year forward returns for the S&P 500 on the year-end value of a valuation ratio to gauge its predictive power over medium (one year) to long (ten year) horizons. Unfortunately, equations (8) – (10) suffer from two major econometric problems:

1. There is significant correlation between adjacent terms on the left hand side of equation (9) on account of overlapping observations, and

2. Price appears, implicitly or explicitly, on both sides of these equations.

These issues violate the standard OLS assumptions of independence and exogeneity, and cause measures of significance such as R^2's and *t*-statistics to be severely inflated, creating an illusion of statistical significance and predictability when there really is none. Nelson and Kim (1993) were perhaps the first to point this out, and Stambaugh (1999), Valkanov (2003), Boudoukh, Richardson and Whitelaw (2008) and Hjalmarsson (2008, 2011) explore this issue in much greater depth. We correct for these effects using a simulation framework and a $\sqrt{q}$ scaling procedure for *t*-statistics due to Valkanov (2003) and Hjalmarsson (2008, 2011).

Under the null hypothesis of no predictability, and with an exogenous regressor (i.e. with a zero correlation γ between the innovations $\varepsilon_{t,t+1}$ and $\delta_{t,t+1}$ in equations (8) and (10) respectively), Hjalmarsson (2011) shows that the *t*-statistic associated with β in a q year univariate predictive regression is too high by a factor of $\sqrt{q}$, i.e.,

$$\frac{t_q(\beta)}{\sqrt{q}} \to N(0,1) \text{ as } T \to \infty. \tag{19}$$

He also shows, using simulations, that $\frac{t_q(\beta)}{\sqrt{q}}$ is a reasonably good proxy for the true test statistic even in the presence of endogeneity. In particular, he shows that for regressions with parameters similar to ours, scaling by $\sqrt{q}$ under-rejects at the 5% level by a factor of at most 3, which is easily cured by raising the acceptance threshold from 1.64 to 2.33. We here adopt Harvey and Liu's (2014) argument that if the relationship being tested has a sound theoretical foundation, most of the sins of statistical inference can be adequately guarded against by raising the threshold for acceptance.

Figures 9a and 9b display the adjusted R^2's of a set of predictive regressions of real and nominal q-year annualized returns against beginning of period valuation ratios over the longest period for which we have data (1935 – 2014). We see immediately that:

1. In all cases, R^2 increases almost linearly with q, while $\frac{t_q(\beta)}{\sqrt{q}}$ is approximately independent of q, as predicted by Boudoukh, Richardson and Whitelaw (2008).

2. In every case, the R^2's associated with nominal returns are higher than the corresponding R^2's for real returns.

3. All six variants of CAPE tested in this exercise (i.e. CAPE constructed using the mean, the median, and the Hodges–Lehmann mean as the measure of location, and with past earnings being weighted by CPI and GDP) have roughly the same R^2.

4. All six variants of CAPE explain forward ten-year returns better than the earnings yield, which in turn has greater explanatory power than the dividend yield.

We recommend the use of revenue and GDP weighting over CPI weighting in spite of the fact that the explanatory power of GDP weighted CAPE is slightly lower than that of CPI weighted CAPE – we would much rather be right on the economics and suffer slightly on the econometrics than the other way around. We ascribe the slight drop in explanatory power to the sharp rise in nominal GDP from 1939 – 1944.

Figures 9c and 9d display the corresponding scaled *t*-statistics $\frac{t_q(\beta)}{\sqrt{q}}$ for our predictive regressions, and given the similarity between the various R^2's in Figures 9a and 9b, we display results only for the Earnings Yield, CPI weighted CAPE using the mean, and GDP weighted CAPE using the Hodges–Lehmann mean. Table 4 has detailed information on the regressions at forecast horizons of one year and ten years. The $\sqrt{q}$ correction shows that long horizon returns are not fundamentally more forecastable than their short horizon relatives.

It is evident from these graphs that the scaled *t*-statistics for nominal returns using earnings based measures are always significant – they consistently exceed 2 and sometimes exceed 3, while those for real returns are typically on the order of 1.5, and rarely exceed 2. In light of these observations, we recommend that CAPE and its variants be used to forecast nominal, not real, returns. The explanatory power of dividends is lower than that of earnings, and Fama and French (2001) show that the propensity of firms to pay dividends has declined over time as share buybacks have supplanted dividends. We therefore do not consider dividends for the remainder of our analysis.

We next explore an additive decomposition of the correlation coefficient to visualize the power of a valuation ratio to forecast forward returns over various time periods and market conditions. We start by writing an expression for the sample correlation between a valuation ratio and one-year forward returns:

$$\rho_{V,r} = \frac{\sum_t (V_t - \bar{V})(r_{t+1} - \bar{r})}{\sqrt{\sum_\tau (V_t - \bar{V})^2}\sqrt{\sum_\tau (r_t - \bar{r})^2}}, \tag{20}$$

where V_t is the value of valuation ratio (E/P, D/P, 1/CAPE etc.) at the end of year t, $\bar{V}$ is its average over the entire period, r_{t+1} is the return of the S&P 500 in year t+1, and $\bar{r}$ is its average over the entire period. We use one year returns to avoid any problems associated with overlapping data. We define the contribution to the correlation in year t, $\rho_{V,r}^t$, to be

$$\rho_{V,r}^t = \frac{(V_t - \bar{V})(r_{t+1} - \bar{r})}{\sqrt{\sum_\tau (V_t - \bar{V})^2}\sqrt{\sum_\tau (r_t - \bar{r})^2}}, \tag{21}$$

so that

$$\rho_{V,r} = \sum_t \rho_{V,r}^t. \tag{22}$$

Figure 10 displays the contribution to the correlation in each year from 1934 to 2013 as well as the cumulative partial sums of these contributions. While all three valuation ratios tend to have occasional bad years, they all perform poorly during the technology bubble from 1994 to 1998 (i.e. forecasting returns from 1995 to 1999), and perform correspondingly well in 2008. 1/CAPE builds up a compelling lead over the other two from its inception, and maintains its lead to the very end, clearly and visibly demonstrating its superiority as a measure of equity market valuation.

The period from 1994 – 1998 is particularly interesting – 1/CAPE performs worse than E/P in each year as earnings surged, so that the market (which was rising even faster than earnings) looked significantly more overvalued relative to an average of historical earnings than it did relative to the most recent year's earnings. When the technology bubble burst in 2000, both 1/CAPE and E/P did well, but 1/CAPE outperformed E/P, as the average of the past earnings of the S&P 500 was more reflective of its future earnings than its elevated one-year earnings in 1999 and 2000. The opposite situation prevailed at the end of 2008, when the S&P 500's P/E was 60.7 on account of the massive write downs that occurred in that year, while the ten-year average held CAPE to a far more reasonable value of 16.6, and 1/CAPE consequently outperformed E/P in 2009.

Our data on revenues starts in 1946, allowing us to compute a revenue weighted CAPE starting in 1955. Figures 11a and 11b display the scaled *t*-statistics associated with three variables – Earnings Yield, Sales to Price and Revenue Weighted Hodges–Lehmann Mean CAPE, while Table 5 provides a comprehensive set of results at one and ten year horizons. Revenue Weighted Hodges–Lehmann Mean CAPE is slightly more powerful than Earnings Yield, but Sales to Price is substantially more powerful than both, and has a long horizon *t*-statistic of over 3 when forecasting nominal returns.

Our data on Cash Flow starts in 1977, allowing us to compare Earnings Yield, Cash Flow Yield, Sales to Price and Revenue Weighted Hodges–Lehmann Mean CAPE from 1978 to 2014. As cash flow is intrinsically less malleable than earnings, one might expect Cash Flow Yield to outperform Earnings Yield when predicting stock market returns. Figures 12a and 12b display the relevant scaled *t*-statistics, while Table 6 displays more detailed results at one and ten year horizons for the period 1978 – 2014. Sales to Price and Cash Flow Yield are more powerful than Earnings Yield and CAPE, with long-horizon adjusted *t*-statistics of about 2.25. In spite of the paucity of data, we recommend that these variables be used to supplement CAPE whenever possible, as they are not subject to many of the distortions that afflict earnings. It is striking that over all three periods, the beta associated with each of the explanatory variables (other than Sales to Price) is on the order of 1, which suggests that equation (4) is a reasonable model for the expected return of equities.

Finally, our data on Operating earnings starts in 1988, and a number of our long-horizon adjusted *t*-statistics (not displayed for economy of space) exceed 4. Unfortunately, many of the betas are on the order of 4, which is sufficiently different from 1 that these results give us pause: they are almost certainly spurious. At some point in the future, when there is sufficient data to better evaluate the betas of all predictors starting in 1988, we believe that operating earnings will, like cash flow, prove to be a valuable addition to our catalog of predictors.

In addition, we conduct a simulation study for Earnings Yield and CAPE over the period 1925 – 2014 to determine if our results are driven by endogeneity. To motivate our framework, we force earnings to a constant value of 1 in equations (9) and (10), i.e.

$$\frac{P_{t+1}}{P_t} - 1 = \alpha + \beta \times \frac{1}{P_t} + \varepsilon_{t,t+1}, \; t = 0,1,2,\cdots,T-1, \tag{23}$$

$$\frac{1}{P_{t+1}} = \mu + \rho \times \frac{1}{P_t} + \delta_{t,t+1}. \; t = 0,1,2,\cdots,T-1. \tag{24}$$

If we simulate a sample path of i.i.d. returns (and, by implication, prices) for T periods and then perform the above predictive regression, we expect that $\hat{\beta}$, the OLS estimate of β, will be indistinguishable from zero. But our intuition is false: Kendall (1954) and Stambaugh (1999) show that $\hat{\beta}$ is in fact biased, and that the bias in the OLS estimate of β is given by

$$E\left[\hat{\beta} - \beta\right] = -\left(\frac{1+3\rho}{T}\right) \times \frac{Cov(\varepsilon,\delta)}{\sigma_\delta^2} + O\left(\frac{1}{T^2}\right). \tag{25}$$

The bias in our estimate of β can be significant for small sample sizes, but diminishes in magnitude and importance as the sample size increases. We simulate the behavior of CAPE and E/P over the longest period for which we have data by generating 80 years of artificial data on prices and earnings, and convert them to real quantities using the actual observed CPI from 1925 to 2014. The initial levels, long run growth rates and volatilities of both earnings and prices are matched to their actual values over this period. Prices are made to follow a lognormal diffusion with drift, while earnings are made to grow along three alternative paths:

E1. Earnings, like prices, follow an i.i.d. geometric Brownian motion. This is unrealistic, but the absence of any linkage between earnings and prices to set a natural limit to P/E induces a wide confidence interval for the *t*-statistic.

E2. Earnings grow with a time varying mean that is estimated by regressing the fractional change in earnings of the S&P 500 against its Earning Yield. The time varying growth rate induces mean reversion in the earnings yield, and ensures that both P/E and CAPE stay bounded. Formally, we estimate the coefficients η and θ in the regression

$$\frac{E_{t+1} - E_t}{E_t} = \eta + \theta \times \left(\frac{E_t}{P_t} - \frac{\overline{E}}{P}\right) + \upsilon_{t+1}, \tag{26}$$

where $\frac{\bar{E}}{P}$ is the average earnings yield over the entire period and v_t is an additive noise term. We use these estimated coefficients to generate sample paths of earnings.

E3. The actual sequence of S&P earnings. Under this choice, all the dependence of future earnings on past earnings is captured in the one sample path of earnings we have.

We use these sequences of earnings and prices to construct Earnings Yields and CAPEs and regress future returns at various horizons against beginning of period valuations. The simulations are repeated 100,000 times, and the percentiles of the scaled *t*-statistics associated with the slope coefficients are displayed in Table 7.

There is a clear upward bias in the distribution: the median scaled *t*-statistic ranges between 0.19 (E2/P, one year) and 1.54 (CAPE3, ten years). The 95th percentile of the *t*-statistic ranges between 1.47 (CAPE2) and 3.17 (CAPE3) and $\frac{t_q(\beta)}{\sqrt{q}}$ is a slowly increasing function of q. By way of comparison, the *t*-statistics associated with CAPE computed using CPI and GDP weights and both the arithmetic mean and the Hodges–Lehmann mean exceed 3.25, which exceeds the 95th percentile for all three simulations, suggesting that our results are the logical outcome of the linear relationship between valuation ratios and expected returns.

Application to International Markets and Sectors

While our study is concentrated in the US because of the availability of data going back to 1925, equations (1) – (5) are applicable to any market, and we use a limited set of country level earnings and price data from MSCI from 1985 to 2014 to explore the performance of CAPE relative to Earnings Yield in thirteen international markets. We cannot expect statistical significance from our results, but, as can be seen from Figure 13, the *t*-statistics associated with one-year regressions using CAPE are almost always greater than those associated with regressions using Earnings Yields. The CAPE methodology can be extended to sectors as well, and we refer the interested reader to Bunn, Staal, Zhuang, Lazanas, Ural and Shiller (2014) and Ural et. al. (2012) for details.

In general, CAPE is not directly comparable across countries or sectors – the first term in equation (4) includes the long-term growth rate of per-share earnings and the book-to-market ratio. Differences in profitability, earnings dilution and accounting rules can induce differences in earnings growth and book-to-market ratios across countries and sectors, and the impact of these factors can be significant.

The Steady State Level of CAPE

A common question that arises when working with CAPE is whether it has a steady state level. In summary, it does not: a steady state level for CAPE is approximately equivalent to a steady-state expected return for equities, and we do not know what the steady state expected return *ought* to be – the Equity Premium Puzzle, first described in Prescott and Mehra (1985), does not as yet have a complete resolution. It is worth pointing out that the empirical evidence in favor of stable expected returns is weak, and Philips (1999, 2003), Arnott and Bernstein (2002) and Fama and French (2002) document a substantial decline in the expected return of equities over time. This is not unreasonable – investors now have ready access to low cost index funds that did not exist 40 years ago, and much of the decline in fees and expenses should rightly translate into a decline in gross expected return, or equivalently, into a persistent increase in CAPE. For these reasons, we strongly recommend that investors not compare the current level of CAPE to its 135 year average, but instead use CAPE in a regression framework to forecast future equity market returns.

Current Forecasts of Equity Market Returns

In Table 8 we show our current (i.e. as of 12/31/2014) forecasts for the annualized ten-year forward returns of the S&P 500, with coefficients estimated over the longest possible interval for each variable using the robust Theil-Sen estimator (Theil 1950, Sen 1968) described in the Appendix. The forecasts range from a low of 4.35% per annum (using Sales / Price) to a high of 7.24% per annum (using E/P) with an average of 6.25% per annum across all metrics, and with the majority lying between 6% and 7% per annum.

Some of the variation can be explained by the interval over which the parameters were estimated. The currently depressed level of Sales / Price does not reflect the currently elevated level of corporate profitability relative to its long term history, and this estimate is therefore biased downward. A large portion of the period for which Cash Flow / Price is evaluated is a period of high realized returns driven by a steady decline in expected returns. The regression coefficients reflect this, biasing this estimate upward. The remaining coefficients were estimated over a period when economic growth was higher than has been experienced in recent years. This, too, will tend to bias their estimates upward.

One reasonable way in which to create a point estimate for future long-term equity returns is to average a subset of these forecasts. We choose to average our forecasts made using Sales / Price, Cash Flow / Price and the Hodges–Lehmann Mean Revenue Weighted CAPE, which yields a forecasted ten-year return of 5.86% per annum. The prospective return of the S&P 500 is clearly lower than it has been in the past, but it is just as clearly higher than that of any investment grade bond index. The current yield to worst of the Barclays U.S. Aggregate index is 2.55%, that of the U.S. Corporate Index is 3.6%, and ten-year Treasury Inflation Protected Securities (TIPS) yield 0.76%, while ten-year breakevens (which proxy the market's estimate of future inflation) trade at 1.5%.

By way of comparison, at the end of 1999, the prospective ten-year return of the S&P 500 was 3.4% per annum, while the Barclays U.S. Aggregate index yielded 7.16%, the U.S Corporate Index yielded 7.70%, ten-year TIPS yielded 4.30%, and ten-year breakevens traded at 2.11%. The estimated ten-year forward return of the S&P 500 at the end of 1999 is the arithmetic average of the forecasts using Sales / Price and the Hodges–Lehmann Mean Revenue Weighted CAPE, as at that point in time, there were only 13 data points for Cash Flow / Price, which is far too few to have any confidence in its estimated regression coefficients. The annualized realized returns of the S&P 500 for the next 10 and 15 years were -0.95% per annum and 4.19% per annum respectively.

But the higher expected return of equities relative to that of bonds bears with it some risk. The primary risks facing equities are a decline in trend growth (which will lower the intercept of the regression) and a decline in corporate profitability (which will increase

CAPE). If prospective economic growth declines by 1%, equation (1) suggests that the prospective return of equities will decline by about 0.6% per annum. If, in addition, corporate profitability declines to its historical average of about 6% of revenues, we expect that prices, too, will decline by about 33%. That said, the increase in capital's share of national income over the past four decades has been extensively studied, but no consensus has emerged on whether this shift is transitory or permanent, and we bring no new insight to this question.

Conclusions, Recommendations, and Future Research

We have shown that there are sound theoretical reasons for CAPE to be able to predict the prospective return of equity markets, and that the primary impact of averaging past earnings is to reduce their variance and to adjust for cyclicality, thus making a widely used valuation ratio (P/E) more robust. We have also proposed a number of enhancements and complements to CAPE, and have shown that they can result in improved forecasts of equity market returns. While the impact of the following ten recommendations for CAPE's construction and use varies from country to country, and in spite of the fact that a number of them have essentially no impact in the U.S., we argue for their universal use, as they reliably protect against a wide range of mishaps that can befall the unwary user, and at worst they do no harm.

1. Use CAPE and its variants to forecast nominal, not real, returns.

2. Supplement forecasts using CAPE with forecasts using Cash Flow / Price and Sales / Price. Do not use Dividends/ Price: Fama and French (2001) show that the propensity of firms to pay dividends has declined significantly over time.

3. Operating Earnings will likely prove to be a good predictor of forward returns, but we have insufficient data to be confident of its regression coefficients. At some point in the future, we expect it will merit inclusion in the chosen list of flows.

4. Weight past earnings by revenues (best) or GDP (second best) in preference to CPI, and use the Hodges–Lehmann mean to moderate the impact of outliers.

5. Use a robust regression method, such as the Thiel-Sen estimator, to estimate the relationship between valuation ratios and prospective returns.

6. If an index has experienced significant changes to its composition, compute the relevant valuation ratio using its current constituents or its current sector composition instead of averaging historical index flows.

7. When evaluating the significance of regressions with overlapping observations, divide all *t*-statistics by $\sqrt{q}$, and use a simulation framework to account for endogeneity.

8. Comparisons of valuations across countries or sectors requires some form of normalization – differences in growth rates, earnings dilution, industry weights, corporate profitability and accounting practices make raw comparisons inappropriate.

9. Do not compare the current level of CAPE to its 135 year average as CAPE does not have a steady state level. Use it instead to estimate the prospective return of equities.

10. Be cautious when using CAPE or its variants as a market timing tool, as markets can rise or fall to outsized levels of valuation for extended periods of time: estimates of the prospective return of equities should be evaluated in relation to those for other asset classes, especially investment grade corporate bonds, and not in isolation.

We leave to future work the construction of time series of book values measured at replacement cost, as well as the development of a better understanding of earnings dilution, which drives a wedge between the growth rate of the economy and that of per-share earnings, as they will allow the estimation of equation (6) using a bivariate regression that responds naturally to changes in growth and valuation. We also leave to future work the construction of time series of index cash flows and revenues for the major stock market indices in each country. These should be as widely available as earnings, though, as demonstrated by the case of Iceland, there exist countries for which even index earnings are not readily available. The Cowles Commission permanently changed the face of stock market studies in the U.S.; we think it likely that a concerted effort can change the face of stock market studies globally.

Acknowledgements

The authors would like to thank Antonio Silva of BlackRock and formerly of Barclays, for his many constructive comments, which greatly improved both the content and the presentation of this paper. Howard Silverblatt of Dow Jones S&P Indices generously gave us access to historical data from old paper copies of the S&P Capital IQ Analyst's Handbook as well as data on the annual per-share cash flow of the S&P 500. Without his generous assistance, this would have been a very different paper. Erik Hjalmarsson was generous with his time and patiently explained his scaled tests to us. It goes without saying that any errors that remain are our own.

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Appendix: Robust Regression

The Theil-Sen estimator (Thiel 1950, Sen 1968) is a robust alternative to univariate OLS that performs well in the presence of outliers. It has long been known that OLS is sensitive to errors in its inputs, and that even a single outlier can induce arbitrarily large errors in its estimates of the slope and the intercept. Theil (1950) and Sen (1968) propose a novel solution to this problem – given a set of points $\{(x_i, y_i)\}$ of cardinality N, they first construct the set of all possible pairs of points $\{(x_i, y_i), (x_j, y_j)\}$ and then compute the slopes of the $N(N-1)/2$ unique straight lines that pass through these pairs of points, i.e they compute the set of slopes $\left\{\beta_{i,j} = \frac{y_i - y_j}{x_i - x_j}\right\}$.

The Theil-Sen slope is given by $\beta_{TS} = \text{median}\left\{\beta_{i,j}\right\}$. There is no uniquely right value for the intercept α_{TS}: it is defined by some authors to be $\text{median}\,\{y_i\} - \beta_{TS} \times \text{median}\,\{x_i\}$, and by others to be the median of $\{y_i - \beta_{TS} \times x_i\}$. The first definition aims to force the regression line to go through the medians of the *x* and *y* coordinates, while the second forces the median error to 0. We define the intercept to be the Hodges-Lehmann Mean of $\{y_i - \beta_{TS} \times x_i\}$, closely mimicking OLS in the absence of outliers, and capturing its spirit in the presence of outliers.

This regression has been widely studied (an expository description can be found in Philips (2012)), and has a breakdown point in large samples of $1 - \frac{1}{\sqrt{2}} = 29.3\%$. Peng, Wang, and Wang (2008) show that it is strongly consistent and superefficient, and derive its asymptotic distribution. An approximate robust *t* statistic for β_{TS} can be derived using Kirchner's (2001) observation that the *t* statistic for the slope coefficient can be written in terms of ρ, the correlation between *x* and y, as follows:

$$\begin{aligned} t &= \frac{\rho}{\sqrt{1-\rho^2}} \times \sqrt{N-2} \\ &\approx \sqrt{(N-2) \times \beta_{TS}(x|y) \times \beta_{TS}(y|x)/(1-\beta_{TS}(x|y) \times \beta_{TS}(y|x))}, \end{aligned} \tag{A1}$$

where the second step uses the fact that $\rho^2 = \frac{Cov(x,y)^2}{\sigma_x^2 \times \sigma_y^2} = \beta(x|y) \times \beta(y|x)$. He also shows that the *t*-statistic for the sample correlation is identical to that for the slope coefficient.

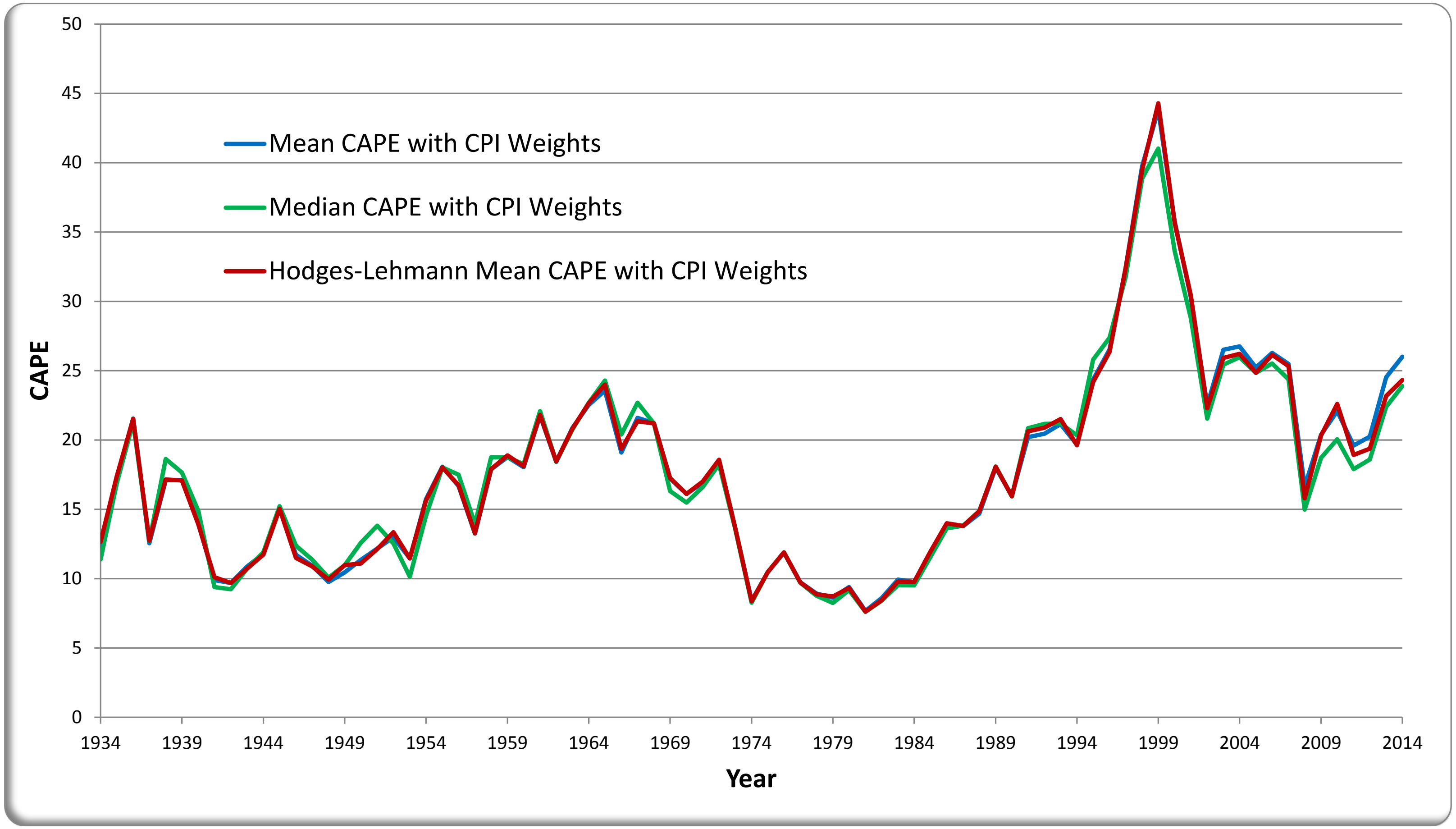

Figure 1. CAPE Computed Using Three Measures of Location*

*Source: Professor Robert Shiller

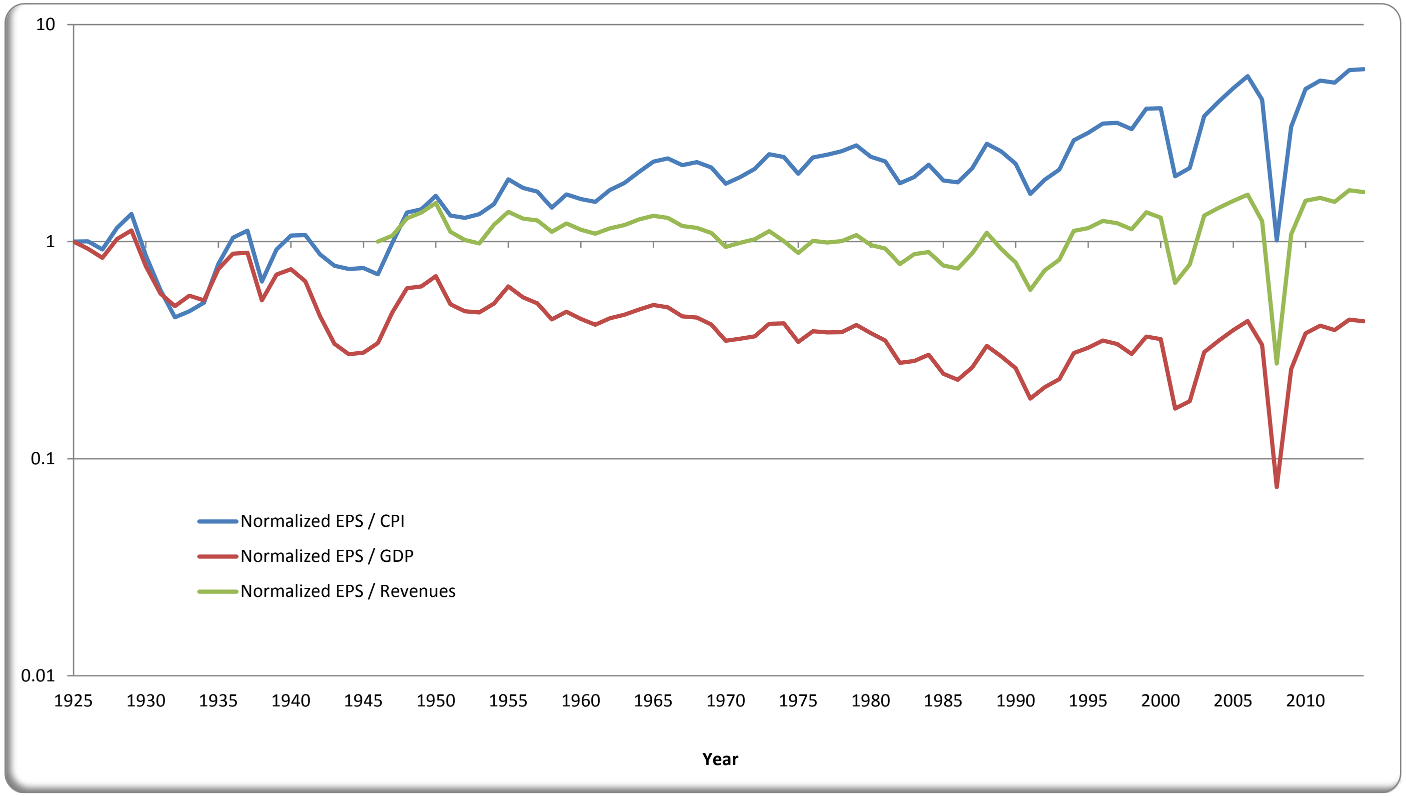

Figure 2. Growth of S&P 500 per-share Earnings relative to GDP, Revenues and CPI*

*Source: Professor Robert Shiller, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

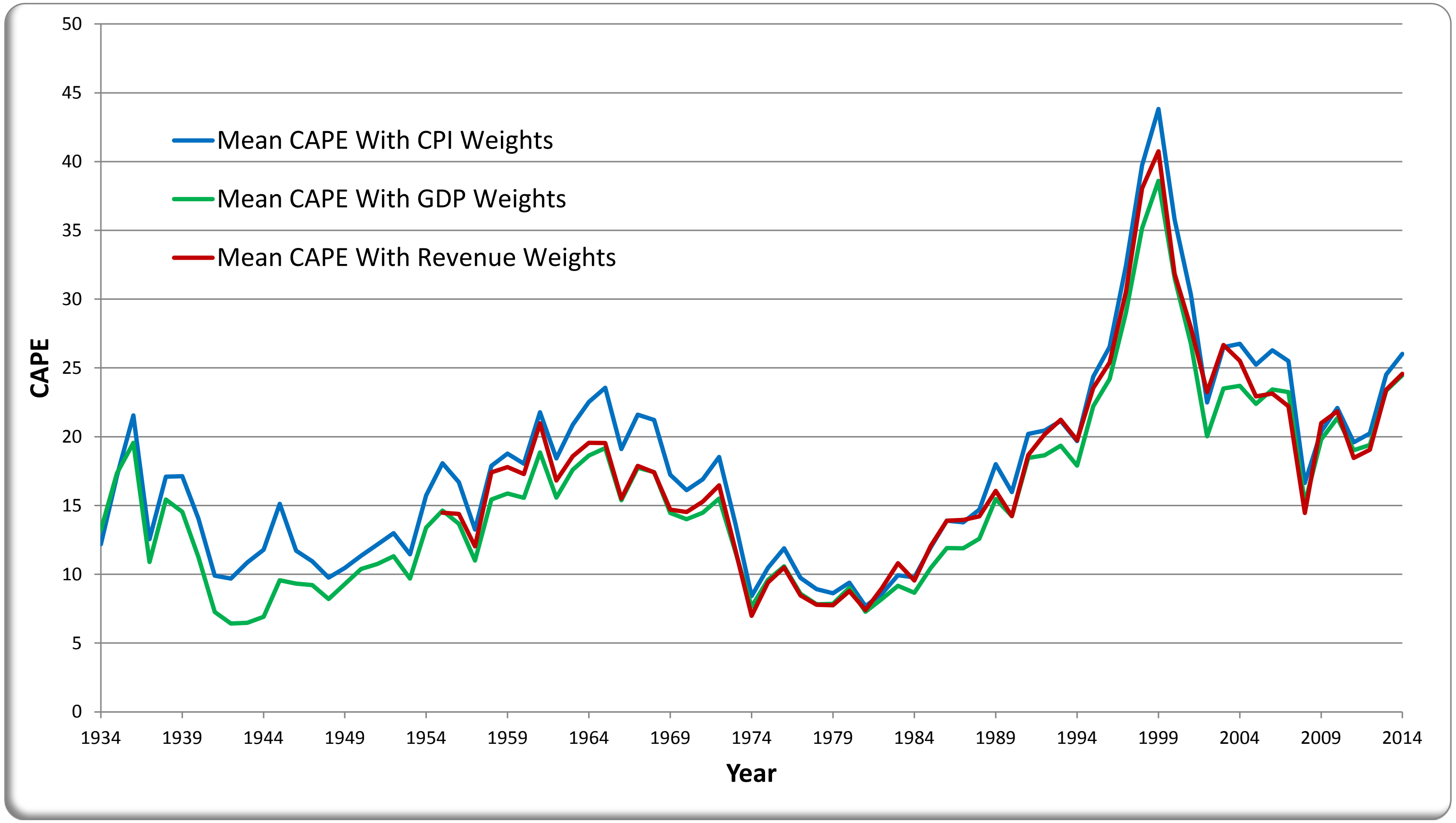

Figure 3. CAPE Computed Using CPI, GDP and Revenue Weights and the Arithmetic Mean*

*Source: Professor Robert Shiller, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

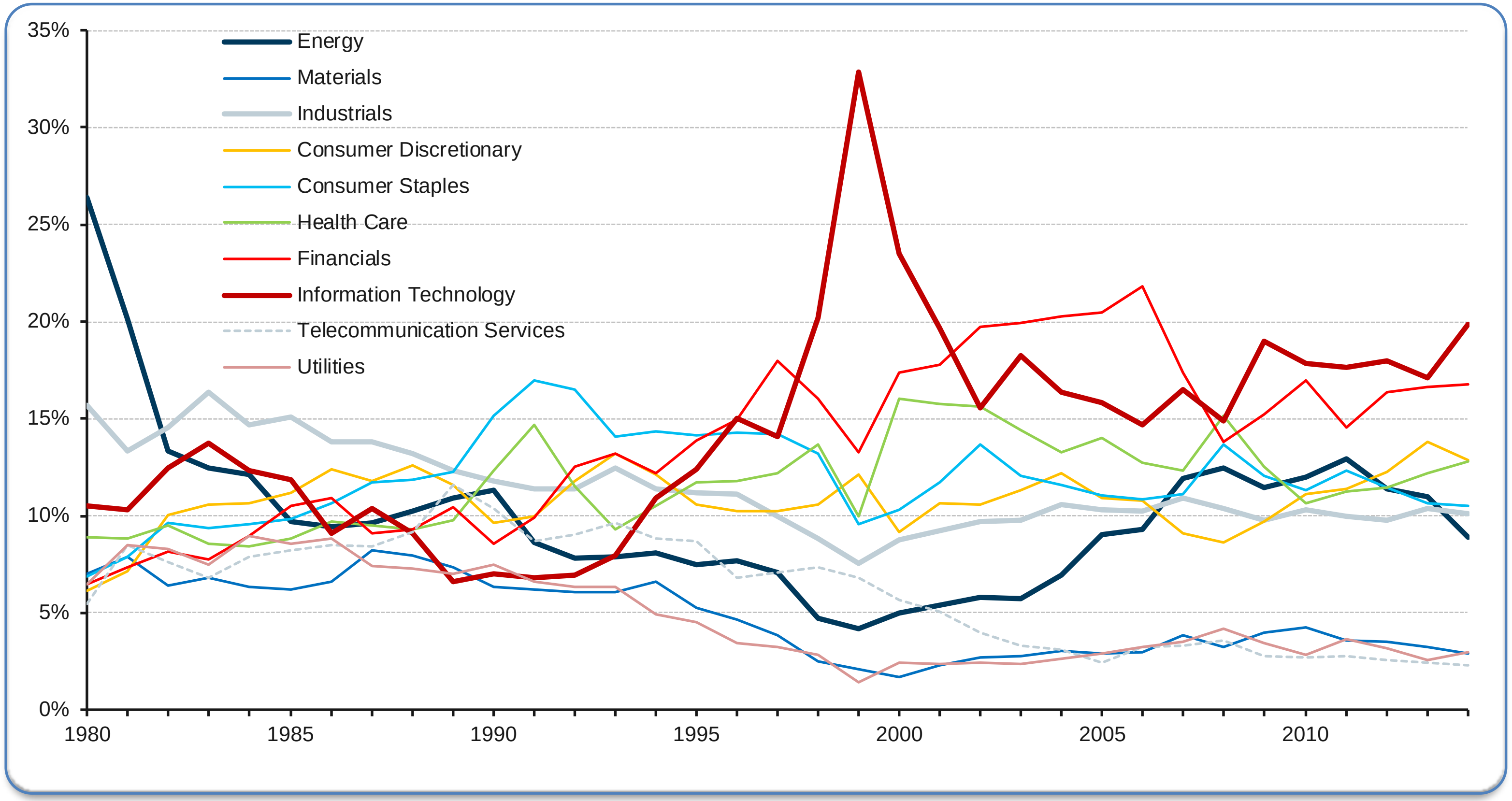

Figure 4. Sector Composition of the U.S. Equity Market vs. Time*

*Source: Compustat

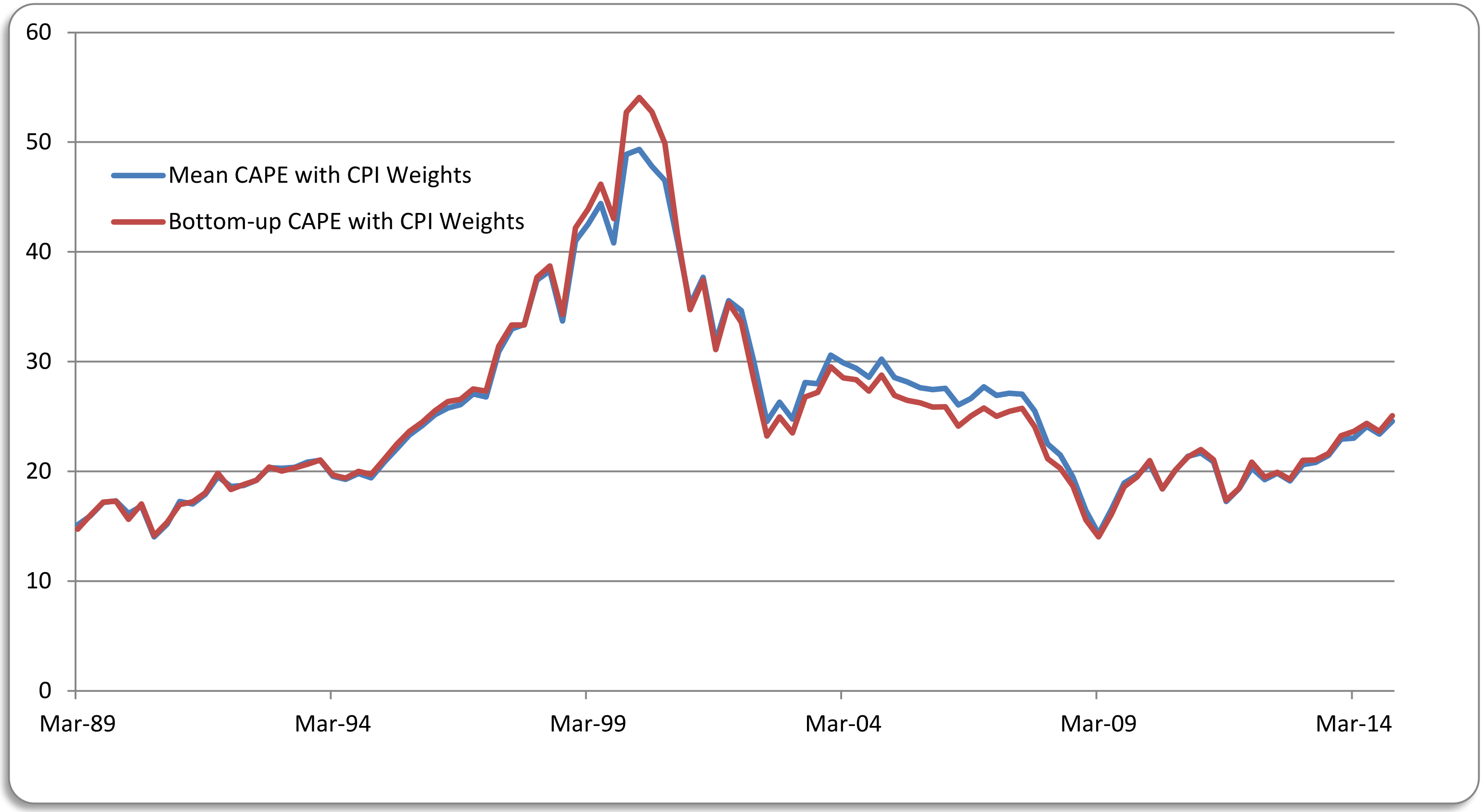

Figure 5. Bottom-up CAPE vs. Standard Top-down CAPE: U.S. Equity Market*

*Source: Compustat

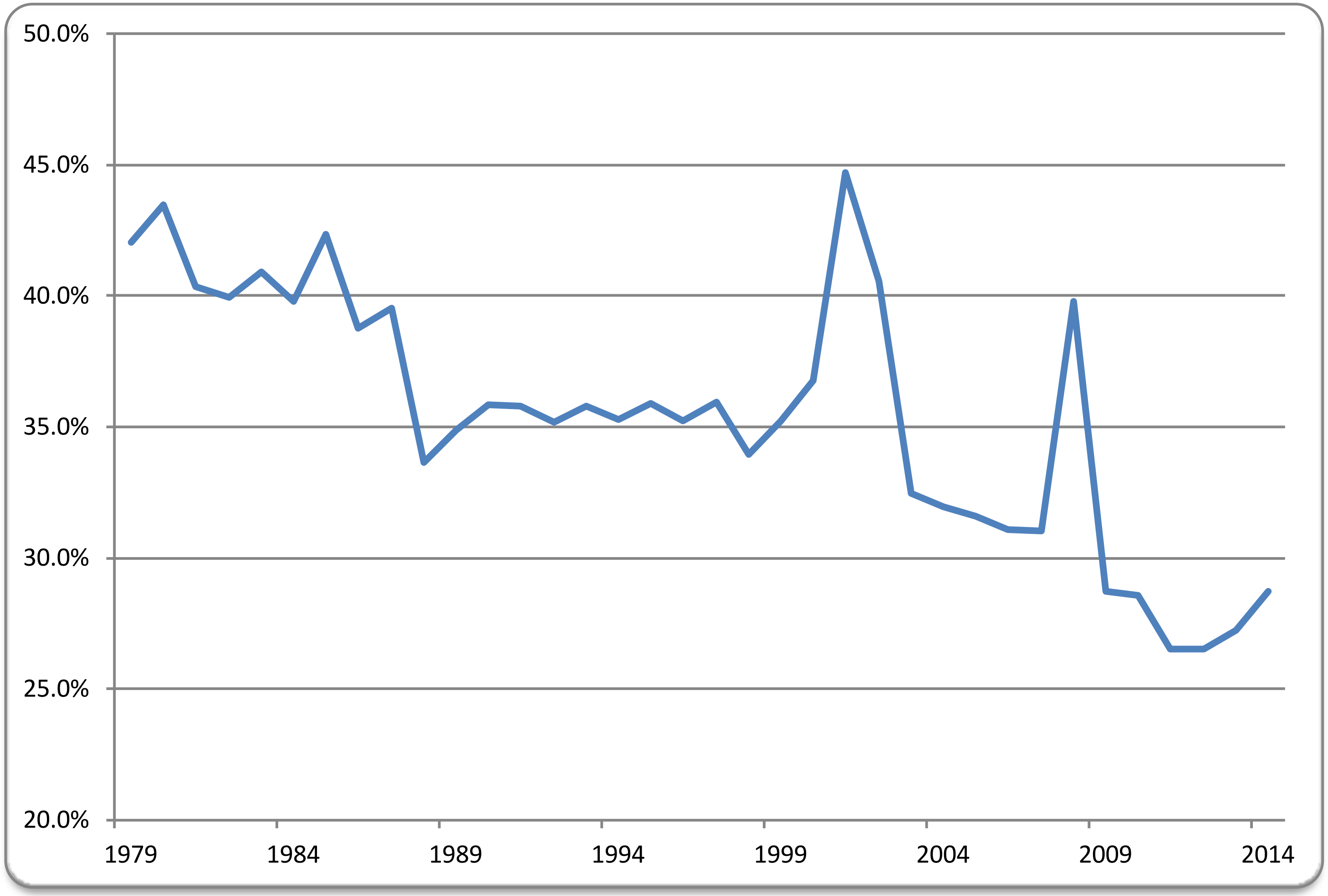

Figure 6. Effective Corporate Tax Rate in the U.S.*

*Source: Compustat

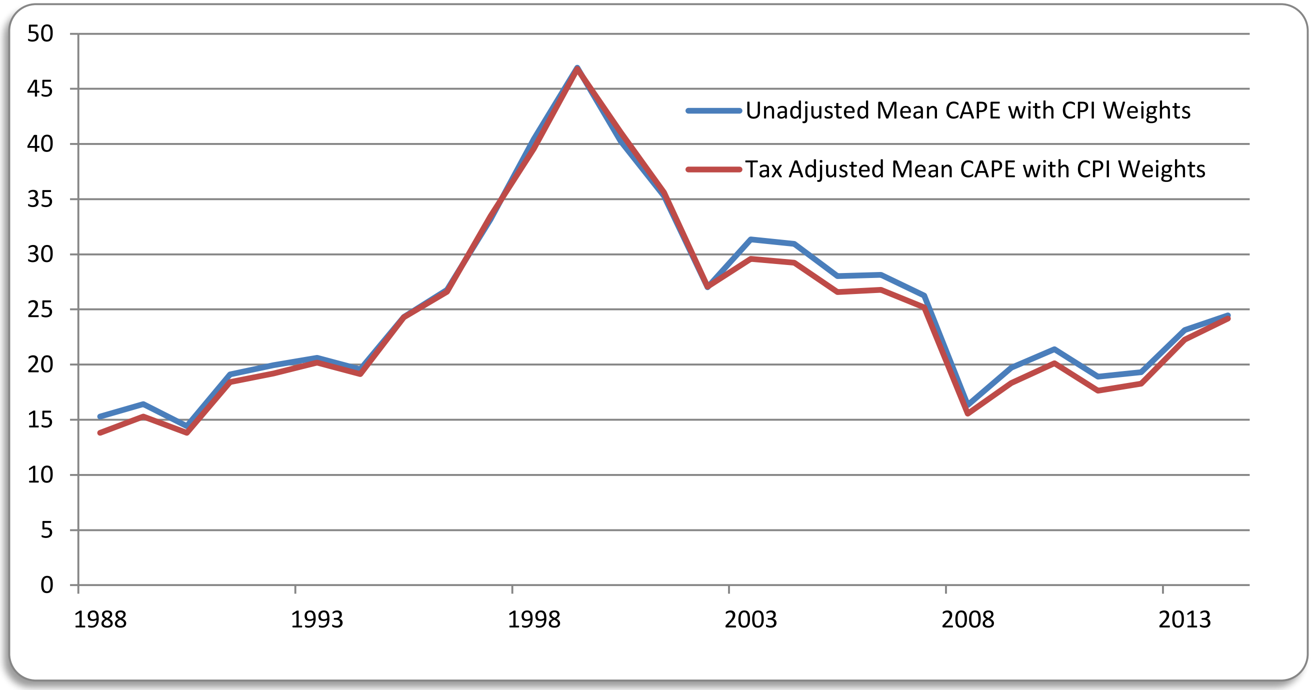

Figure 7. CAPE Computed With and Without Tax Adjustment*

*Source: Compustat

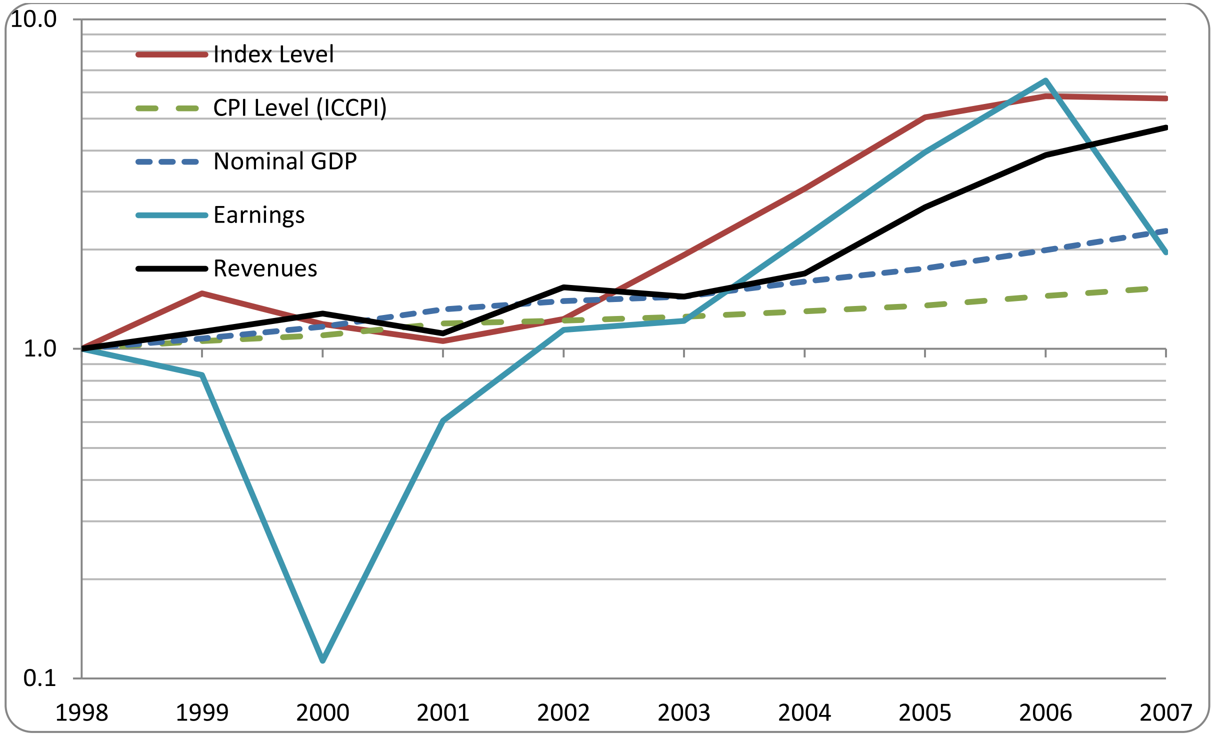

Figure 8. Growth of Earnings, Revenues, Index Level, Nominal GDP and Consumer Prices in Iceland: 1998-2007*

*Source: Bloomberg, Nasdaq OMX, Worldscope

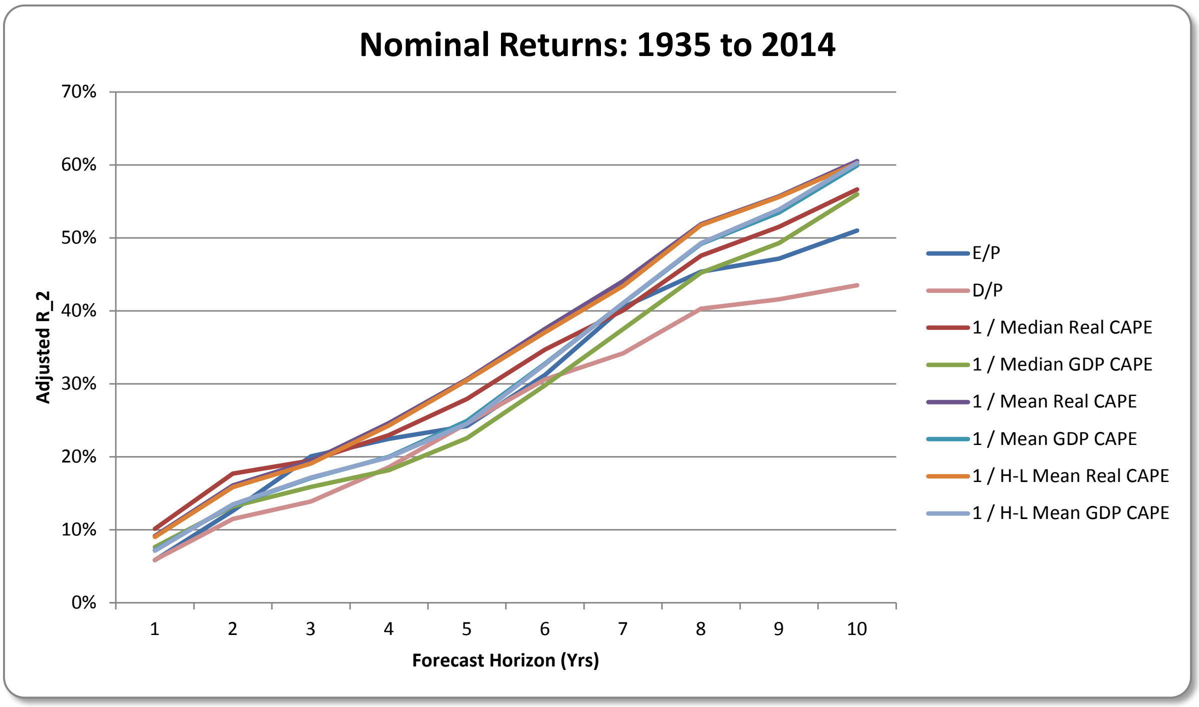

Figure 9a. Adjusted R^2 vs. Forecast Horizon for S&P 500, Nominal Returns: 1935-2014*

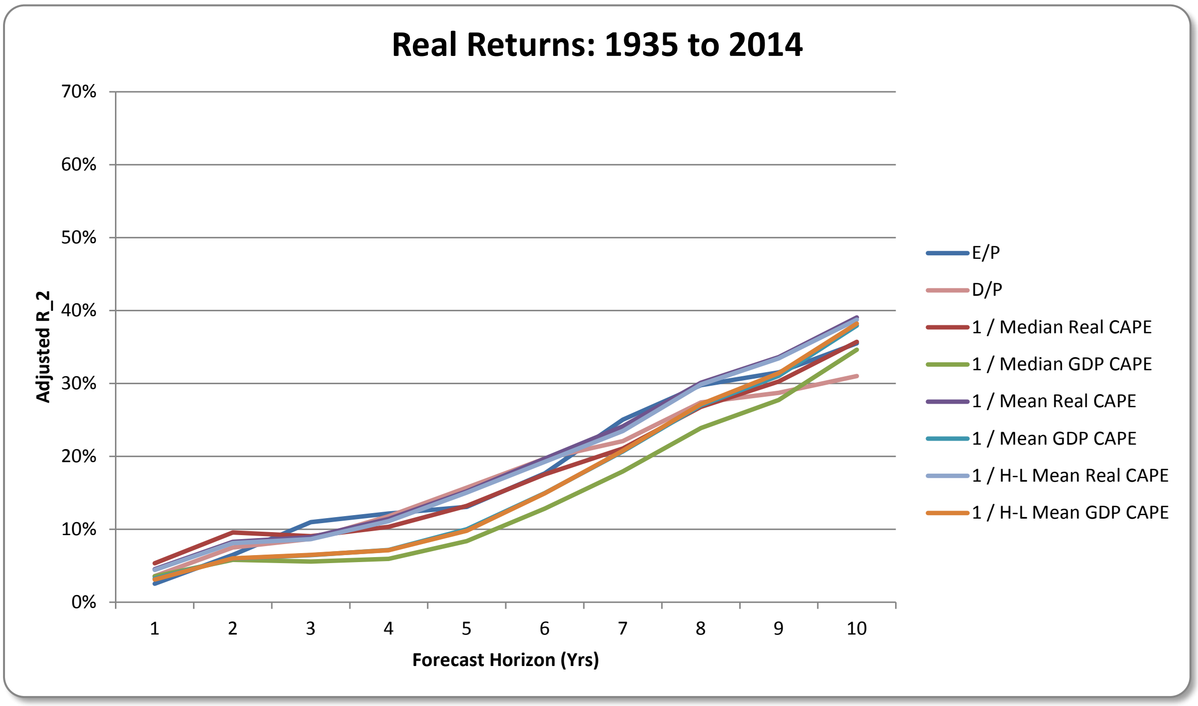

Figure 9b. Adjusted R^2 vs. Forecast Horizon for S&P 500, Real Returns: 1935-2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

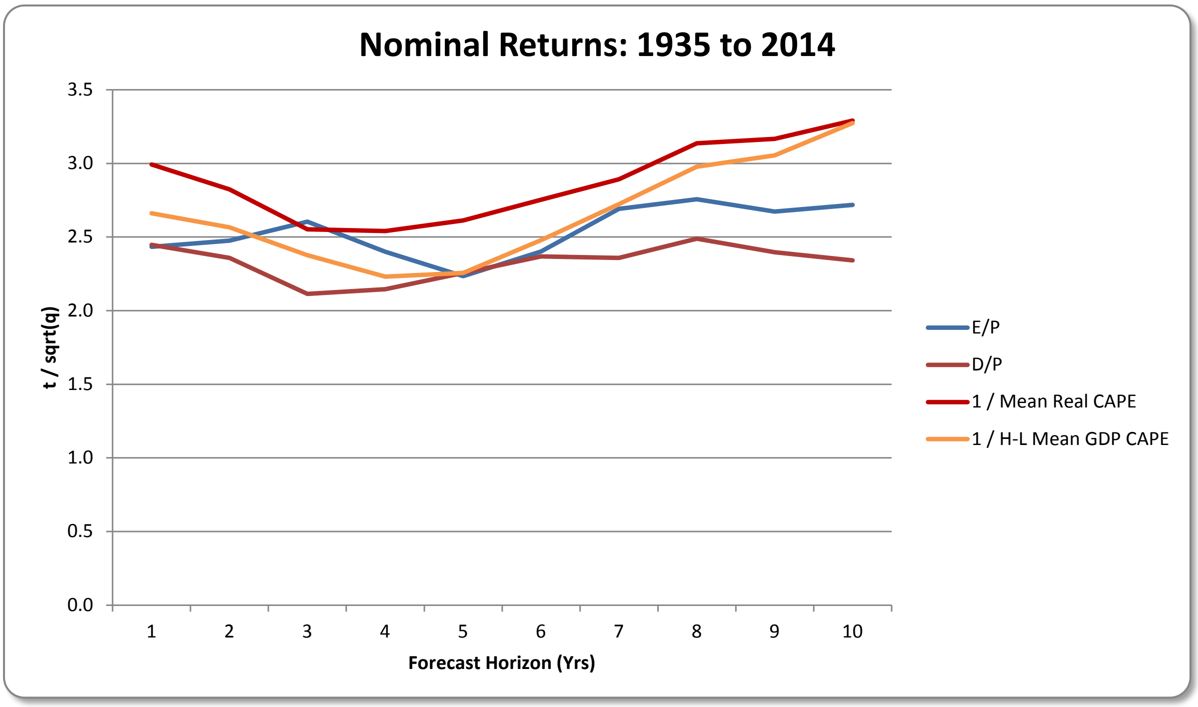

Figure 9c. $t_q(\beta)\ /\ \sqrt{q}$ vs. Forecast Horizon for S&P 500, Nominal Returns: 1935-2014*

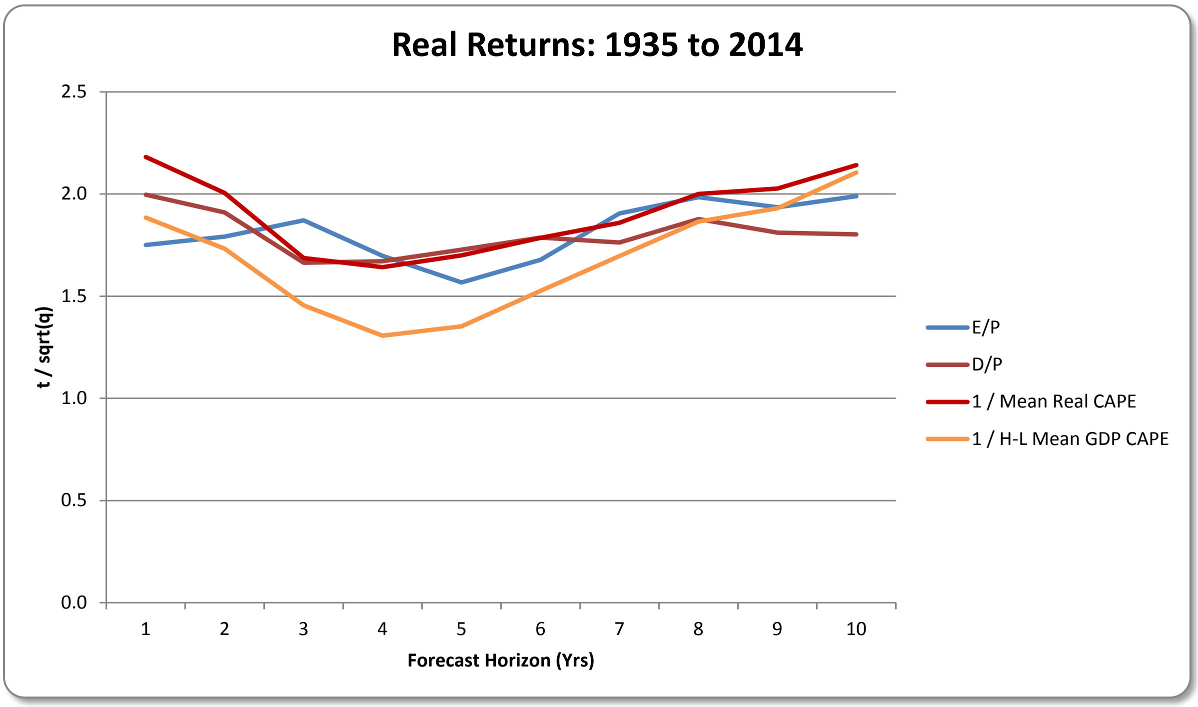

Figure 9d. $t_q(\beta)\ /\ \sqrt{q}$ vs. Forecast Horizon for S&P 500, Real Returns: 1935-2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

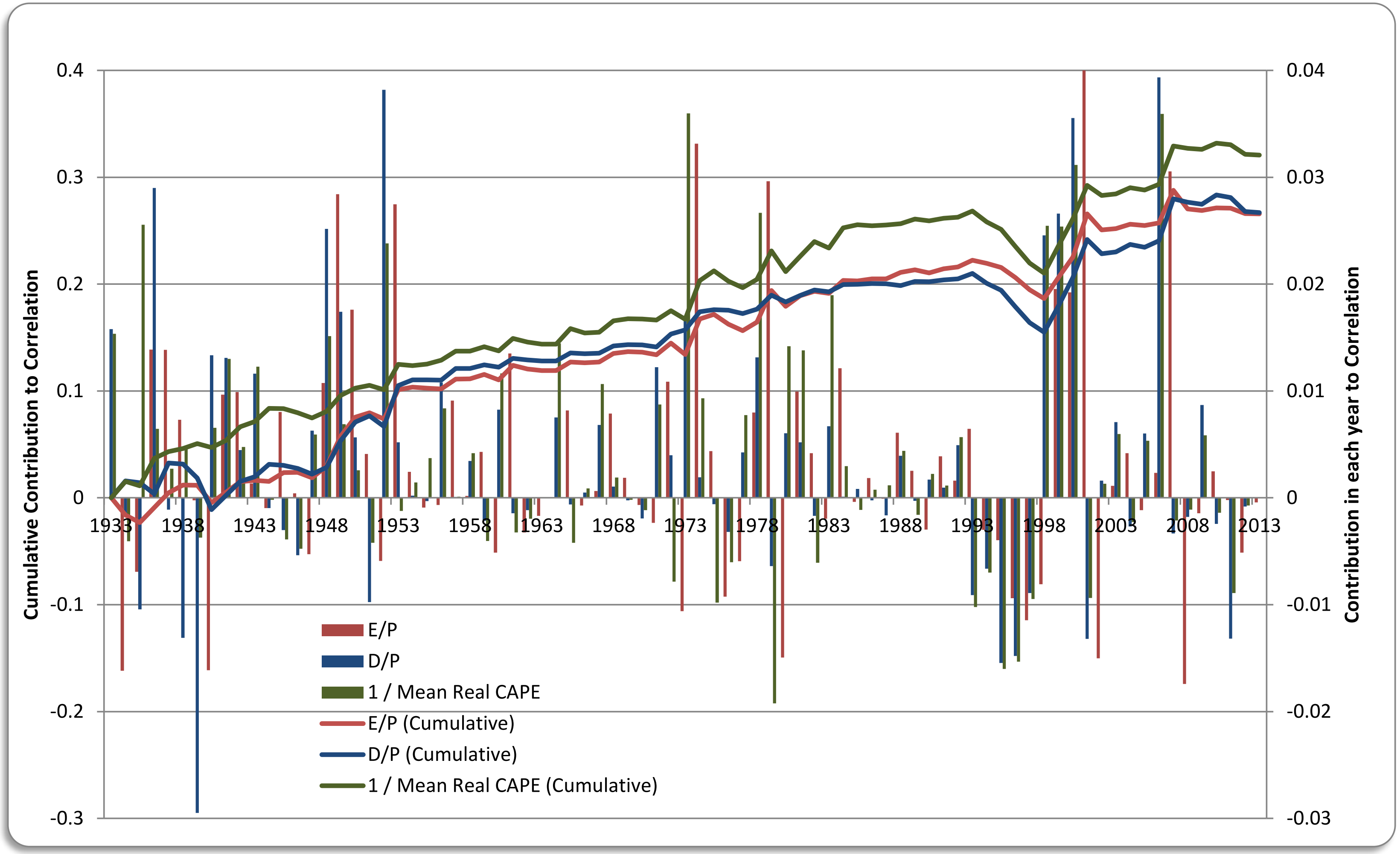

Figure 10. Partial Correlations for Nominal Returns: 1935-2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

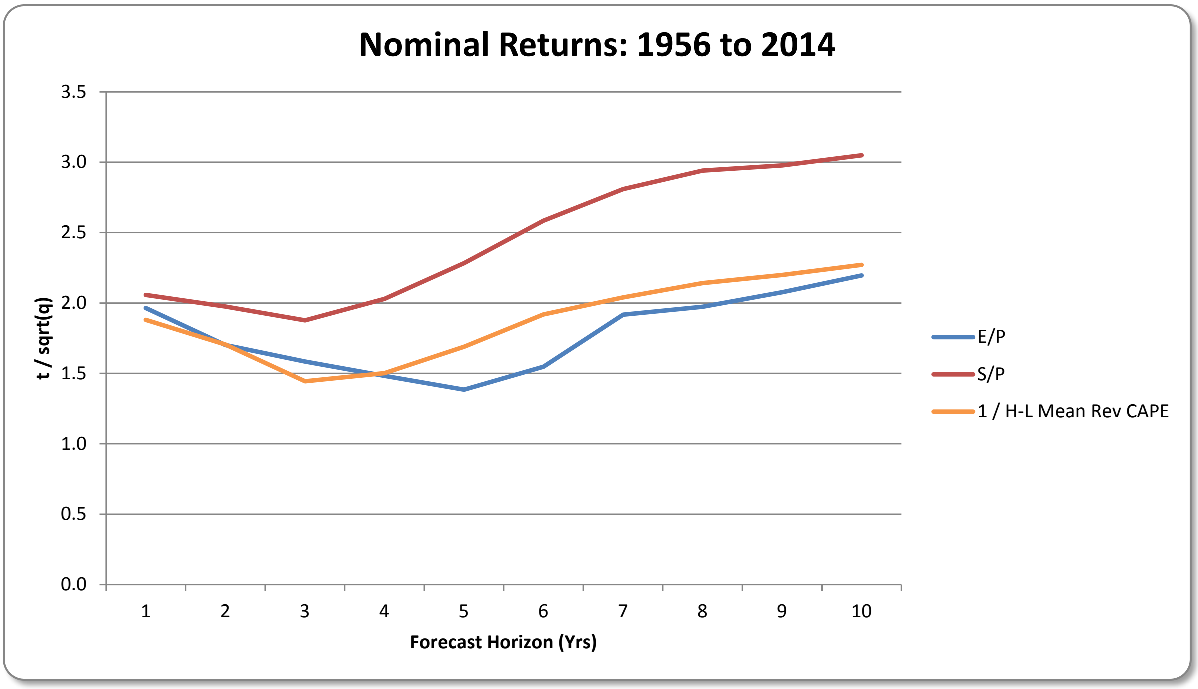

Figure 11a. $t_q(\beta) \,/\, \sqrt{q}$ vs. Forecast Horizon for S&P 500, Nominal Returns: 1956-2014*

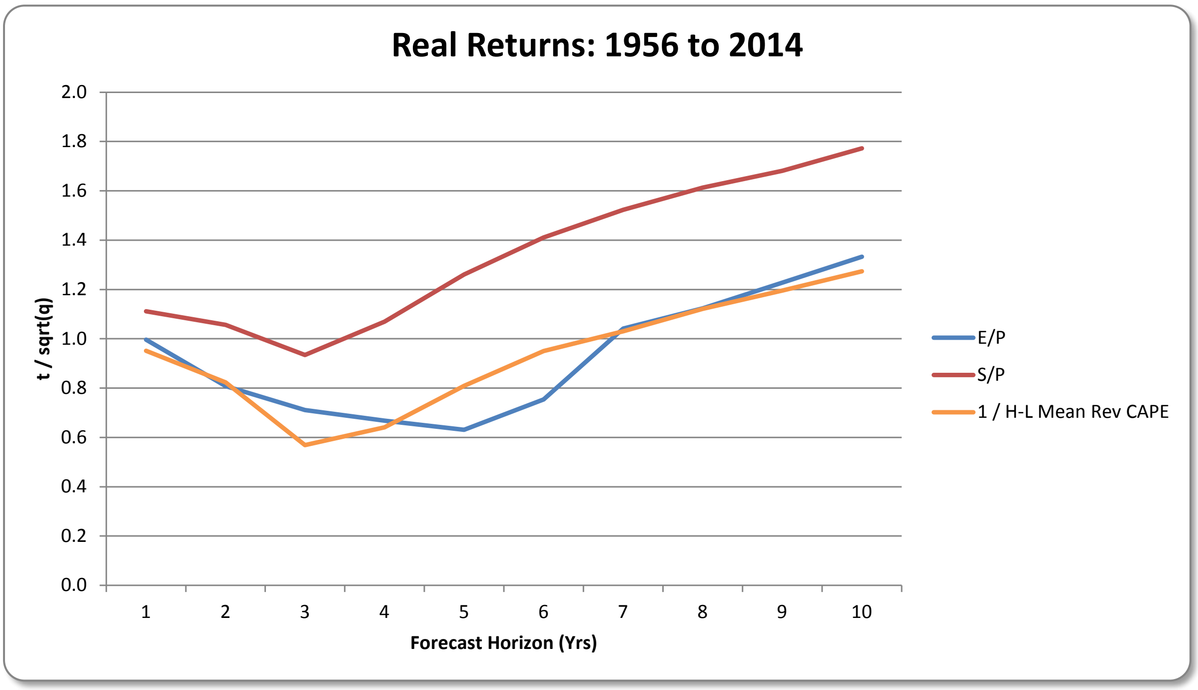

Figure 11b. $t_q(\beta) \,/\, \sqrt{q}$ vs. Forecast Horizon for S&P 500, Real Returns: 1956-2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

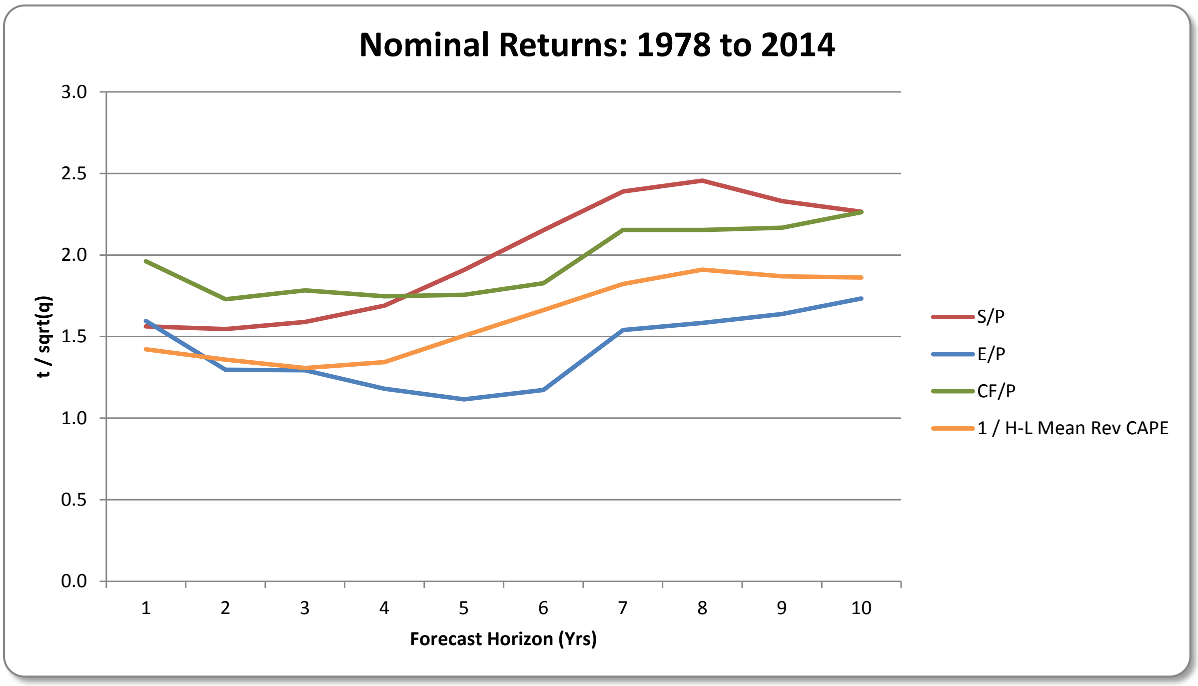

Figure 12a. $t_q(\beta) \,/\, \sqrt{q}$ vs. Forecast Horizon for S&P 500, Nominal Returns: 1978-2014*

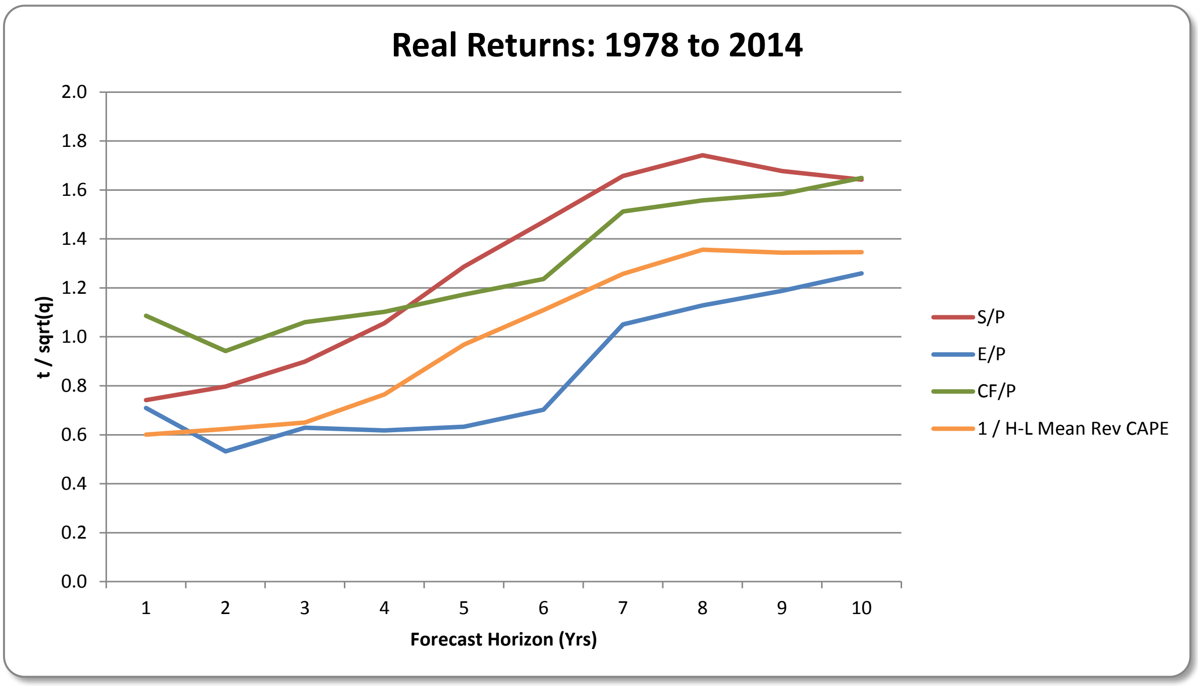

Figure 12b. $t_q(\beta) \,/\, \sqrt{q}$ vs. Forecast Horizon for S&P 500, Real Returns: 1978-2014*

*Source: Professor Robert Shiller, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

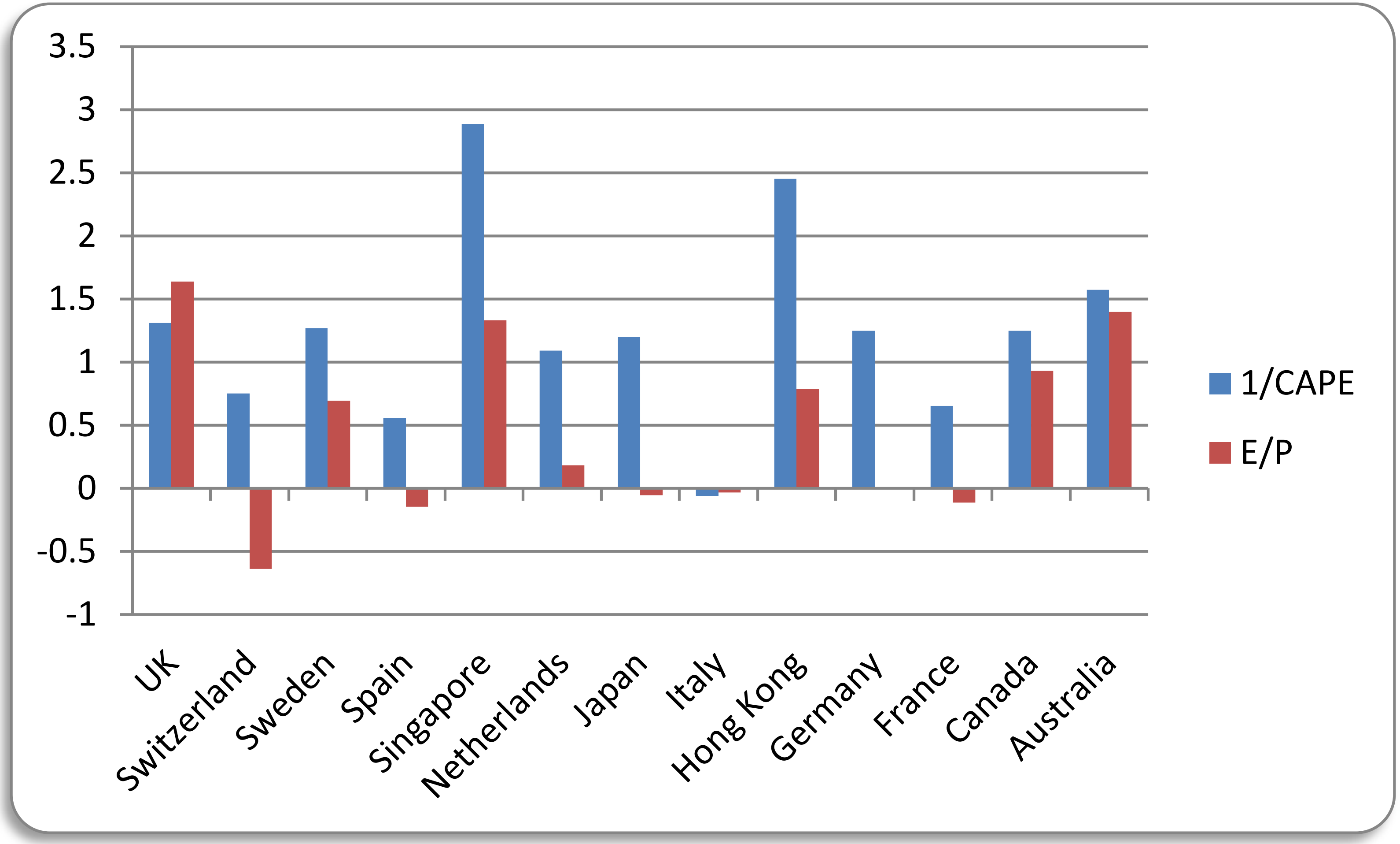

Figure 13. $t(\beta)$ for E/P and 1/CAPE in 13 International Markets, 1 Yr. Nominal Returns: 1994-2014*

*Source: MSCI

	Number of Missing Items		
Year	**Earnings**	**Market Value**	**Revenues**
1998	1	3	1
1999	1	2	1
2000	3	5	3
2001	1	2	1
2002	0	2	0
2003	4	6	4
2004	1	3	1
2005	2	3	2
2006	0	2	0
2007	1	1	1
2008	3	7	9
Average	**1.5**	**3.3**	**2.1**

Table 1. Number of Missing Data Items in Each Year: OMX Iceland 15 Index*

*Source: Bloomberg, Worldscope

Year	Year End Index Level	GDP (ISK bn)	Year End CPI Level (ICCPI)	Index Earnings per Share	Index Revenues per Share
1998	1097.59	602.4	183.70	138.27	927.56
1999	1618.36	647.5	194.00	115.33	1045.14
2000	1305.90	703.4	202.10	15.63	1188.65
2001	1159.03	793.7	219.50	83.75	1034.22
2002	1352.03	841.9	223.90	157.75	1426.48
2003	2114.34	868.7	230.00	168.08	1337.00
2004	3359.60	964.2	239.00	301.81	1571.82
2005	5534.39	1058.0	248.90	546.43	2492.75
2006	6410.48	1200.2	266.20	902.12	3591.03
2007	6318.02	1373.8	281.80	271.33	4357.41
2008	352.16	1547.8	332.90	-4708.41	1319.05
Average				-182.54	1844.65
Average excluding 2008				270.05	1897.21
Median				157.75	1337.00
Hodges-Lehmann Mean				177.54	1499.15

Table 2. Index Levels, Earnings, Revenues, Nominal GDP and Inflation: OMX Iceland 15 Index*

*Source: OMX Nasdaq, Bloomberg, Worldscope

		Year	
CAPE Based On	Measure of Location	12/31/2007	12/31/2008
Real Index Earnings	Average	20.3	-2.8
	Median	30.2	1.5
	Hodges-Lehmann Mean	26.1	1.4
GDP Weighted Index Earnings	Average	17.1	-3.9
	Median	23.5	1.2
	Hodges-Lehmann Mean	21.5	1.2
Revenue Weighted Index Earnings	Average	10.6	-1.2
	Median	11.8	2.4
	Hodges-Lehmann Mean	11.0	2.4
Bottom-Up Earnings of Current Index Constituents	Average	9.4	9.2
	Median	9.6	2.6
	Hodges-Lehmann Mean	8.7	4.7

Table 3. Alternative Computations of CAPE for the OMX Iceland 15 Index as of 12/31/2007 and 12/31/2008*

*Source: OMX Nasdaq, Bloomberg, Worldscope

Explanatory Variable	q (Yrs)	Adjusted R2 (Nominal Returns)	Adjusted R2 (Real Returns)	Constant (Nominal Returns)	Constant (Real Returns)	Beta[predictor] (Nominal Returns)	Beta[predictor] (Real Returns)	t(Beta) / sqrt(q) (Nominal Returns)	t(Beta) / sqrt(q) (Real Returns)
E/P	1	5.9%	2.5%	0.84%	-0.03%	1.62	1.21	2.43	1.75
	10	51.0%	35.5%	1.67%	-1.58%	1.26	1.15	2.72	1.99
D/P	1	5.9%	3.6%	1.00%	-1.00%	3.09	2.61	2.45	2.00
	10	43.5%	31.0%	2.10%	-1.30%	2.31	2.13	2.34	1.80
1 / Median Real CAPE	1	10.2%	5.3%	-3.33%	-3.61%	2.38	1.85	3.15	2.33
	10	56.6%	35.7%	0.56%	-2.14%	1.54	1.33	3.04	2.00
1 / Median GDP CAPE	1	7.6%	3.6%	-0.67%	-1.23%	1.70	1.28	2.74	1.98
	10	56.0%	34.6%	1.14%	-1.56%	1.24	1.06	3.00	1.95
1 / Mean Real CAPE	1	9.1%	4.5%	-2.75%	-2.95%	2.31	1.77	2.99	2.18
	10	60.5%	39.1%	-0.06%	-2.78%	1.63	1.43	3.29	2.14
1 / Mean GDP CAPE	1	7.2%	3.2%	-0.31%	-0.84%	1.66	1.24	2.68	1.91
	10	59.9%	37.9%	0.61%	-2.10%	1.30	1.13	3.25	2.09
1 / H-L Mean Real CAPE	1	9.0%	4.4%	-2.70%	-2.89%	2.30	1.76	2.97	2.16
	10	60.2%	38.7%	0.00%	-2.72%	1.62	1.42	3.27	2.13
1 / H-L Mean GDP CAPE	1	7.1%	3.1%	-0.35%	-0.81%	1.66	1.23	2.66	1.88
	10	60.3%	38.2%	0.57%	-2.15%	1.31	1.14	3.27	2.10

Table 4. Predictive OLS Regressions for the S&P 500: 1935-2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

Explanatory Variable	q (Yrs)	Adjusted R2 (Nominal Returns)	Adjusted R2 (Real Returns)	Constant (Nominal Returns)	Constant (Real Returns)	Beta[predictor] (Nominal Returns)	Beta[predictor] (Real Returns)	t(Beta) / sqrt(q) (Nominal Returns)	t(Beta) / sqrt(q) (Real Returns)
S/P	1	5.3%	0.4%	2.01%	2.26%	0.08	0.04	2.06	1.11
	10	65.2%	38.3%	0.60%	-1.86%	0.07	0.06	3.05	1.77
E/P	1	4.7%	0.0%	0.95%	2.04%	1.61	0.83	1.96	1.00
	10	49.1%	25.5%	0.83%	-1.29%	1.36	1.04	2.20	1.33
D/P	1	6.6%	1.8%	-1.83%	-1.12%	4.31	2.79	2.25	1.43
	10	53.9%	28.9%	-1.42%	-3.13%	3.51	2.72	2.41	1.45
1 / Median Real CAPE	1	5.3%	0.7%	1.15%	1.40%	1.66	0.98	2.05	1.19
	10	55.6%	30.2%	1.01%	-1.29%	1.41	1.09	2.50	1.49
1 / Median Rev CAPE	1	4.3%	-0.1%	1.51%	2.23%	1.48	0.78	1.90	0.98
	10	50.0%	23.5%	1.16%	-0.74%	1.28	0.93	2.24	1.27
1 / Median GDP CAPE	1	5.1%	0.6%	0.54%	1.14%	1.56	0.91	2.02	1.15
	10	55.1%	28.8%	0.26%	-1.73%	1.35	1.03	2.47	1.44
1 / Mean Real CAPE	1	5.5%	0.9%	0.86%	1.15%	1.73	1.04	2.10	1.23
	10	57.5%	31.8%	0.64%	-1.63%	1.47	1.15	2.59	1.54
1 / Mean Rev CAPE	1	4.1%	-0.2%	2.01%	2.67%	1.42	0.73	1.86	0.93
	10	50.8%	23.7%	1.20%	-0.69%	1.28	0.93	2.27	1.28
1 / Mean GDP CAPE	1	5.0%	0.5%	0.85%	1.42%	1.53	0.88	2.01	1.13
	10	57.2%	30.4%	0.06%	-1.93%	1.38	1.06	2.58	1.50
1 / H-L Mean Real CAPE	1	5.8%	1.0%	0.70%	0.94%	1.75	1.07	2.14	1.27
	10	57.0%	31.5%	0.74%	-1.56%	1.46	1.14	2.57	1.54
1 / H-L Mean Rev CAPE	1	4.2%	-0.2%	1.82%	2.51%	1.45	0.75	1.88	0.95
	10	50.8%	23.7%	1.19%	-0.70%	1.28	0.93	2.27	1.27
1 / H-L Mean GDP CAPE	1	5.1%	0.5%	0.64%	1.26%	1.56	0.90	2.03	1.15
	10	57.2%	30.4%	0.07%	-1.93%	1.37	1.06	2.58	1.50

Table 5. Predictive OLS Regressions for the S&P 500: 1956-2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices

Explanatory Variable	q (Yrs)	Adjusted R2 (Nominal Returns)	Adjusted R2 (Real Returns)	Constant (Nominal Returns)	Constant (Real Returns)	Beta[predictor] (Nominal Returns)	Beta[predictor] (Real Returns)	t(Beta) / sqrt(q) (Nominal Returns)	t(Beta) / sqrt(q) (Real Returns)
S/P	1	3.9%	-1.3%	5.09%	5.27%	0.06	0.03	1.56	0.74
	10	65.1%	49.0%	1.58%	0.33%	0.07	0.06	2.27	1.64
E/P	1	4.1%	-1.4%	4.00%	5.01%	1.42	0.63	1.60	0.71
	10	51.8%	35.5%	2.41%	1.24%	1.33	0.99	1.73	1.26
D/P	1	6.0%	0.0%	2.53%	3.22%	3.68	2.04	1.81	1.00
	10	70.8%	55.2%	0.10%	-0.96%	3.63	2.84	2.58	1.85
CF/P	1	7.3%	0.5%	0.47%	2.01%	1.04	0.58	1.96	1.09
	10	65.0%	49.2%	-0.46%	-1.27%	0.91	0.71	2.26	1.65
1 / Median Real CAPE	1	3.2%	-1.3%	4.93%	5.02%	1.30	0.65	1.48	0.74
	10	54.2%	39.0%	2.69%	1.31%	1.31	0.99	1.81	1.35
1 / Median Rev CAPE	1	2.5%	-1.9%	5.22%	5.78%	1.20	0.50	1.38	0.58
	10	53.6%	37.1%	2.62%	1.37%	1.27	0.95	1.79	1.30
1 / Median GDP CAPE	1	3.8%	-1.0%	4.15%	4.46%	1.29	0.67	1.55	0.80
	10	55.7%	40.2%	2.07%	0.83%	1.27	0.96	1.87	1.38
1 / Mean Real CAPE	1	3.5%	-1.2%	4.78%	4.90%	1.36	0.68	1.52	0.77
	10	56.8%	41.6%	2.36%	1.01%	1.38	1.05	1.91	1.42
1 / Mean Rev CAPE	1	2.6%	-1.9%	5.44%	5.92%	1.19	0.49	1.40	0.58
	10	55.6%	38.8%	2.61%	1.34%	1.29	0.96	1.86	1.35
1 / Mean GDP CAPE	1	3.7%	-1.2%	4.58%	4.89%	1.26	0.62	1.54	0.76
	10	59.9%	43.9%	1.88%	0.64%	1.31	1.00	2.03	1.49
1 / H-L Mean Real CAPE	1	3.8%	-1.0%	4.60%	4.67%	1.38	0.72	1.56	0.81
	10	56.1%	40.9%	2.47%	1.10%	1.36	1.04	1.88	1.40
1 / H-L Mean Rev CAPE	1	2.8%	-1.8%	5.24%	5.76%	1.22	0.51	1.42	0.60
	10	55.5%	38.8%	2.61%	1.34%	1.29	0.96	1.86	1.35
1 / H-L Mean GDP CAPE	1	3.7%	-1.2%	4.43%	4.79%	1.28	0.63	1.55	0.77
	10	59.7%	43.8%	1.86%	0.62%	1.31	1.00	2.03	1.48

Table 6. Predictive OLS Regressions for the S&P 500: 1978-2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst’s Handbook, Dow Jones S&P Indices

		Percentiles of the distribution of t(β)/sqrt(q)				
Explanatory Variable	**q (yrs)**	**50**	**90**	**95**	**98**	**99**
E1/P (i.i.d. Earnings)	1	1.04	2.29	2.66	3.08	3.37
	10	0.97	2.24	2.64	3.13	3.48
1/CAPE1 (i.i.d. Earnings)	1	1.15	2.40	2.76	3.18	3.46
	10	1.08	2.53	3.01	3.60	4.03
E2/P (Mean Reverting E/P)	1	0.29	1.60	1.97	2.41	2.69
	10	0.32	1.21	1.47	1.79	2.00
1/CAPE2 (Mean Reverting E/P)	1	0.56	1.85	2.22	2.65	2.92
	10	0.53	1.69	2.06	2.52	2.85
E3/P (Actual Earnings)	1	1.37	2.47	2.81	3.19	3.45
	10	1.42	2.44	2.77	3.17	3.45
1/CAPE3 (Actual Earnings)	1	1.50	2.58	2.91	3.29	3.57
	10	1.54	2.76	3.17	3.69	4.06

Table 7. Percentiles of the Distribution of the Simulated *t*-statistic for Three Earnings Processes*

*Source: Professor Robert Shiller

Explanatory Variable	Robust Constant (Nominal Returns)	Robust Beta [predictor] (Nominal Returns)	Estimation Interval	Valuation Ratio as of 12/31/2014	10 Yr. Return Forecast
S/P	-0.37%	0.08	1947-2014	56.50%	4.35%
E/P	0.78%	1.30	1926-2014	4.97%	7.24%
D/P	1.79%	2.18	1926-2014	1.92%	5.96%
CF/P	-0.07%	0.87	1978-2014	8.00%	6.92%
1 / Median Real CAPE	0.00%	1.60	1935-2014	4.19%	6.68%
1 / Median Rev CAPE	0.47%	1.35	1955-2014	4.53%	6.58%
1 / Median GDP CAPE	0.30%	1.33	1935-2014	4.52%	6.31%
1 / Mean Real CAPE	-0.73%	1.70	1935-2014	4.52%	6.97%
1 / Mean Rev CAPE	0.42%	1.36	1955-2014	4.07%	5.95%
1 / Mean GDP CAPE	-0.03%	1.36	1935-2014	4.09%	5.54%
1 / H-L Mean Real CAPE	-0.54%	1.68	1935-2014	4.11%	6.37%
1 / H-L Mean Rev CAPE	0.53%	1.34	1955-2014	4.31%	6.32%
1 / H-L Mean GDP CAPE	0.04%	1.36	1935-2014	4.42%	6.04%

Table 8. Predicted Annualized 10 yr. Forward Returns as of 12/31/2014*

*Source: Professor Robert Shiller, Professor Aswath Damodaran, Bureau of Economic Analysis, S&P Capital IQ Analyst's Handbook, Dow Jones S&P Indices