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Earnings per Share: Stylized Facts and New Paradigms

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The paradigm that inspired the equity price bubble of the 1990s is inconsistent with the long-term earnings expectations that a rational agent could draw from the stylized facts available in real time. The paper identifies the stylized facts that characterize the behavior of accounting earnings per share (EPS) that Standard & Poor's has reported for the S&P 500 index since 1935. Estimation of an unobserved components model in state-space form shows that the long-run component of earnings is predictable, and that its growth rate has obeyed a deterministic process for three-quarters of a century. It is impossible to reconcile a deterministic slope in log EPS with the new paradigms and other delusions regarding earnings that periodically generate equity bubbles. The evidence is inconsistent with market rationality, and buttresses a behavioral theory of finance in which folly occasionally occupies center stage.

keywords: *Unobserved components models, Market rationality, Earnings expectations, JEL Codes: C490, G140*

> The Pied Piper lifted the pipe to his lips and, once again, blew a haunting melody into the air. This time, clapping, and clattering, skipping and chattering, the children came. Robert Browning, *The Pied Piper of Hamelin*.

The purpose of this paper is to identify the stylized facts that characterize the behavior of quarterly accounting earnings per share (EPS) that Standard & Poor's has reported for the S&P 500 index since first-quarter 1935. The empirical evidence in this paper suggests that folly and sentiment regarding future earnings prospects vie with rationality as the basis for investor behavior.[1] Earnings underpin all equity valuation models; therefore, understanding the behavior of earnings would help to set rational bounds for equity values. Moreover, identifying the stylized facts of time series has been an important part of research in both empirical economics and finance; see, e.g., Harvey [1989, 1997], Hodrick and Prescott [1980], Nelson and Plosser [1982], and Blanchard and Fisher [1989].

This paper does not take sides on the long-standing debate regarding the importance of earnings versus dividends in equity valuation.[2] Rather, this paper focuses on earnings instead of dividends. Because the dividend per share series that Standard & Poor's has reported since 1935 is a four-quarter moving sum, it is impossible to determine the level of dividends in a given quarter; in contrast, the EPS series is a true quarterly series.

Several measures of EPS for the S&P 500 index are available. Accounting, or as reported EPS, is the oldest, broadest, and the least useful measure of performance. This measure of earnings does not accurately portray a firm's underlying earnings, because it includes unrelated transitory factors that distort and occasionally dominate the picture. Another measure, operating earnings, focuses more sharply on the earnings from a firm's principal operations. The inception date of the operating earnings series for the S&P 500 index is first-quarter 1988, or 1988:Q1. In 2001, Standard & Poor's proposed another measure called core earnings that excludes additional transitory factors. Core earnings begins with accounting earnings as defined by Generally Accepted Accounting Principles (GAAP) but excludes goodwill impairment charges, gains/losses from asset sales, pension gains, unrealized gains/losses from hedging activities, merger/acquisition related expenses, and litigation or insurance settlements and proceeds. As measures of performance, operating earnings, and core earnings are more useful than accounting earnings; however, their relatively short histories detract from their use in empirical work. This paper proposes a measure of permanent earnings that is smoother than core earnings because it filters out all transitory factors, including the effects of macroeconomic shocks.

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Univariate Unobserved Components Model of EPS

Structural time-series models (STMs) are formulated in terms of unobserved components, such as trend, cycle, and seasonals that have a direct and clear interpretation and that represent the stylized features of the series. There is a close affinity between STMs and ARIMA models; univariate STMs have a reduced form ARIMA representation. Harvey [1989] showed that time-varying coefficient models, autoregressive moving average models, and unobserved-components time series models admit state-space representation. He also popularized the use of the Kalman filter for obtaining maximum likelihood estimates of parameters in state-space models through prediction error decomposition. State space models have been used to model many economic problems, including rational expectations (Wall [1980], Burmeister and Wall [1982], Watson [1989], Imrohoroglu [1993]), permanent income, potential GDP, the NAIRU, and unobserved components (cycles and trends). Hamilton [1994a, 1994b], Harvey [1989], Koopman, Shephard and Doornik [1999], and Koopman, Harvey, Doornik and Shephard [2000] provide examples of uses of state space models.

The following STM views the log of EPS, y_t, as the sum of four components, trend μ_t, cycle ψ_t, seasonal γ_t, and an irregular or white noise process ε_t

$$y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t, \quad \varepsilon_t \sim \text{NID}(0, \sigma_\varepsilon^2) \qquad (1)$$

The cycle is a transitory component that dissipates without lasting impact, while the trend is the permanent component that, when extrapolated, gives the clearest indication of the future long-term movement of the series. In the most general case, a local linear trend model, the trend consists of level and slope both evolving stochastically as random walks,

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \quad \eta_t \sim \text{NID}\left(0, \sigma_\eta^2\right) \qquad (2)$$

$$\beta_t = \beta_{t-1} + \zeta_t, \quad \zeta_t \sim \text{NID}\left(0, \sigma_\zeta^2\right) \qquad (3)$$

β_t is the slope or one-period growth in μ_t, while η_t and ζ_t are independent disturbances with variances, σ_η^2 and σ_ζ^2 , respectively. The presence of η_t allows the level to shift up or down in response to shocks, while ζ_t allows the slope to change. Different trends arise depending on the variances of the disturbances. In the local linear trend model both σ_η^2 and σ_ζ^2 are positive. Another possibility is a smooth trend model in which only the slope is stochastic, i.e., $\sigma_\eta^2 = 0$, and $\sigma_\zeta^2 > 0$. In this case, the trend is an integrated random walk, and characteristically varies smoothly over time. The Hodrick-Prescott (1980) filter emerges as special case that constrains the noise-to-signal ratio $(\sigma_\varepsilon^2/\sigma_\zeta^2)$, to a predetermined value depending on the frequency of the data. The trend is a random walk with drift when $\sigma_\eta^2 > 0$, and $\sigma_\zeta^2 = 0$. Finally, a deterministic trend emerges if both σ_ζ^2 and σ_η^2 are zero. Model selection is data-dependent, and may be based on a measure of goodness of fit, such as prediction error variance. The STM may also include dummy or intervention variables to account for outliers, structural breaks, and other data irregularities. Theory, inspection of the data prior to estimation, and inspection of the residuals may indicate the need for residual intervention variables, or for dummy variables to model shifts in the level, or the slope.

Estimation Results

Each of the four models described above included a stochastic seasonal, and six dummy variables to account for one-time shocks. Table 1 shows the results of estimating a *Basic Structural Model* that allows for a stochastic level and slope, stochastic trigonometric seasonal, and an irregular component. Figures 1–9 show additional details. The estimated variances of the disturbances of the level, σ_ζ^2, and of the slope, σ_η^2, are both zero, but the variance of the seasonal component is positive. Further, estimation of a local linear trend model, smooth trend model, deterministic trend model, and random walk with drift model, all yielded identical prediction error variances and parameter values, including zero values for the unconstrained terms, σ_ζ^2, and σ_η^2. Therefore, a deterministic trend model emerges as fully congruent with the data. It is worth noting that a deterministic trend model also emerges in the absence of the six dummy variables.

The estimated coefficients of the final state vector and their t-statistics strongly reject the null of a zero slope. The slope implies an annualized long-run growth rate of EPS of 6.13%. Table 1 also shows that the coefficients of the dummy variables are negative and highly significant. By far the largest outlier occurred on 2002:Q4, when log EPS dropped below trend by 1.07 log units, or equivalently, a 43% drop in the logged series.

Figure 1 shows the log of EPS and the estimated trend or long-run component; the shaded areas represent recessions. Deviations from the permanent component or linear trend obey unpredictable cyclical factors, random shocks, and stochastic seasonality. Since the parameters of the state space model were estimated using all of the sample data, it is premature to conclude that the trend is predictable. Clearly, a real-time agent formulates expectations at each point t using only data through $t - 1$. The way to meet this objection is to use the Kalman filter to obtain the one-step-ahead prediction of the state vector at each point. Thus, unlike the smoothed trend in Figure 1, the filtered trend at each point t is based only on information available through

Table 1. *Estimation is by Maximum Likelihood using Stamp (2005) of Koopman, Harvey, Doornik, and Shephard. Signal Extraction: 1935: Q1–2004: Q4*

T = 280. The dependent variable is the log of quarterly earnings per share (LEPSQ). Prediction error variance is 0.015001

Estimated variances of disturbances for LEPSQ

Irregular	0.00000
Level	0.00000
Slope	0.00000
Cycle	0.012237
Seasonal	3.4744e-005

Estimated Coefficients of the Final State Vector

Variable	Coefficient	R.m.s.e.	t-value [P-value]
Level	2.5958	0.067276	38.585[0.0000]
Slope	0.015317	0.00041605	36.815[0.0000]
Cycle_1	0.12679	0.074514	
Cycle_2	0.050499	0.20063	
Seasonal_1	−0.047563	0.027625	−1.7217 [0.0862]
Seasonal_2	0.061057	0.026701	2.2867 [0.0230]
Seasonal_3	−0.040277	0.019415	−2.0745 [0.0390]

Anti-log trend analysis
Trend value at end of period is 13.4074.
Growth rate at end of period is 0.015317 (6.1268 % per 'year').

Estimated Coefficients of Intervention Variables

Variable	Coefficient	R.m.s.e.	t-value [P-value]
d383	−0.35506	0.093360	−3.8031 [0.0002]
d393	−0.31035	0.092951	−3.3389 [0.0010]
d872	−0.45065	0.091408	−4.9301 [0.0000]
d914	−0.41258	0.091429	−4.5125 [0.0000]
d012	−0.32584	0.092431	−3.5253 [0.0005]
d024	−1.0708	0.093814	−11.415 [0.0000]

Seasonal Analysis (at end of period)
Seasonal Chi^2(3) test is 11.9732 [0.0075].

	Seasonal 1	Seasonal 2	Seasonal 3	Seasonal 4
Value	0.10133	0.0072859	−0.020780	−0.087840
Anti-log	1.1066	1.0073	0.97943	0.91591
Percentage	10.665	0.73126	−2.0565	−8.4093

Cycle Analysis

The amplitude of the cycle is 0.0741537 (that is approximately 7.41537 % of the trend).
The cycle variance is 0.0465482.
The cycle period is 44.1947 (11.0487 'years').

$t-1$, which also excludes all dummy variables. Figure 2 shows the smoothed trend (solid line), and the filtered trend (dotted line). The filtered trend is unstable in the early part of the sample due the paucity of observations and to the impact of seismic events such as the Great Depression and World War II; however, the two trends converge as the sample expands. This buttresses the view that the permanent component of earnings is predictable in a rational expectations framework. Consider an individual who estimated a deterministic trend model sampling 1935:Q1–1985:Q4, and forecasted log EPS for 1986:Q1–2004:Q4 without using data or coefficients for the forecast period. As shown in Figure 3, the out-of-sample forecast and the filtered trend remain in close proximity.

A similar view comes from the slope, which in a structural time series model provides information about change. Figure 4 shows the corresponding smoothed (solid horizontal line) and filtered (dotted line) growth rates. Aside from the catastrophe of the Depression, World War II, and the sharp recovery in the early post-war years, the filtered slope is almost indistinguishable from the smoothed growth rate. This is remarkable given the diversity of macroeconomic conditions in three-quarters of a century: several wars; 12 recessions; a long period of low inflation, low

FIGURE 1
Log of EPS and its Trend.
1935:1–2004:4

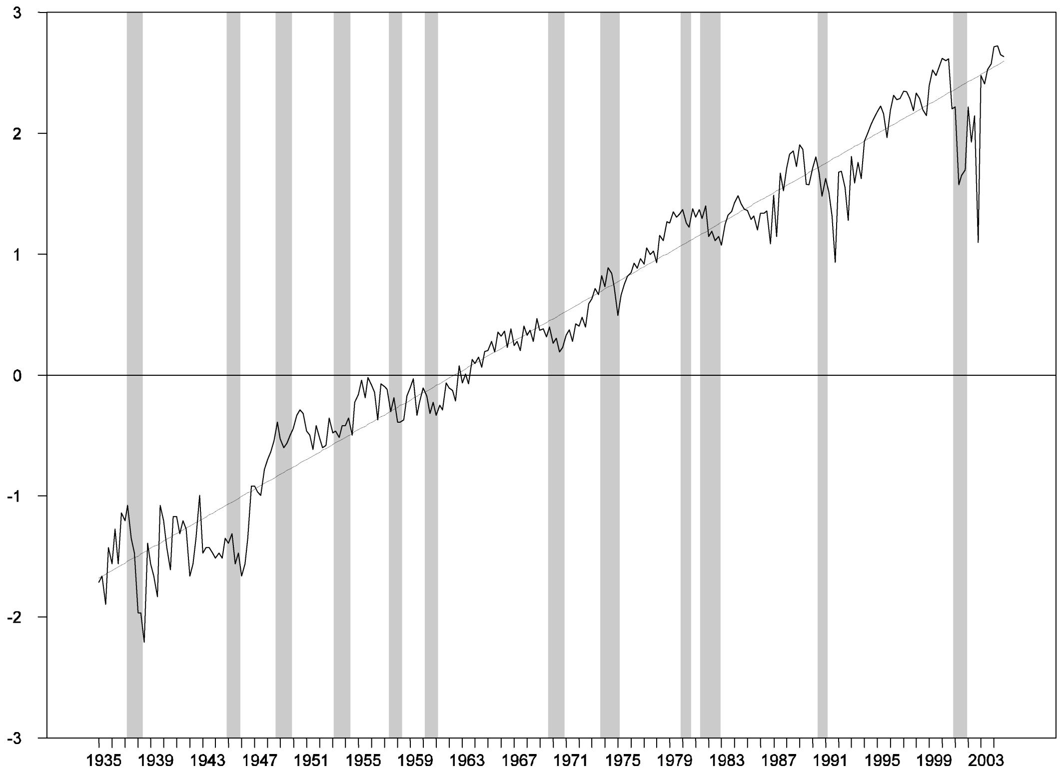


FIGURE 2
Smoothed and Filtered Trends.
1935:1–2004:4

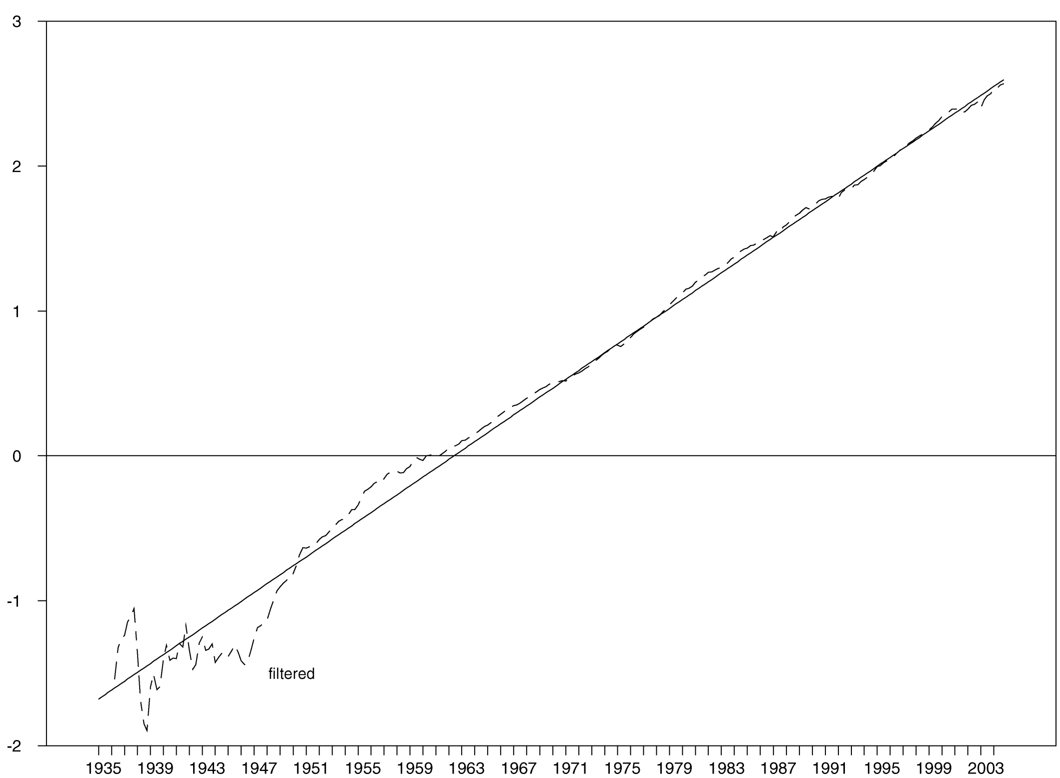


FIGURE 3
Forecasted and Filtered Trends, 1986:Q1-2004:Q4.

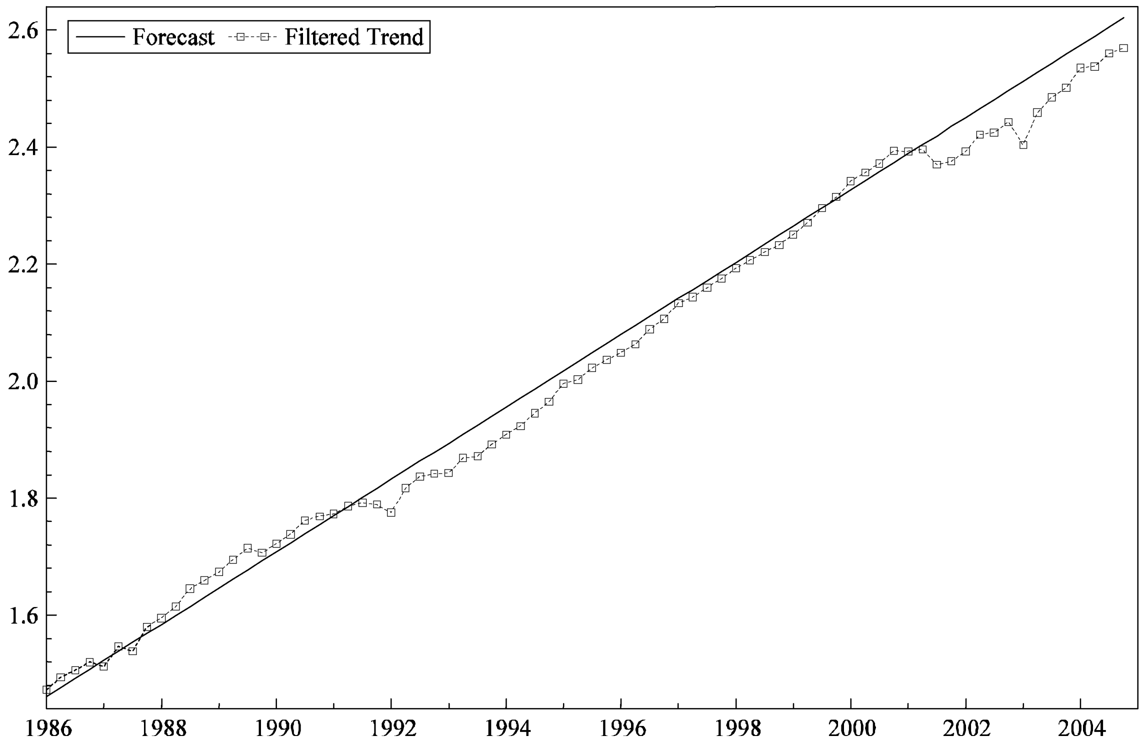


FIGURE 4
Smoothed and Filtered Growth Rates.
1935:1–2004:4

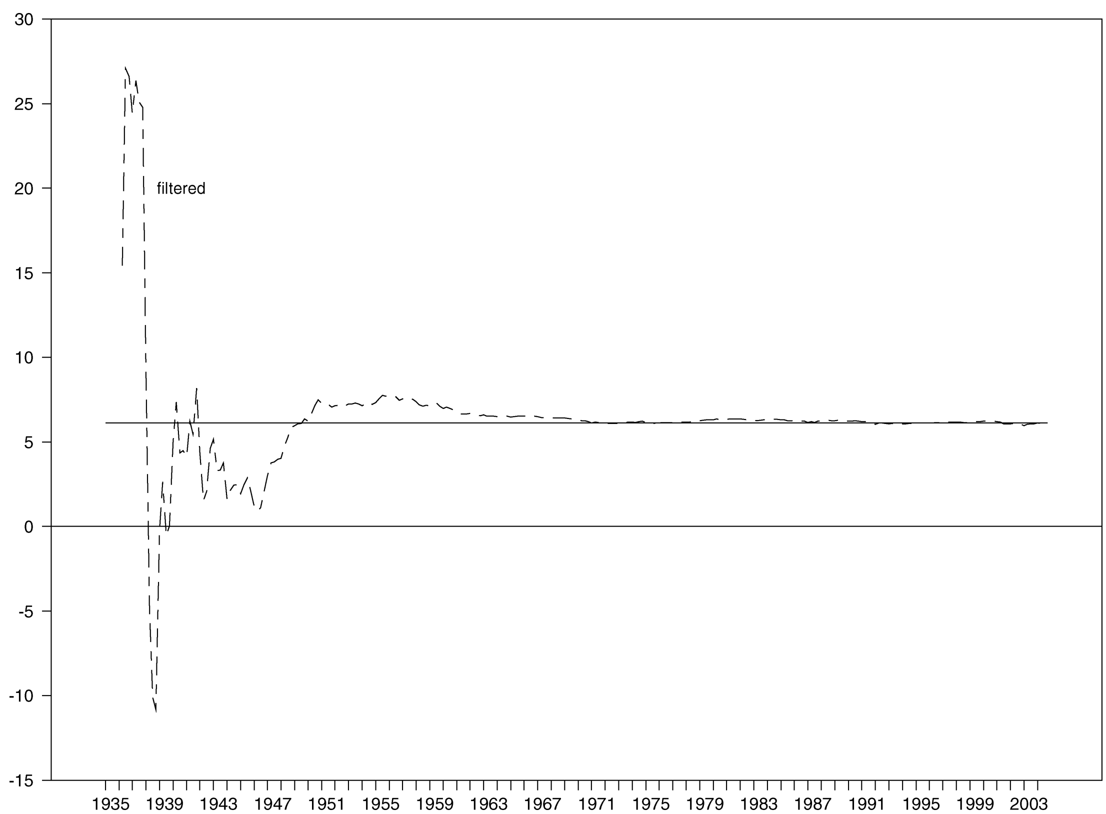
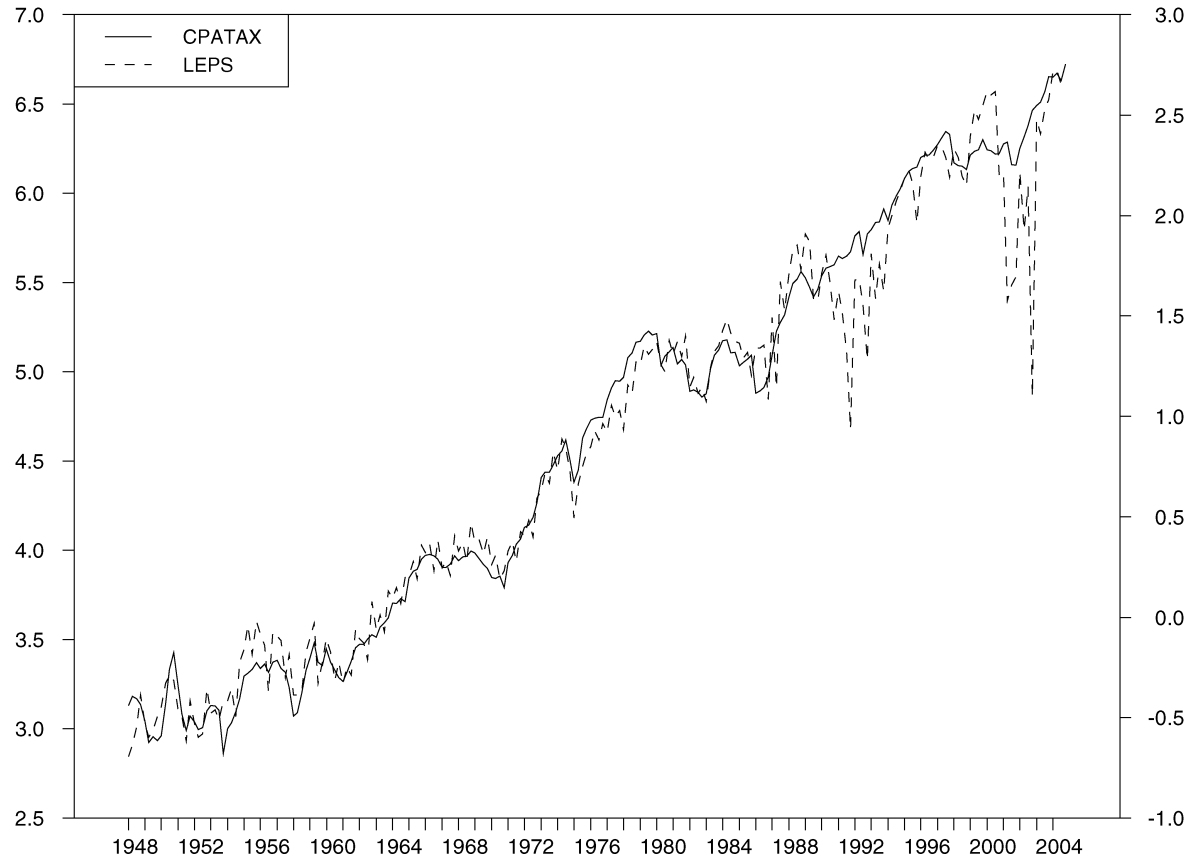


FIGURE 5
Log of Corporate Profit After-Tax and of EPS.
1948:1–2004:4



unemployment, and rapid productivity growth; and a nearly equally long span of high unemployment, high inflation, and protracted productivity slowdown; and finally the productivity miracle of the 1990s. Notwithstanding this amazing range of economic conditions, the empirical evidence indicates that the long-run growth rate of trend EPS is deterministic. It is worth noting that, as shown in Figure 5, the behavior of log EPS has closely mirrored that of after-tax corporate profits; the log of annualized corporate profits (billions of dollars) appears on the left axis, and the log of EPS on the right axis.[3] Peculiarly, beginning in 1997 corporate profits began to decrease and then failed to grow for the next four years, yet analysts were predicting that earnings would grow at an accelerated rate.

During the 1990s, Abby Joseph Cohen, chief investment strategist for Goldman Sachs, and Ralph Acampora, chief technical analyst for Prudential Securities, touted the paradigm that earnings in the future would grow at a much higher rate. In the popular culture the new paradigm came to justify permanently higher valuation ratios for equities. Analysts also viewed earnings prospects through rose colored glasses. Figure 6 shows analysts' consensus long-term (five-year), expected EPS growth rates for the S&P 500 index. During 1985-90 they predicted that EPS would grow at an average annual rate of 11.2% per year, but after 1995 they raised their growth forecasts in line with the new paradigm. At the end of 1998, the analysts surveyed by Thomson Financial predicted that earnings would grow at a rate of 14.9% for the next five years, and in August 2000 they predicted a five-year growth rate of 18.7% per year. In the euphoria of the moment, Glassman and Hassett [1999] predicted that the DJIA could sensibly reach 36,000 by early 2005, but lest they err on the side of forbearance, they cautioned that it could reach that level "much earlier." The paradigm that inspired the equity price bubble of the 1990s is inconsistent with the long-term earnings expectations that a rational agent could draw from the stylized facts available in real time.

Figure 7 shows the stochastic cycle of log EPS along with the recession chronology. Since 1935, the cycle has fallen during recessions and has rebounded sharply once economic growth resumed. Log EPS is above (below) trend when the cycle is positive (negative).The cycle period (the time needed to observe a full range of values), is 11 years and the amplitude of the cycle is approximately 7.4% of the trend. One may reasonably conclude that the cyclical component is unpredictable

FIGURE 6
Expected Earnings Growth rate (%).
Average Annual/Growth Rates: 1985–2005

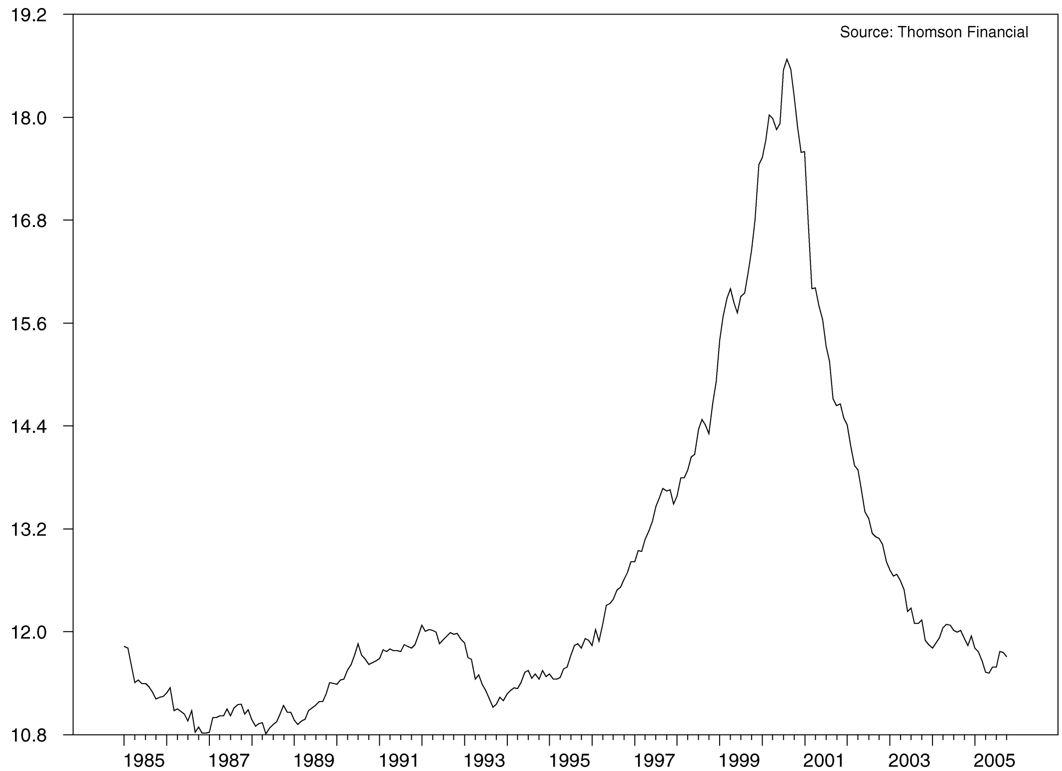


FIGURE 7
Stochastic Cycle of EPS.
1935:1–2004:4

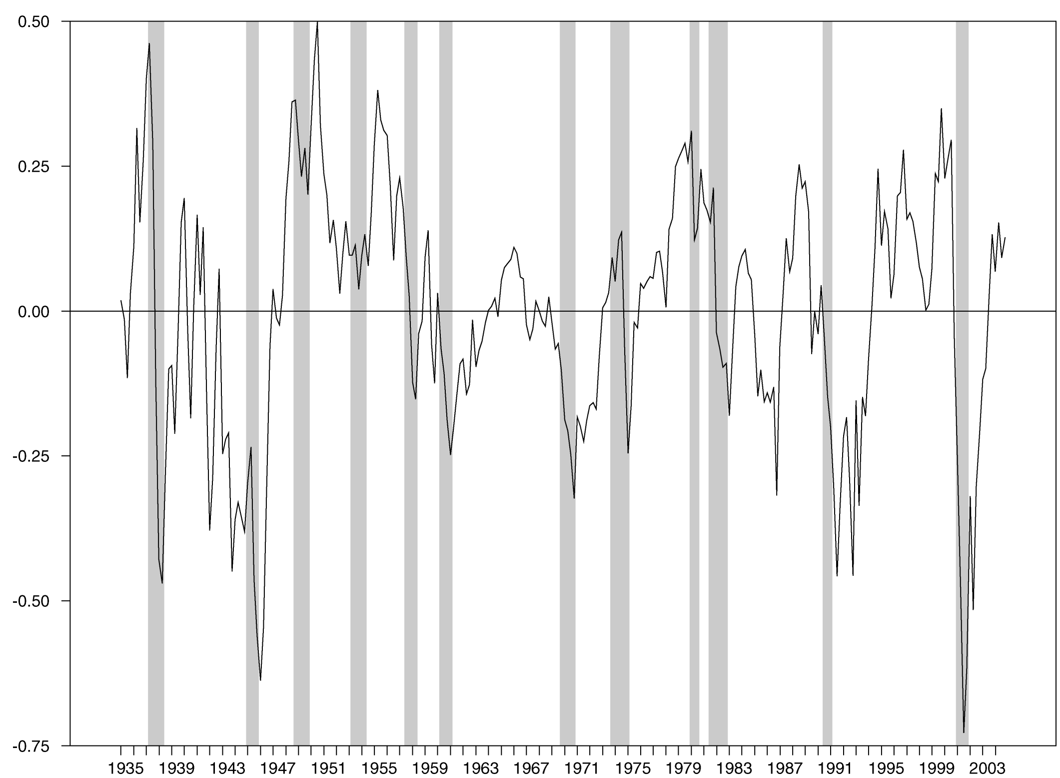
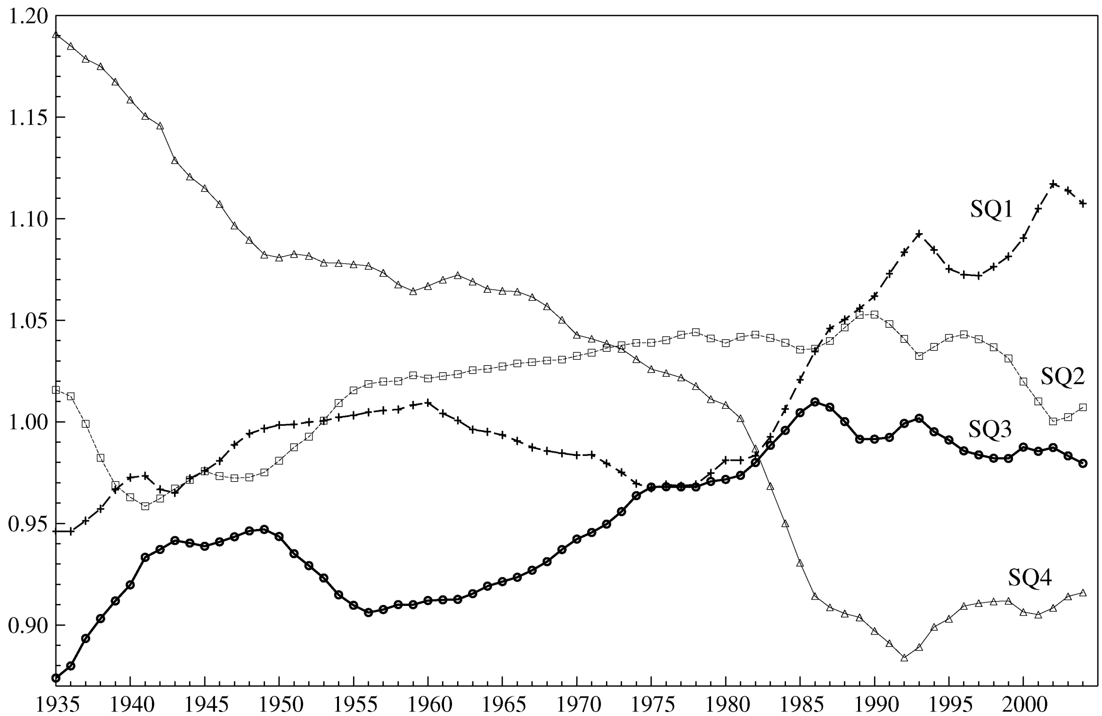


FIGURE 8
Evolving Seasonality, 1935:Q1-2004:Q4



given that it obeys the vicissitudes of the business cycle. Zarnowitz's [1967] excellent review of the literature did not find evidence that turning points in the business cycle are predictable.

There is a statistically significant stochastic seasonal component in EPS as evidenced by the $\chi^2(3)$ test which rejects the null of no seasonality with a P-value of 0.007. Figure 8 shows distinctly different seasonal patterns during the beginning and end of the sample, the 1970s being a transitional phase. Each seasonal is a factor of proportionality that indicates in percentage terms, how much higher or lower the level of EPS is, on average, in a given quarter. At the beginning of the sample the fourth quarter seasonal (SQ4) was 1.18, indicating that EPS tended to increase by about 18% in the fourth quarter. However, at the end of the sample, 70 years later, SQ4 was associated with an 8.3% drop in EPS. Since the mid 1980s the first quarter seasonal (SQ1) has risen; it now dominates on the positive side. On the other hand, SQ4 has become the largest negative seasonal.

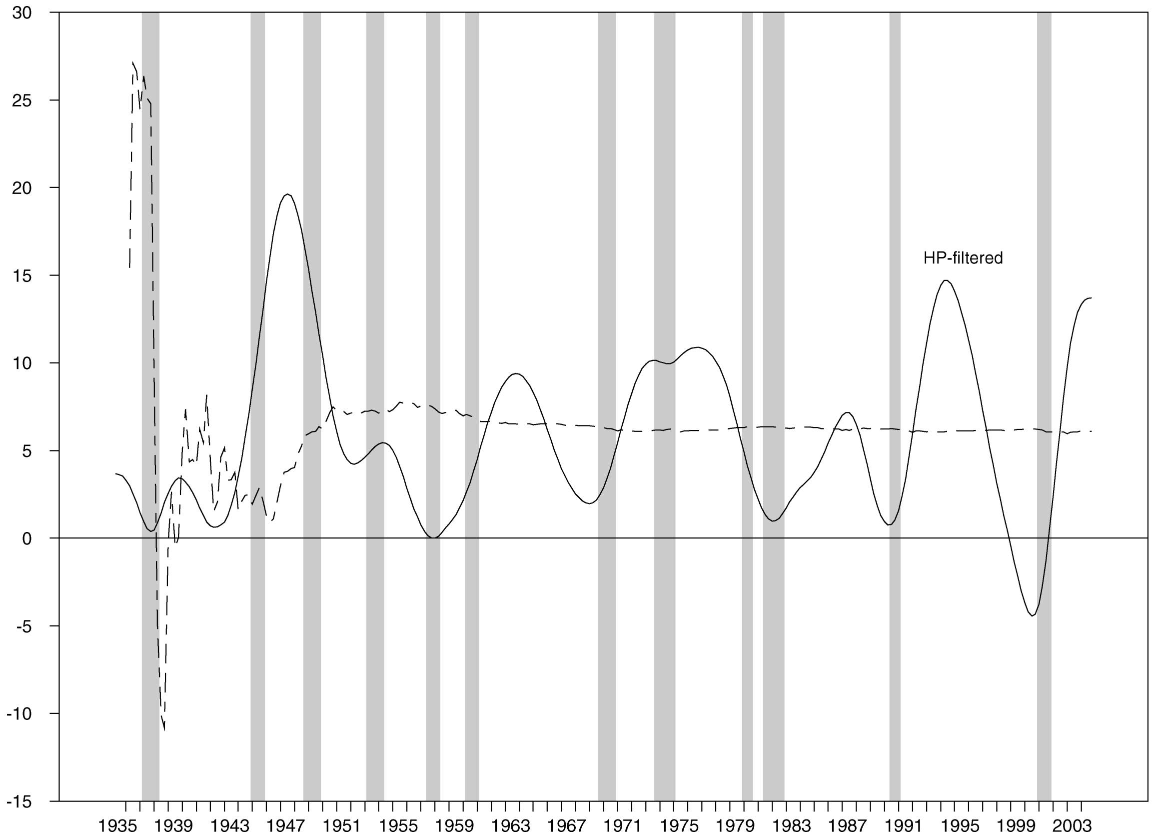
Testing for a Unit Root

During the apogee of the unit root revolution, testing for unit roots became almost mandatory. Harvey [1997] criticized the indiscriminate testing as unnecessary, or misleading in many cases. As an alternative, he proposed the use of structural time series models. Nevertheless, it worth checking if these two different frameworks point in the same direction; especially, since several authors have reported that the time series properties of firms' earnings are consistent with a random walk with drift (see, e.g., Ball and Watts [1972], Albrecht et al. [1977], Watts and Leftwich [1977]). More recently, Brown [1993] also concurred that the random walk with drift model is a reasonable characterization of firms' annual earnings.

Schmidt and Phillips [1992] and Elliott, Rothenberg and Stock [1996] have developed more powerful tests of the unit root null than the widely used Dickey-Fuller tests [1981]. The Schmidt and Phillips (SP) Lagrange Multiplier test allows for a trend under both the null and the alternative, without introducing irrelevant parameters as in the Dickey-Fuller tests. For the sample period 1935:Q1–2004:Q4, the SP test statistic, -7.69, is well below the 1% critical value, -3.59, decisively rejecting the unit root null. The Elliott, Rothenberg, and Stock (ERS) modified ADF test, the so-called DF-GLS test dominates the ADF test (Maddala and Kim [1998]). Sampling 1935:Q1–2004:Q4, the DF-GLS test with four autoregressive lags yields a test statistic, -5.08, that also falls below the 1% critical value, -3.48. It is worth noting that the results are not an artifact of the given sample.

An alternative to the unit root null is to test the trend stationary null as proposed by Kwiatkowski, Phillips, Schmidt and Shin [1992]. The KPSS test rejects the null if the test statistic, η_τ exceeds the critical values

FIGURE 9
HP-Filtered and STM-Filtered Growth Rates.
1935:1–2004:4



tabulated by Kwiatkowski et al. In the present case, none of the test statistics exceeds the 5% critical value, 0.146, e.g., $\eta_\tau(3) = 0.105$; $\eta_\tau(4) = 0.089$; $\eta_\tau(5) = 0.0794$; $\eta_\tau(6) = 0.0725$; $\eta_\tau(7) = 0.0677$; and $\eta_\tau(8) = 0.0639$. The lag truncation parameter, shown in parentheses, corrects for error autocorrelation. Therefore, this test provides confirmatory evidence that log EPS is trend-stationary, which is consistent with the results from the STM model. This has important implications for the valuation of the aggregate market.

An Alternative Filtering Technique: The Hodrik-Prescott Filter

The low-pass HP filter of Hodrick and Prescott [1980] has been widely used, although Harvey and Jaeger [1993] and Cogley and Nason [1995] show that it can give rise to spurious cyclical behavior and to considerable distortion. The HP algorithm solves a linear system involving a banded Toeplitz matrix in order to minimize the sum of squared differences between the trend and the actual series, subject to a penalty term that constrains the size of the second differences. Moreover, the HP filter constrains σ_η^2 to equal zero, and also *a priori* constrains the noise-signal ratio or smoothness parameter, λ, to equal 1600 for quarterly data. When $\lambda = 0$, the HP filter returns the original series without smoothing. As $\lambda \to \infty$, the HP filter returns an OLS trend for interior points of the sample, but distortions occur near the sample endpoints. However, in a structural time series model the signal-noise ratio is estimated not imposed *a priori*. Figure 9 compares the filtered growth rate of EPS from the STM (dotted line) and the growth rate from the HP filter (solid line). The former is stable, but the latter exhibits cyclicality; it tends to decrease before recessions and to increase afterwards. Evidently, in this case the STM filters the cyclical component of EPS more efficiently than the HP filter, since the trend (long-run component) should not exhibit cyclicality.

Conclusions

An unobserved components model provides a framework for establishing the stylized facts that characterize the behavior of EPS for the aggregate market.

The evidence indicates that during three-quarters of a century the growth rate of permanent earnings has obeyed a deterministic process.

Adults adduced all manner of reasons why a break in the slope of the earnings series occurred in the 1990s. In the age of rationality, children followed the Pied Pipers of the new paradigm through the door and into the forest, notwithstanding the fact that analysis of real-time data offered not a scintilla of evidence in support, see, e.g., the filtered trend in Figure 3, and the filtered slope in Figure 4.

Well-informed investors who formulate rational expectations about future earnings render markets efficient. However, it is impossible to reconcile a deterministic slope in log EPS with the delusions regarding future earnings that seize markets periodically. Evidently, these delusions arise from ascribing permanence to cyclical and other transitory phenomena.

Notes

1. See among others, Shleifer [2000], Shefrin and Statman [1984], Thaler [1993], and DeBondt and Thaler [1986].
2. Williams [1938] argued that common stock has value only because it pays dividends. However, Nobel laureates Miller and Modigliani [1961] posited that the dividend decision does not affect stock prices and that earnings are the proper basis for establishing the market value of equity. They developed a stock valuation model in which price is the present value of rationally expected earnings adjusted for the firm's capital investments. Sharpe, Alexander and Bailey [1999] present a similar model in which the market value of a firm's equity is independent of the dividend decision. However, the presumed irrelevancy of the dividend decision does not invalidate dividend discount models, since under some conditions the Miller-Modigliani earnings discount model is equivalent to the dividend discount model (Shiller [1990]). Others argue that the dividend decision matters because dividends and capital gains are taxed differently (Ang, Blackwell and Megginson [1991]).
3. The profit series is from the Business Cycle Indicators database of the Conference Board, series ID A0Q016.

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