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UNDER/OVER-VALUATION OF THE STOCK MARKET AND CYCLICALLY ADJUSTED EARNINGS

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Abstract

The ratio between current earnings per share and share price (the EP ratio) is widely considered to be an effective gauge of under/over-valuation of a corporation's stock. Arguably, a more reliable indicator (the cyclically-adjusted EP ratio) can be obtained by replacing current earnings with a measure of 'permanent earnings', i.e. the profits that the corporation is able to earn, on average, over the medium to long run. I propose a state-space model to filter business-cycle oscillations out of current earnings and compute the cyclically-adjusted EP ratio. I estimate the model with euro-area aggregate stock market data. I find periods, notably around the 2008 financial crisis, when the adjusted and the unadjusted EP ratios provide economically and statistically different indications. I propose a method to make the adjusted EP ratio easier to interpret by translating its values into estimates of the probability that the stock market is under/over-valued. These estimates clearly indicate periods of mis-valuation in my sample. Furthermore, some simulations suggest that the model would have been able to provide early warning signs of mis-valuation in real time.

JEL Classification: G10, C46.
Keywords: earnings/price ratio, cyclically adjusted earnings, undervaluation/overvaluation of stocks.

Contents

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1 Introduction[1]

The earnings/price (EP) ratio has long been considered a quick but effective gauge of under/over-valuation of the stock market. As demonstrated by numerous studies in empirical finance, it is a good predictor of excess returns on stocks (e.g.: Basu - 1983, Fama and French - 1992, Anderson and Brooks - 2006). In recent years, it has also grown in popularity among policy makers (see e.g.: ECB - 2009, IMF - 2009, Swiss National Bank - 2009), because it has become clear that simple and intuitive instruments to understand asset valuations are essential for an effective monitoring of the stability of the financial system. In this paper, I address two issues that are crucial for the assessment of stock valuations through the EP ratio: the cyclical adjustment of earnings and the precise definition of under/over-valuation based on the EP ratio.

Since the seminal work of Shiller (2000), it has become evident that very volatile and cyclical components of earnings must be filtered out in order to obtain more stable and reliable EP ratios. The EP ratio is used to judge how expensive the stock of a corporation is, relative to its ability to earn profits; if such ability is judged only on the basis of current earnings, without filtering out business cycle oscillations, one incurs the risk of obtaining myopic assessments of the valuation of a stock. For this reason, it is desirable to use some sort of measure of 'permanent earnings', the profits that corporations are able to earn on average over the medium to long run. The ratio between 'permanent earnings' per share and the share price, known as 'cyclically-adjusted EP ratio', is the main object of interest of this paper.

While rather informal procedures have been adopted so far to filter out the cyclical components of earnings, I propose a formal method, based on state-space time series models, that has several advantages over previously used procedures. First, the appropriate filter for earnings is estimated by rigorous statistical methods so that the researcher or financial analyst does not need to engage in subjective (and error-prone) judgements about the best method to filter earnings. Second, the uncertainty associated with the choice of the right filter is properly taken into account, so that one obtains not only a point estimate of adjusted earnings, but their entire probability distribution. Thus, it is possible not only to obtain measures of 'permanent earnings', but also to assess how noisy these measures are. Third, one can distinguish between *ex-ante* and *ex-post* adjustments, i.e. those that can be made in real time and those that can be made only with the benefit of hindsight. This is especially important when using the EP ratio to carry out policy-related analyses, because an analyst is allowed to understand whether the

[1] Any views expressed in this article are the author's and do not necessarily reflect those of the Bank of Italy. I wish to thank seminar participants at the Bank of Italy and at Tor Vergata University, as well as anonymous referees, for providing comments on previous versions of the paper.

indications provided by the ratio are useful for real-time monitoring of the financial system or are only suited for retrospective studies.

After calculating the adjusted EP ratio, it is not obvious how to use it to produce rigorous statements about the probability that the stock market is under/over-valued. To solve this problem, I propose a formal definition of under/over-valuation, based on the adjusted EP ratio, and a statistical method that allows to form statements about the probability of mis-valuation (e.g.: "There is a 5 per cent probability that the stock market is over-valued"). These statements take into account two sources of uncertainty: the uncertainty associated with the estimation of the parameters of the state-space model and the uncertainty associated with the separation of the unobservable cyclical component of earnings from the permanent component, for given model parameters. In other words, the measure of mis-valuation proposed in this paper aims to build on the intuitive appeal of Shiller's (2000) approach, providing a method to transparently take into account the fact that the cyclical component of earnings is not directly observable and, therefore, statements about mis-valuation based on the adjusted EP ratio are inherently imprecise and subject to statistical uncertainty.

In the empirical part of the paper, I analyze a eurozone stock market index. First, I use very simple de-trending methods to conduct a preliminary analysis of the cyclical behavior of earnings. It clearly emerges from the analysis that the cyclical component of earnings is very persistent and that periods of above (below) average growth tend to come in clusters, giving rise to prolonged phases of expansion (contraction) and to pronounced cycles. These stylized facts are used to specify the main features of the state-space model that I use to separate corporate earnings into a permanent and a transitory (or cyclical) component. Furthermore, a specification analysis is carried out to compare the model with alternative models and validate its main assumptions: the performance of the model seems to be satisfactory both as regards its out-of-sample predictive ability and as regards its posterior odds with respect to other models. Estimates from the model provide evidence that the cyclical component explains a considerable portion of the overall variability of earnings.

I use the estimates of the permanent component of earnings obtained from the state-space model to produce estimates of the adjusted EP ratio. I find several periods when the median[2] adjusted EP ratio is remarkably different from the unadjusted one, confirming the results found with simpler techniques, such as Shiller's (2000) moving-average smoothing. After giving a definition of under/over-valuation based on the distribution of the adjusted EP ratio, I am able to estimate

[2]Since the adjusted EP ratio is unobservable, the model produces as an output an entire probability distribution over the possible values of the adjusted EP ratio. Here, I consider the median of this distribution as an estimate of the true value.

the probability that the market is under/over-valued in any given period of my sample. I find several periods when this probability is high. One such period is during the so-called 'tech bubble' occurred in the late Nineties: according to my model, over-valuation was a virtual certainty during this period. Also from 2006 to mid-2008, before the inception of the financial crisis, the probability that the stock market was over-valued is estimated to be very high. Interestingly, these periods of mis-valuation are clearly detected by the model not only *ex-post*, but also *ex-ante*, hinting to a potential usefulness of the model also in real-time applications.

The two years immediately before the 2008 financial crisis provide an interesting testbed for the model. During those years the median adjusted EP ratio remained consistently below the unadjusted one, because the cyclical component of earnings was amply positive and, as a consequence, earnings were well-above their permanent level. The difference between the adjusted and the unadjusted EP ratio observed during those years has a straightforward economic interpretation: the cyclical boost in earnings temporarily inflated the unadjusted EP ratio, making stock prices look cheaper than they really were; the adjusted EP ratio, on the contrary, made stock prices look dearer, by removing the positive cyclical component of earnings. Unlike simpler models, the state-space model also allows to understand to what degree of precision the difference between the two ratios could be estimated: it turns out that the difference could be estimated with low precision in real time; however, as time elapsed and the difference could be assessed *ex-post*, the precision of this assessment increased considerably; with the benefit of hindsight, at the end of the sample the difference was estimated to be very significant from a statistical viewpoint. Despite the low precision of the *ex-ante* estimate of the adjusted EP ratio, translating it into a probability of over-valuation gave clear-cut indications: for example, at the beginning of 2007 the model-based real-time assessment of the probability of over-valuation was higher than 70%. This assessment was confirmed and strengthened, *ex-post*, by the arrival of new data. In other words, the model could have been able to produce an easily interpretable early warning signal of a potential over-valuation (a similar and even stronger early warning signal had been observed before the burst of the 'tech bubble'). Although these early warnings certainly warrant further scrutiny by financial analysts and policy makers, the ability of the model to produce them make it a potential candidate to complement the set of tools and indicators that are routinely utilized to monitor financial stability.

This paper is related to several strands of economic and financial literature. The cyclicality of corporate earnings is analyzed using well-established time-series methods: in particular, my model falls into the class of unobserved components (UC) models popularized by Harvey (1985), Watson (1986) and Clark (1987). The paper makes two main contributions to this literature: on the technical side, it proposes a novel two-step MCMC algorithm for Bayesian estimation of the model that seems to enjoy very good properties in terms of accuracy and ability to generate samples with low serial correlation; on the empirical side, the paper is the first (to my knowledge) to carry out a specification analysis of UC models specifically aimed at modelling the cyclicality of corporate earnings.

Following Shiller (2000), my model uses historical earnings to assess the relation between earnings and stock prices. One may argue that stock prices reflect expectations regarding future earnings, therefore it could be misleading to assess stock valuations using, as this paper does, backward-looking measures of earnings constructed with historical data. This is a well-founded critique, which has been addressed by many research papers (e.g.: Sorensen and Williamson - 1985, Lander, Orphanides and Douvogiannis - 1997, Ohlson and Juettner-Nauroth - 2005); the vast majority of these papers propose to consider earnings forecasts made by financial analysts in place of backward-looking measures based on historical earnings. The approach proposed by these papers, albeit theoretically appealing, has been challenged by numerous other studies (e.g.: Trueman - 1994, Berry and Dreman - 1995, Easterwood and Nutt - 1999, Claus and Thomas - 2001) that provide evidence of several biases in analysts' forecasts of earnings. My paper belongs to a still burgeoning literature (see Campbell and Thompson - 2008 for a review) that, in the absence of definitive evidence on the reliability of analysts' earnings forecasts, uses backward-looking statistical techniques to analyze the relationship between corporate earnings and stock prices.

Finally, this paper proposes a method to translate the adjusted EP ratio into an estimate of the probability of mis-valuation. While, to my knowledge, this is the first such attempt, the idea of estimating a probability of mis-valuation is similar in spirit to the idea, put forward by some empirical studies on speculative bubbles, of computing the probability that a market is experiencing a bubble or that a bubble is going to crash (e.g.: van Norden - 1996, van Norden and Schaller - 1999, Brooks and Katsaris - 2005).

The paper is organized as follows: Section 2 conducts a preliminary analysis of the data; Section 3 presents the state-space model and the estimation method and discusses the estimates of the adjusted EP ratio; Section 4 describes the method used to translate the estimates of the EP ratio into estimates of the probability of mis-valuation and presents the empirical application of the method; Section 5 concludes; the Appendix contains technical details about the estimation method and the specification analysis.

2 Data and preliminary evidence

The analysis is carried out on an aggregate stock market index for the euro area (the Datastream EMU stock market index - ticker TOTMKEM). Two monthly time series are considered: the price and the price/earnings ratio. The time series of earnings[3] is calculated as the ratio between these two. The sample period goes from January 1973 to December 2009.

Time series of corporate earnings are widely known to exhibit a cyclical behavior: they often experience prolonged periods of fast growth followed by periods of stagnation or contraction. In this section I illustrate some preliminary evidence on the cyclicality of earnings, aimed at introducing and justifying subsequent modelling choices.

During the sample period I consider, corporate earnings exhibited a long-run growth trend: eurozone corporations grew their earnings at an average monthly rate of 0.56% (with a standard deviation of 2.31%).

Earnings also exhibited a pronounced cyclical behavior. Figure 1 displays two preliminary estimates of the cyclical component of earnings: the first one is obtained by subtracting a linear trend from the logarithm of earnings, while the second one is obtained HP-filtering the natural logarithm of earnings (the frequency parameter is 129,600). Table 1 reports the results of a regression analysis of these preliminary estimates of the cyclical component of earnings.

In a first set of regressions, the cyclical component is regressed on a constant and its first lag. The estimates indicate that the cyclical component is very persistent: the auto-regressive coefficient is greater than 0.95 for both methods of calculating the cyclical component. This means that deviations from the long-run growth trend are long-lasting: their half-life is in all cases estimated to be longer than 16 months.

In a second set of regressions, the first difference of the cyclical component is regressed on a constant and its first lag. Also first differences are characterized by a statistically significant degree of persistence, although the persistence is more significant with de-trending than with HP-filtering. Hence, when the growth rate of earnings is above average in a certain month, it tends to stay above average also in subsequent months, generating prolonged phases of rapid expansion. On the contrary, months of below average growth tend to come in clusters, giving rise to prolonged phases of stagnation or contraction.

Subtracting these preliminary estimates of the cyclical component from the level of earnings, I obtain filtered time series of earnings, which are a proxy of the 'permanent' level of earnings, the part of earnings which is not subject to

[3] These are, of course, earnings per share. From now on I will always refer to them as earnings, without specifying that they are per share.

cyclical fluctuations. Dividing filtered earnings by prices, I obtain the so-called adjusted EP ratio. The rationale for this procedure, pioneered by Shiller (2000), is intuitive: the EP ratio is used to assess how expensive the stock of a corporation is, relative to its ability to earn profits; if this ability is judged only on the basis of current earnings, which are subject to temporary boosts and declines associated with the business cycle, one incurs the risk of obtaining myopic assessments of the valuation of a stock. For this reason, it is desirable to use some sort of measure of 'permanent' earnings, the profits that corporations are able to earn on average over the medium to long run.

Figure 2 displays the adjusted and the unadjusted EP ratios. It also includes the adjusted ratio calculated according to Shiller's (2000) methodology, i.e. substituting earnings with their 10-year moving average. It clearly emerges from the pictures that, although the correlation between the adjusted and the unadjusted ratios is high, there are periods when they provide substantially different indications. For example, looking at recent years, it is possible to notice that from 2006 to mid-2008 the adjusted ratio is substantially lower than the unadjusted one, as a consequence of the fact that earnings in the same period are estimated to be well above their 'permanent' level. On the contrary, during 2009 the adjusted ratio is much higher than the unadjusted one, because earnings fall below their long-run level. It is not possible, however, to tell whether these differences are statistically significant: for one to be able to tell, one needs a statistical procedure that allows to measure the uncertainty related to the estimation of the permanent component; I propose such a procedure in the next section.

3 Cyclically-adjusted earnings

3.1 The state-space model

I use a state-space model to separate earnings into a cyclical and a permanent component. The model is specified so as to capture the following fundamental features of the dynamics of corporate earnings, already highlighted in the previous section:

1. earnings display a long-run growth trend;

2. there are persistent deviations from the long-run trend;

3. periods of high growth tend to be followed by other periods of high growth and periods of low (or negative) growth tend to be followed by other periods of low (or negative) growth, giving rise to so-called cycles.

To capture stylized fact 2), the logarithm of earnings $e_t = \ln(E_t)$ is modeled as the sum of a permanent component π_t and a transitory component τ_t:

$$e_t = \pi_t + \tau_t \tag{1}$$

To mimic fact 1), the permanent component is assumed to follow a random walk with drift:

$$\pi_t = \mu + \pi_{t-1} + u_t \tag{2}$$

where u_t is normally distributed with mean zero and variance σ_u^2. If $\mu > 0$, then earnings display a positive long-run growth trend. Furthermore, if $\sigma_u^2 > 0$, the level of earnings can be affected by permanent shocks u_t. An alternative interpretation is that the permanent component grows at a stochastic growth rate $\mu + u_t$.

The transitory component is an $AR(1)$ process with time varying drift:

$$\tau_t = \delta_{t-1} + \rho\tau_{t-1} + v_t \tag{3}$$

where $\rho < 1$, v_t is normally distributed with mean zero and variance σ_v^2 and u_t and v_t are assumed to be independent. δ_{t-1} is the time-varying drift of τ_t. To reproduce stylized fact 3), δ_t is also modelled as an $AR(1)$ process:

$$\delta_t = \varphi\delta_{t-1} + w_t \tag{4}$$

where $\varphi < 1$, w_t is normally distributed with mean zero and variance σ_w^2 and is independent of both u_t and v_t. The two assumptions $\rho < 1$ and $\varphi < 1$ guarantee that the transitory component τ_t is a zero-mean stationary process.

To get an intuitive grasp of the workings of the model, think of a steady state in which $\tau = \delta = 0$: if $\varphi > 0$ and $\rho > 0$ and the system is perturbed by a positive shock to δ $(w > 0)$, then the transitory component τ starts increasing and keeps drifting upwards until $\delta > (1-\rho)\tau$. Eventually, the decay $(1-\rho)\tau$ becomes larger than the positive drift δ [4]: when this happens, τ stops increasing and progressively decreases towards zero. This can reproduce the typical hump-shaped pattern of cycles and the fact that phases of fast growth tend to be followed by phases of stagnation or contraction. The system can also be subject to other types of shocks, that differ as to their persistence: the error term u_t represents permanent shocks to the level of earnings, while v_t represents transitory shocks that start to be reabsorbed immediately after they happen.

As a whole, equations (1-4) form a state-space model, belonging to the class of unobserved components (UC) models popularized by Harvey (1985), Watson (1986) and Clark (1987): the permanent component is a random walk with drift and the cyclical component is a zero-mean ARMA(2,1) process[5]. A section of the Appendix analyzes how these specifications of the permanent and cyclical components compare with other popular specifications.

[4] δ remains positive but gradually converges towards zero.

[5] τ_t can be written as an ARMA(2,1) process, by substituting for δ_{t-1} in equation (3).

3.2 The estimation method

The model is estimated by Markov chain Monte Carlo methods, simulating from the posterior distribution of the six parameters μ, ρ, φ, σ_u, σ_v and σ_w. The model can be written in state-space form, with observation equation:

$$e_t = \begin{bmatrix} 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} \pi_t \\ \tau_t \\ \delta_t \end{bmatrix} \tag{5}$$

and transition equation:

$$\begin{bmatrix} \pi_t \\ \tau_t \\ \delta_t \end{bmatrix} = \begin{bmatrix} \mu \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & \rho & 1 \\ 0 & 0 & \varphi \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ \tau_{t-1} \\ \delta_{t-1} \end{bmatrix} + \begin{bmatrix} u_t \\ v_t \\ w_t \end{bmatrix} \tag{6}$$

Since the error terms are jointly normal, the states of the model and its likelihood can be computed using the Kalman filter for any fixed vector of parameters (e.g.: Lütkepohl - 2006).

To keep the analysis objective, the following uninformative and mutually independent priors are assigned to the parameters:

- μ: uniform improper on $(-\infty, \infty)$
- ρ, φ: uniform proper on $[0, 1)$
- σ_u, σ_v, σ_w: uniform improper on $[0, \infty)$

Furthermore, to allow for analytical updating of the Kalman recursions, a jointly normal and (relatively) uninformative prior is assigned to the initial states:

$$\begin{bmatrix} \pi_0 \\ \tau_0 \\ \delta_0 \end{bmatrix} \sim N\left(\begin{bmatrix} e_0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} e_0^2 & 0 & 0 \\ 0 & e_0^2 & 0 \\ 0 & 0 & 0.05^2 \end{bmatrix} \right) \tag{7}$$

Simulation is conducted in two steps. In a first step the random walk Metropolis-Hastings algorithm with block structure[6] (e.g.: Bagasheva et al. - 2008) is employed to simulate the parameters. Each block is sampled 50,000 times, for a total of 300,000 draws. The first 50,000 draws are used for tuning the proposal distribution (targeting an acceptance rate between 30 and 40 per cent) and then discarded. The remaining draws are employed in the second step to form a proposal distribution to be used in an Independence-Chain Metropolis-Hastings algorithm. I

[6] Each of the six parameter constitutes a separate block.

employ the Expectation-Maximization algorithm to fit a mixture of 20 multivariate normal distributions to the empirical distribution of the 250,000 draws from the previous step. Then, I use the mixture as a proposal distribution for the Independence-Chain Metropolis-Hastings algorithm and I produce a new set of 300,000 draws from the posterior distribution of the parameters. The acceptance rate is about 55 per cent. Only the draws from the second step are used to make inferences.

Raftery and Lewis' (1995) run length control diagnostic indicates that the sample size is more than 300 times the minimum required size[7]. The same diagnostic indicates that the effective sample size obtained in the second step by running the Independence-Chain algorithm is roughly 25 times the effective sample size obtained in the first step with the random walk algorithm[8], quite a remarkable improvement.

I compute real-time estimates of the states (i.e. estimates that do not take into account information about parameter values received *ex-post*) for all months after December 1992, so that a minimum of 20 years of data is used to compute real-time estimates of the states. These estimates are obtained adding one observation at a time and repeating the MCMC simulation each time an observation is added.

More details about the estimation methodology are provided in the Appendix.

3.3 The empirical evidence

Table 2 reports the posterior distribution of the parameters of the model. The probability that the long-run growth trend μ is positive is higher than 99.99 per cent. The posterior mean of the persistence parameters ρ and φ is high, indicating that both the cyclical component and its time-varying drift are highly persistent. The latter fact implies that periods of above (below) average growth tend to come in clusters, giving rise to cycles. The standard deviation of the transitory shocks (σ_v) is estimated to be approximately twice the standard deviation of the permanent shocks (σ_u) and three-times the standard deviation of the shocks to the drift (σ_v).

To better understand the relative importance of the various shocks at different forecasting horizons, a variance decomposition of earnings is reported in Table 3. It clearly emerges that shocks to the time-varying drift are by far the most important, at forecasting horizons between 1 and 10 years, explaining a fraction of variance that can range from 65% to 80%. Transitory shocks to the cyclical com-

[7]The parameters of the diagnostic are set in such a way that the minimum required size allows to estimate the 2.5% quantile committing an error less than 1% with probability 95%. The minimum size is estimated to be 937.

[8]Roughly speaking, the effective sample size is the number of independent observations that would be equivalent to the number of dependent observations in the sample at hand.

ponent explain about 25% of the variance at short horizons, but their importance declines by increasing the horizon. Finally, permanent shocks explain roughly 10% of the variance at short horizons and then become more important at longer horizons. Even though permanent shocks dominate asymptotically, their importance increases very slowly: even on a 10-year horizon they explain less than 30% of the variance.

In Figure 3, I use the posterior distribution of the permanent component of earnings to compute the posterior distribution of the adjusted EP ratio. The adjusted EP ratio is the ratio between the permanent component of earnings and the price. Hence, the uncertainty in the estimation of the permanent component of earnings naturally translates into uncertainty in the estimation of the adjusted EP ratio. In Figure 3, the uncertainty is taken into account by reporting the 5th and the 95th percentile of the posterior distribution of the EP ratio. I also distinguish between *ex-ante* and *ex-post* uncertainty.

Ex-ante uncertainty about the ratio in any given period is the uncertainty generated by an estimation process that uses only information available up to that same period (technically, it is the uncertainty surrounding the filtered estimates produced by the Kalman filter). *Ex-post* uncertainty, instead, is the uncertainty generated by an estimation process that uses also information available after the period to which the estimates refer (technically, it is the uncertainty surrounding the smoothed estimates produced by performing backward Kalman recursions that start from the end of the sample).

In Figure 3, the solid black line represents the median of the posterior distribution of the adjusted EP ratio. Its correlation with the unadjusted EP ratio (the solid cyan line) is fairly high, but there are several periods when the two ratios provide substantially different indications. Despite the considerable dispersion of the posterior distribution of the permanent component of earnings[9], there are also several time periods when the difference between the adjusted and the unadjusted ratio is, *ex-post*, highly significant (the level of significance implicitly used in Figure 3 is 10 per cent). During the period for which also *ex-ante* estimates are available (from 1993 to 2009), there was only one prolonged period (from 2006 to 2009) of noticeable divergence between the unadjusted EP ratio and the median of the *ex-ante* distribution of the adjusted ratio. The difference recorded during

[9] Several colleagues kindly provided comments on preliminary versions of this paper and observed that, given the considerable uncertainty surrounding the estimates of the permanent component, there is a legitimate suspicion that also the trend-cycle decomposition provided by the model be, as a whole, barely significant. In response to this critique, one may reply, with a slight abuse of frequentist terminology in this Bayesian context, that the low significance of the cyclical component period-by-period does not imply that jointly (i.e. considering all periods together) the cyclical component is statistically insignificant; indeed, the parameter estimates and the specification analysis provide strong evidence to the contrary.

this period was not highly significant *ex-ante*, but it became significant at 90% confidence *ex-post*.

Unlike the simpler de-trending methods presented in Section 2, the state-space model allows to understand how precisely the adjusted EP ratio can be estimated: from Figure 3 it is evident that estimates of the adjusted EP ratio are affected by a considerable amount of statistical uncertainty, especially *ex-ante*. Therefore, it is important to take this uncertainty into account when using the adjusted EP ratio to form statements about the valuation of stocks: to this end, the next section proposes a method that allows to think about stock valuations in probabilistic terms, by fully taking into account the uncertainty related to the estimation of the adjusted EP ratio.

Before ending this section, it is worthwhile to comment on the divergence between the adjusted and the unadjusted EP ratio observed in proximity of the 2008 financial crisis and of the severe drop in stock prices that accompanied the crisis. The state-space model confirms the findings of the simpler methods presented in Section 2: before the crash, corporate earnings were experiencing a phase of sustained positive cyclical growth and remained well-above their permanent level. As a consequence, according to the adjusted EP ratio, stock prices were more expensive than indicated by the unadjusted EP ratio. Roughly speaking, the unadjusted EP ratio was artificially inflated by the cyclical boost in earnings, while the adjusted EP ratio provided a more realistic picture of the long-run ability of listed firms to generate profits, suggesting a more cautious valuation of stock prices. In the aftermath of the financial crisis, on the contrary, the quick collapse of corporate earnings artificially depressed the unadjusted EP ratio while the adjusted ratio remained higher, anticipating that the downturn would not be long-lived and making stocks look cheaper. Anecdotally speaking, the indications provided by the adjusted EP ratio revealed themselves to be quite accurate in both cases: the cyclical deviations of earnings from their long-run path were eventually re-absorbed and stock prices adjusted accordingly. From a statistical viewpoint, however, the precision of the *ex-ante* estimate of the adjusted EP ratio was not high; the next section will show that, despite their low precision, these estimates could have been used to derive clear early warning signals of mis-valuation during these years.

4 Assessing under/over-valuation

4.1 A definition

In this section I propose a definition of under/over-valuation based on the state-space model presented above. A widespread practice is to assess whether the stock market is over/under-valued in three steps:

1. compute a time-series of adjusted EP ratios;
2. calculate the sample average of the time series computed in step 1;
3. fix a threshold, say 30%, and assess whether the stock market is under/over-valued based on this threshold. For example, if the adjusted EP ratio (computed in step 1) in a given period is more than 30% below its sample average (computed in step 2), then one concludes that the stock market is over-valued in that period.

While the practice is of course crude and questionable from many theoretical viewpoints, it is nonetheless intuitive and transparent and has proved effective in identifying major stock market bubbles and depressions (e.g.: Shiller - 2000). The main idea behind this procedure is that the sample average of the EP ratio, taken over a long sample, provides an estimate of the level at which the stock market is correctly valued: when the EP ratio equals its long-run average the stock market is neither under-valued nor over-valued. On the contrary, large deviations from the long-run average are not sustainable and tend to be corrected by adjustments of the stock price. This line of reasoning relies on the implicit assumption that the EP ratio has a mean-reverting behavior, whereby deviations from the unconditional mean, albeit possibly persistent, tend to gradually vanish over the long-run. The definition of stock market under/over-valuation I propose aims at making the three-step procedure described above sounder from a statistical viewpoint, by taking into account the uncertainty related to the estimation of model parameters and unobservable state variables.

Let P_t be the stock price at time t and p_t its logarithm. Let D_t denote the data observed up to time t, i.e.:

$$D_t = \{e_0, p_0, e_1, p_1, \ldots, e_t, p_t\} \tag{8}$$

Denote the adjusted EP ratio by $EP_t = \exp(\pi_t - p_t)$. Suppose EP_t is ergodic stationary and denote its unconditional mean by $\overline{EP}$. Let $f(\pi_t|D_s)$ be the conditional density of π_t at time t given the data observed up to time s. Let $\Omega \in (0,1)$. A first definition of under-valuation is now proposed.

Definition 1 *The stock price at time t is ex-ante Ω-under-valued with probability α if*

$$\int_{\{\pi_t - p_t > \omega\}} f(\pi_t|D_t)\, d\pi_t = \alpha \tag{9}$$

where ω satisfies:

$$\omega = \ln\left(\mathrm{E}\left[\overline{EP}|D_t\right]\right) + \ln(1+\Omega) \tag{10}$$

Equation (10) is derived from the under-valuation condition:

$$EP_t > \overline{EP}\,(1+\Omega)$$

and takes into account the fact that both π_t and $\overline{EP}$ are not known with certainty. $\mathrm{E}\left[\overline{EP}|D_t\right]$ is the estimate of $\overline{EP}$ given information available at time t. Ω is the threshold used to decide whether the stock is under-valued. For example, if $\Omega = 30\%$ and $\pi_t - p_t > \omega$, this means that the adjusted EP ratio is more than 30% above its estimated equilibrium value; as a consequence, the stock is considered 30%-under-valued, according to the definition.

Note that π_t is unobservable, hence its true value can never be known with certainty; however, using the Kalman filter, one can assign probability distributions to π_t, conditional on available information. The integral in (9) reflects this uncertainty: one can only estimate the probability α that the stock is under-valued ($\pi_t - p_t > \omega$), without ever being able to tell with certainty whether a stock is under-valued or not.

Also note that the probability density and the expected value in Definition 1 are conditional on D_t, the information received up to period t. Hence, the probability that the stock is under-valued in a given period t is estimated using only information available up to that period. This is why Definition 1 is an *ex-ante* definition of under-valuation: it does not exploit information received after t to estimate the parameters and the unobservable states at time t. In a sense, this definition allows to reproduce the statements that - say - a policy maker could make in real time using available information.

The following definition of over-valuation follows exactly the same logic of the above definition of under-valuation.

Definition 2 *The stock price at time t is ex-ante Ω-over-valued with probability α if*

$$\int_{\{\pi_t - p_t < \omega\}} f(\pi_t|D_t)\, d\pi_t = \alpha \qquad (11)$$

where ω satisfies:

$$\omega = \ln\left(\mathrm{E}\left[\overline{EP}|D_t\right]\right) + \ln(1-\Omega) \qquad (12)$$

Let now T denote the last observation in the sample. *Ex-post* under-valuation is defined as follows:

Definition 3 *The stock price at time t is ex-post Ω-under-valued with probability α if*

$$\int_{\{\pi_t - p_t > \omega\}} f(\pi_t|D_T)\, d\pi_t = \alpha \qquad (13)$$

where ω satisfies:

$$\omega = \ln\left(\mathrm{E}\left[\overline{EP}|D_T\right]\right) + \ln(1+\Omega) \qquad (14)$$

Everything is as in Definition 1, except for the fact that the information set is now D_T and not D_t. Hence, stock prices at time t are evaluated with the benefit of hindsight, using also information received after time t. The information is used to update both the estimate of the long-run mean $\overline{EP}$ and the estimate of the unobservable states of the model. Technically, the latter is achieved by running backward Kalman recursions to smooth the forward estimates of the unobservable states. This *ex-post* definition can help put stock market developments in historical perspective, exploiting also information received after the developments under scrutiny take place.

The following definition of *ex-post* over-valuation completes the set of definitions:

Definition 4 *The stock price at time t is ex-post Ω-over-valued with probability α if*

$$\int_{\{\pi_t - p_t < \omega\}} f(\pi_t | D_T)\, d\pi_t = \alpha \tag{15}$$

where ω satisfies:

$$\omega = \ln\left(\mathrm{E}\left[\overline{EP}|D_T\right]\right) + \ln(1-\Omega) \tag{16}$$

The empirical analysis in the next subsection exploits all of the above definitions. For a fixed Ω, the integrals are approximated by sample averages of the MCMC draws and the expected values of $\overline{EP}$ are estimated by path-wise sample means of EP_t, obtaining the probabilities of under/over-valuation in each time period.

4.2 The empirical evidence

I compute the posterior probabilities of under/over-valuation fixing Ω at 30%. In other words, I consider the stock market over-valued if the adjusted EP ratio is more than 30% below its long-run mean. Analogously, I consider it under-valued if the adjusted EP ratio is more than 30% above its long-run mean. Figures 4 and 5 display the *ex-ante* and *ex-post* posterior probabilities. The same calculations could of course be performed fixing a different threshold Ω: the likelihood of under/over-valuation would increase (decrease) by decreasing (increasing, respectively) Ω; when Ω tends to infinity, the posterior probability of under/over-valuation tends to zero in any time period.

The estimates depicted in Figure 4 show that eurozone stock markets have undergone only two periods when over-valuation was, *ex-post*, a virtual certainty (probability greater than 90%): the first one is at the end of the Nineties, before the burst of the dot-com bubble; the second one is around the years 2006 and 2007, before the financial crisis of 2008. In both these periods, also the *ex-ante* probability of over-valuation was very high (greater than 90% for the dot-com bubble and greater than 70% in 2007). In other words, in both periods the model was able to provide an early warning signal of over-valuation, which was then confirmed by the subsequent arrival of new data. Anecdotally speaking, these two signals would have also been good predictors of subsequent market developments: they were both followed by severe drops in stock prices.

Besides the two aforementioned periods, over-valuation was highly probable *ex-ante* also before the 1987 stock market crash and before the start of the Gulf War[10] in 1990. Since the *ex-ante* simulations start from 1993, it is not possible to tell whether these two episodes of over-valuation were detected by the model also *ex-ante*.

Finally, the model also indicated *ex-ante* a period of likely over-valuation (with a maximum probability of around 70%) in 1994: *ex-post*, the probability of over-valuation was estimated to be much lower. The reason for this difference between the *ex-ante* and the *ex-post* evaluation was that *ex-ante* the model was under-estimating the permanent level of earnings; *ex-post*, an upward revision of the permanent level of earnings caused a downward revision of the probability of over-valuation. Interestingly, this was the same reason that induced former Federal Reserve Chairman Alan Greenspan to revise his own assessment of the probability of over-valuation of the US stock market:

"When we moved on February 4th, I think our expectation was that we would prick the bubble in the equity markets. What in fact occurred is that, as evidence of the dramatic shift in the economic outlook began to emerge after we moved and long-term rates began to move up, we were also clearly getting a major upward increase in expectations of corporate earnings." (FOMC meeting minutes, March 22, 1994).

As far as the probability of under-valuation is concerned, it remained very low in the two most recent decades, except for one episode of very likely under-valuation in 2009, after the market crash linked to the 2008 financial crisis: the probability of over-valuation was higher than 80%, both *ex-ante* and *ex-post*. In 2002 and 2003, when the market reached a bottom after the burst of the dot-com bubble, neither the *ex-ante* nor the *ex-post* probabilities of under-valuation ever exceeded 40%. The years between 1975 and 1985 were instead characterized by many episodes of highly probable under-valuation (note, however, that the probability of under-valuation is computed only *ex-post* for these years).

It must of course be emphasized that these results could depend on a number of assumptions. First of all, I have arbitrarily fixed the threshold Ω at 30%: different choices would increase or decrease probabilities as explained above. Secondly, the

[10] Interestingly, all the four periods of over-valuation detected by the model ended with a stock market crash (with stock prices falling more than 25% in few months).

results might also substantially depend on the choice of the sample period: for example, longer samples might significantly increase the estimate of the long-run mean of the adjusted EP ratio, which is used as a benchmark to define under/over-valuation. Finally, in interpreting the results a caveat should be borne in mind: the above calculations rely on the assumption that the adjusted EP ratio is a stationary mean-reverting process; if there are structural breaks that permanently change the unconditional mean of the adjusted EP ratio, the above inferences cease to be valid. To take possible breaks into account, however, one would need much more complicated regime-shifting models of the joint behavior of prices and earnings. I leave this kind of extension for future research.

5 Conclusions

The earnings/price (EP) ratio is a quick and effective measure of under/over-valuation of the stock market, used by practitioners, policy makers and academic researchers. I have addressed two issues that are crucial for the assessment of stock valuations through the EP ratio: the cyclical adjustment of earnings and the precise definition of under/over-valuation based on the EP ratio.

Since the seminal work of Shiller (2000), it has become customary to remove cyclical components from earnings, before calculating the EP ratio. The reason for doing so is intuitive: the EP ratio is used to assess how expensive the stock of a corporation is, comparing its profitability with its stock price; if profitability is judged only on the basis of current earnings, which are subject to temporary boosts and declines associated with the business cycle, one incurs the risk of obtaining myopic assessments of the valuation of a stock. For this reason, it is desirable to compare the stock price with a measure of 'permanent' earnings, the profits that the corporation is able to earn on average over the medium to long run.

I have proposed a state-space model to estimate the permanent component of earnings. The model allows to capture several stylized facts about the dynamics of earnings and allows to rigorously take into account the uncertainty inherent in the estimation of the permanent component. I use euro area aggregate stock market data to estimate the model. Estimates of the adjusted EP ratio (the ratio between the permanent component of earnings and the stock price) are highly correlated with the unadjusted EP ratio. However, there are periods when the two ratios provide substantially different indications and the difference is statistically significant. One such period is from 2006 to 2007, before the 2008 financial crisis, when earnings were much above their trend level and the unadjusted EP ratio made stock prices look cheaper than suggested by the adjusted ratio.

After calculating the adjusted EP ratio, it is not obvious how to use it to produce rigorous statements about the probability that the stock market is under/over-valued. As a possible solution of this problem, I have proposed a formal definition of under/over-valuation, based on the adjusted EP ratio, and a statistical method that allows to form statements about the probability of under/over-valuation, taking into account the uncertainty associated with the estimation of the unobservable cyclical component of earnings. Using the proposed definition, I have found two periods when over-valuation was highly probable, both *ex-ante* and *ex-post*: the first one is at the end of the Nineties, before the burst of the dot-com bubble; the second one is around the years 2006 and 2007, before the financial crisis of 2008. The probability of under-valuation, instead, was always estimated to be very low in the two most recent decades, except for one episode of very likely under-valuation in 2009, after the market crash linked to the financial crisis.

Simulating a real-time use of the model proposed in this paper, I found that the model would have been able to provide early warning signals of some episodes of mis-valuation in real time. Although these early warnings certainly warrant further scrutiny by financial analysts and policy makers, the ability of the model to produce them make it a potential candidate to complement the set of tools and indicators that are routinely utilized to monitor financial stability.

6 Appendix

6.1 Estimation method - details

In this section I provide more details on the estimation method outlined in Section 3.2.

6.1.1 First step: the random-walk Metropolis Hastings algorithm with block structure

In the first step of the procedure I generate a sample from the posterior distribution of the parameters using a random-walk Metropolis Hastings algorithm with block structure.

Denote the vector of parameters by θ:

$$\theta = \left[\begin{array}{cccccc} \mu & \rho & \varphi & \sigma_u & \sigma_v & \sigma_w \end{array}\right]$$

and its entries by $\theta_1, \ldots, \theta_6$ (each entry constitutes a block).

The value of θ at the n-th iteration of the Markov Chain is denoted by θ^n (n goes from 0 to 300,000) and its i-th entry by θ_i^n.

Also denote by I_t the data observed up to time t:

$$I_t = \{e_0, e_1, \ldots, e_t\}$$

and by T the last observation in the sample.

The posterior density of a generic draw θ^n, denoted by $f\left(\theta^n \left| I_T \right.\right)$, is known up to a constant of proportionality that does not depend on θ^n:

$$f\left(\theta^n \left| I_T \right.\right) \propto f\left(I_T \left| \theta^n \right.\right) f\left(\theta^n\right)$$

where $f\left(I_T \left| \theta^n \right.\right)$ is equal to the usual likelihood of a Gaussian linear state-space model (see e.g. Lütkepohl - 2006) and:

$$f\left(\theta^n\right) = \left\{\begin{array}{ll} 1 & \text{if } \theta^n \in (-\infty, \infty) \times [0,1) \times [0,1) \times [0,\infty) \times [0,\infty) \times [0,\infty) \\ 0 & \text{otherwise} \end{array}\right.$$

Define a 6×1 vector κ of standard deviations of the random-walk increments that will be adaptively adjusted to target an acceptance rate between 30 and 40 per cent; the starting value for κ is:

$$\kappa = \left[\begin{array}{cccccc} 0.005 & 0.005 & 0.005 & 0.005 & 0.005 & 0.005 \end{array}\right]$$

The chain starts from $\theta^0 = \left[\begin{array}{cccccc} 0.006 & 0.850 & 0.950 & 0.015 & 0.030 & 0.015 \end{array}\right]$. The n-th iteration is made up of the following steps:

1. set $l = n - 6\,[n/6]$ where $[n/6]$ denotes the integer part of $n/6$.
2. draw a random number z_n from a standard normal distribution;
3. build a new 6×1 vector $\overline{\theta}$ such that $\overline{\theta}_i = \theta_i^{n-1}$ for $i \neq l$ and $\overline{\theta}_i = \theta_i^{n-1} + \kappa_i z_n$ for $i = l$;
4. compute the acceptance probability a_n as follows:
$$a_n = \min\left(1, \frac{f\left(I_T \left|\overline{\theta}\right.\right) f\left(\overline{\theta}\right)}{f\left(I_T \left|\theta^{n-1}\right.\right) f\left(\theta^{n-1}\right)}\right)$$
5. draw a random number u_n from the uniform distribution on $[0, 1]$;
6. if $u_n \leq a_n$ then set $\theta^n = \overline{\theta}$; otherwise, set $\theta^n = \theta^{n-1}$;
7. if $n \leq 50,000$, adjust k_l [11];
8. if $n = 300,000$ end the algorithm, otherwise go back to step 1.

The $300,000$ vectors θ^1,...,$\theta^{300,000}$ thus obtained constitute a sample of serially dependent draws from the posterior distribution of θ.

6.1.2 Second step: fitting a mixture of multivariate normal distributions to the MCMC sample

In the second step of the procedure I fit a mixture of 20 multivariate normal distributions[12] to the MCMC sample obtained in the previous step (I discard the first 50,000 draws). The fitting procedure, based on the Expectation-Maximization algorithm of Dempster, Laird and Rubin (1977), is described by McLachlan and Peel (2000) and implemented in the MATLAB Statistics package (see also the MATLAB help for more details on the algorithm). Drawing random samples from this mixture of distributions is straightforward (see again McLachlan and Peel - 2000). In what follows, the density of this mixture is denoted by $\widetilde{f}\,(\theta)$.

[11] The adjustment is done as follows: at each iteration, if an exponentially weighted moving average (with forgetting factor equal to 0.99) of past acceptance probabilities is below 30 per cent for block θ_i, I decrease κ_i multiplying it by a factor of 0.99; if the same moving average is above 40 per cent, I increase κ_i by a factor of 1.01. This choice of parameters for adjusting κ, although admittedly arbitrary, maintained the acceptance rate broadly on target over a number of repetitions of the algorithm.

[12] The number of multivariate distributions in the mixture is set to 20 in order to achieve a satisfactory compromise between computational speed and the granularity of the approximation.

6.1.3 Third step: the Independence-Chain Metropolis Hastings algorithm

In the third step, I generate a sample from the posterior distribution of the parameters using an Independence-Chain Metropolis Hastings algorithm where the proposal distribution is equal to the mixture of distributions fitted in the previous step.

Again, the chain starts from $\theta^0 = \left[\begin{array}{cccccc} 0.006 & 0.850 & 0.950 & 0.015 & 0.030 & 0.015 \end{array} \right]$. The n-th iteration is made up of the following steps:

1. draw a random vector $\overline{\theta}$ from the mixture of normals previously fitted;

2. compute the acceptance probability a_n given by:

$$a_n = \min \left(1, \frac{f\left(I_T \left| \overline{\theta} \right.\right) f\left(\overline{\theta}\right)}{f\left(I_T \left| \theta^{n-1} \right.\right) f\left(\theta^{n-1}\right)} \frac{\widetilde{f}\left(\theta^{n-1}\right)}{\widetilde{f}\left(\overline{\theta}\right)} \right)$$

3. draw a random number u_n from the uniform distribution on $[0, 1]$;

4. if $u_n \leq a_n$ then set $\theta^n = \overline{\theta}$; otherwise, set $\theta^n = \theta^{n-1}$;

5. if $n = 300,000$ end the algorithm, otherwise go back to step 1.

The $300,000$ vectors θ^1,...,$\theta^{300,000}$ thus obtained constitute a sample of serially dependent draws from the posterior distribution of θ. Raftery and Lewis' (1995) diagnostics indicate that the sample is equivalent to a sample of 43,731 independent draws.

6.1.4 Ex-ante estimates

To obtain an ex-ante estimate of the distribution of the permanent component π_t at time t, I proceed as follows:

1. I employ the first t observations to extract an MCMC sample of parameters θ from the posterior distribution $f\left(\theta \left| I_t \right.\right)$, using the algorithms described above; the $300,000$ draws from the distribution are denoted by θ^1,...,$\theta^{300,000}$;

2. for each $i = 1, \ldots, 300,000$, I draw π_t from $f\left(\pi_t \left| I_t, \theta^i \right.\right)$, a normal distribution whose mean and variance are computed using the Kalman filter; denote the i-th draw by π_t^i;

3. the $300,000$ draws π_t^1,...,$\pi_t^{300,000}$ thus obtained constitute a sample of serially dependent draws from the posterior distribution of $f\left(\pi_t \left| I_t \right.\right)$.

6.1.5 Ex-post estimates

To obtain an ex-post estimate of the distribution of the permanent component π_t at time t, I proceed as follows:

1. I employ T observations (remember that T is the last observation in the sample) to extract an MCMC sample of parameters θ from the posterior distribution $f(\theta | I_T)$, using the algorithms described above; the 300,000 draws from the distribution are denoted by $\theta^1, \ldots, \theta^{300,000}$;

2. For each $i = 1, \ldots, 300,000$, I draw π_t from $f(\pi_t | I_T, \theta^i)$, a normal distribution whose mean and variance are computed using the Kalman smoother; denote the i-th draw by $\widetilde{\pi}_t^i$;

3. The 300,000 draws $\widetilde{\pi}_t^1, \ldots, \widetilde{\pi}_t^{300,000}$ thus obtained constitute a sample of serially dependent draws from the posterior distribution of $f(\pi_t | I_T)$.

6.2 Specification analysis

In this section I examine how some modelling choices I have made compare with the choices made in other popular trend-cycle models.

First, in my model the long-run growth rate μ is constant (e.g.: Watson - 1986; Perron and Wada - 2009), while in another popular specification (e.g.: Harvey - 1985; Clark - 1987; Koopman and Lee - 2009) μ follows a random walk:

$$\mu_t = \mu_{t-1} + \varepsilon_t$$

where ε_t is normally distributed with mean zero and variance σ_ε^2.

Second, in my model the drift of the permanent component δ_t is time-varying, which implies that the transitory component τ_t follows and ARMA(2,1) process (as, for example, in Harvey - 1985 and Harvey, Trimbur and Van Dijk - 2007); however, a more parsimonious specification (δ_t constant and equal to zero, i.e. τ_t follows a zero-mean AR(1) process) has been shown to work well for several macroeconomic time series (e.g.: Clark - 1989; Crespo - 2008; Cable and Jackson - 2008).

To understand how my modelling choices compare with the alternatives mentioned above, I also estimate the following three models:

- Alternative model 1: μ_t follows a random walk, δ_t is constant and equal to zero;

- Alternative model 2: μ_t follows a random walk and δ_t is time-varying;

- Alternative model 3: μ_t is constant, δ_t is constant and equal to zero.

I compare my model with the three alternative models enumerated above using two different criteria: out-of-sample predictive accuracy and posterior odds ratios. In both cases, I use the first twenty years of data (240 observations) as a training sample[13].

To assess out-of-sample predictive accuracy I look at the mean squared prediction error. The prediction error at period t is calculated as follows: first, I use the previous $t-1$ observations to update the priors; using the updated priors, I form a predictive distribution for e_t, denoted by $f(e_t \,|I_{t-1})$; then, the prediction $\widehat{e_t}$ of e_t is computed as:

$$\widehat{e_t} = \int_{-\infty}^{\infty} e_t f(e_t \,|I_{t-1}) \, de_t$$

i.e. the prediction is equal to the expected value under the predictive distribution; for each t, the prediction error is equal to $e_t - \widehat{e_t}$; since the first 240 observations are used as a training sample, the mean squared prediction error is:

$$MSE = \frac{1}{T-240} \sum_{t=241}^{T} (e_t - \widehat{e_t})^2$$

Table 4 reports the MSEs thus calculated for the baseline model and the three alternative models. Furthermore, it reports the results obtained with a random-walk model ($\widehat{e_t} = e_{t-1}$). The baseline model has a smaller MSE than the three alternatives and the random walk. The ordering is as follows:

$$\text{Baseline} < \text{Alt. 2} < \text{Alt. 1} < \text{Alt. 3} < \text{Random walk}$$

Hence, the baseline model is preferred to the alternatives in terms of forecasting performance, although the performance of Alternative model 2 is only slightly worse than that of the baseline model.

Posterior odds ratios[14] are computed as the ratio between the marginal density of the data under the baseline model (denoted by B) and the marginal density of the data under the alternative model (denoted by A). To avoid indeterminacy (see above) I use the first 240 observations as a training sample, i.e. I use as priors the posteriors formed using the first 240 observations. Hence, the posterior odds ratio R for a generic alternative model A is:

$$R = \frac{\int f(e_{t+1}, e_{t+2}, \ldots, e_T \,|\theta_B, X_t, B) \, f(\theta_B, X_t \,|I_t, B) \, d\theta_B dX_t}{\int f(e_{t+1}, e_{t+2}, \ldots, e_T \,|\theta_A, X_t, A) \, f(\theta_A, X_t \,|I_t, A) \, d\theta_A dX_t}$$

[13] Note that using a training sample is needed to avoid indeterminacy (Jeffreys - 1961) in the computation of posterior odds ratios, since I use improper priors. The use of training samples for the construction of non-subjective Bayes factors is thoroughly discussed by Ghosh, Delampady and Samanta (2006).

[14] The prior odds ratio is assumed to be equal to one, so that the posterior odds ratio and the Bayes factor coincide.

where $t = 240$, θ_A and θ_B are the vectors of parameters for model A and B respectively, X_t is the vector of state variables (π_t, τ_t and δ_t in the case of the baseline model) and the integrals are approximated summing over the MCMC simulated samples.

Table 4 reports the posterior odds of the three alternative models described above. In all three cases the baseline model has much higher odds than the alternative. The ordering is the same already reported in the case of forecasting performance.

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7 Tables and figures

Table 1 - The persistence of the cyclical component of earnings[15]

Diff.	Filter	Constant	First lag
No	HP	-0.0007 (0.7574)	0.9597 (0.0000)
No	Lin. Trend	-0.0005 (0.8150)	0.9814 (0.0000)
Yes	HP	-0.0006 (0.7811)	0.0893 (0.0610)
Yes	Lin. Trend	-0.0005 (0.8421)	0.1250 (0.0086)

[15] The table reports the results of a preliminary regression analysis of the cyclical component of earnings. In the first two rows (Diff.='No' in the first column), the cyclical component is regressed on a constant and its first lag. In the last two rows (Diff.='Yes' in the first column), the first difference of the cyclical component is regressed on a constant and its first lag. The second column indicates the method used to extract the cyclical component of earnings: 'HP' indicates that the HP filter has been used, while 'Lin. Trend' indicates that a linear trend has been subtracted from the logarithm of earnings. The last two columns contain the parameter estimates, with p-values in parentheses. The sample period is from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

Table 2 - The state-space model
Posterior distribution of the parameters[16]

	μ	ρ	φ	σ_u	σ_v	σ_w
Mean	0.0059	0.8799	0.9238	0.0184	0.0337	0.0117
Standard dev.	0.0011	0.0874	0.0627	0.0136	0.0106	0.0037
1st percentile	0.0028	0.5675	0.6833	0.0002	0.0020	0.0060
5th percentile	0.0040	0.7164	0.7974	0.0012	0.0088	0.0072
Median	0.0061	0.8997	0.9430	0.0152	0.0379	0.0110
95th percentile	0.0075	0.9789	0.9838	0.0429	0.0436	0.0186
99th percentile	0.0085	0.9940	0.9934	0.0450	0.0450	0.0252

[16] The table reports the mean, the standard deviation and selected percentiles of the posterior distribution of the parameters of the state-space model used to filter out the cyclical component of earnings. The posterior distribution is simulated by MCMC methods. μ is the monthly growth rate of the permanent component of earnings. ρ is the persistence of the cyclical component of earnings. φ is the persistence of the time-varying drift in the cyclical component; it measures the extent to which periods of high growth tend to be followed by other periods of high growth and periods of low (or negative) growth tend to be followed by other periods of low (or negative) growth. σ_u is the volatility of the permanent shocks to earnings. σ_v is the volatility of the transitory shocks to earnings. σ_w is the volatility of the shocks to the time-varying drift. The sample period used to estimate the parameters goes from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

Table 3 - The variance decomposition of earnings[17]

	12 mo.	24 mo.	60 mo.	120 mo.
Perm.	9.5%	8.9%	15.1%	26.1%
Trans.	24.1%	11.9%	8.3%	7.2%
To drift	66.4%	79.2%	76.6%	66.7%

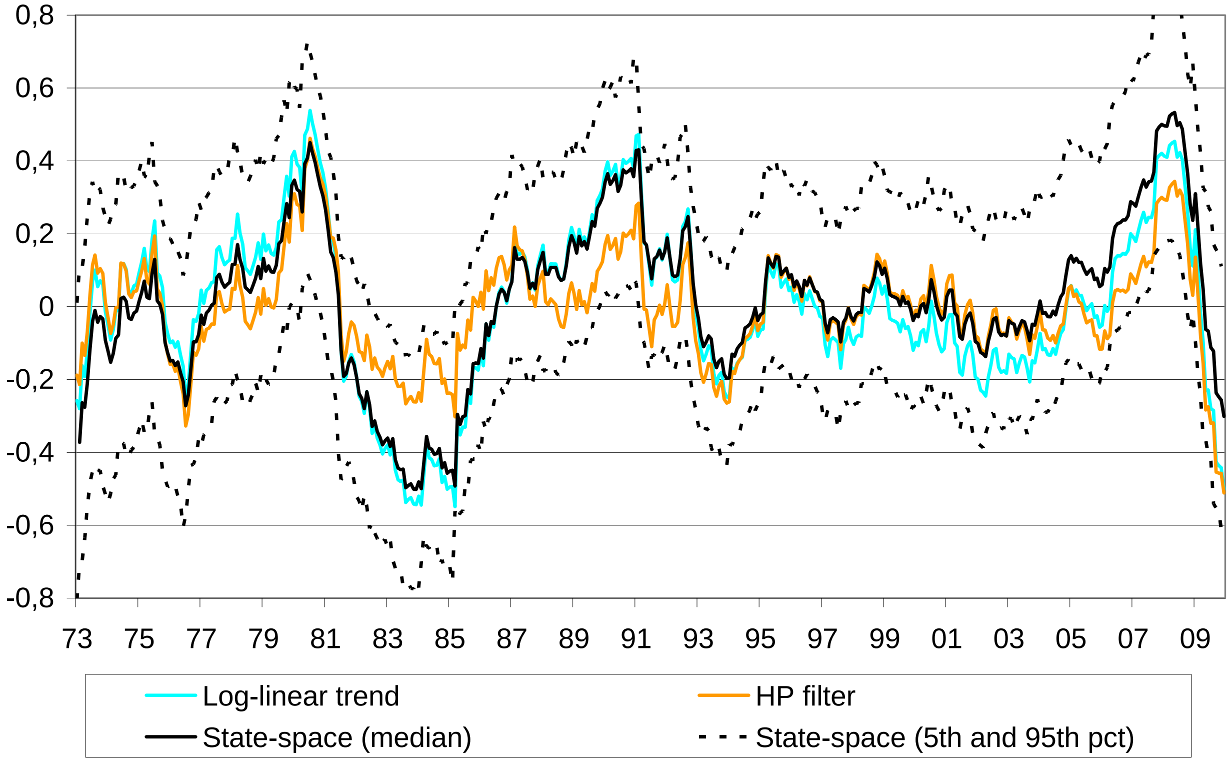
[17] The table reports the variance decomposition of earnings, obtained using the state space model. Parameter values are set equal to the median of their posterior distribution. There are three independent shocks in the model: permanent shocks (Perm.), transitory shocks to the cyclical component (Trans.) and shocks to the time-varying drift of the cyclical component (To drift). Each column refers to a different forecasting horizon (12, 24, 60 and 120 months). The sample period used to estimate the parameters goes from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

Table 4 - Comparison with alternative models[18]

	MSE	Posterior odds
Baseline	$1.571 \cdot 10^{-3}$	1
Alternative 1	$1.622 \cdot 10^{-3}$	58,45
Alternative 2	$1.582 \cdot 10^{-3}$	12,36
Alternative 3	$1.648 \cdot 10^{-3}$	3966,50
Random walk	$1.655 \cdot 10^{-3}$	n/a

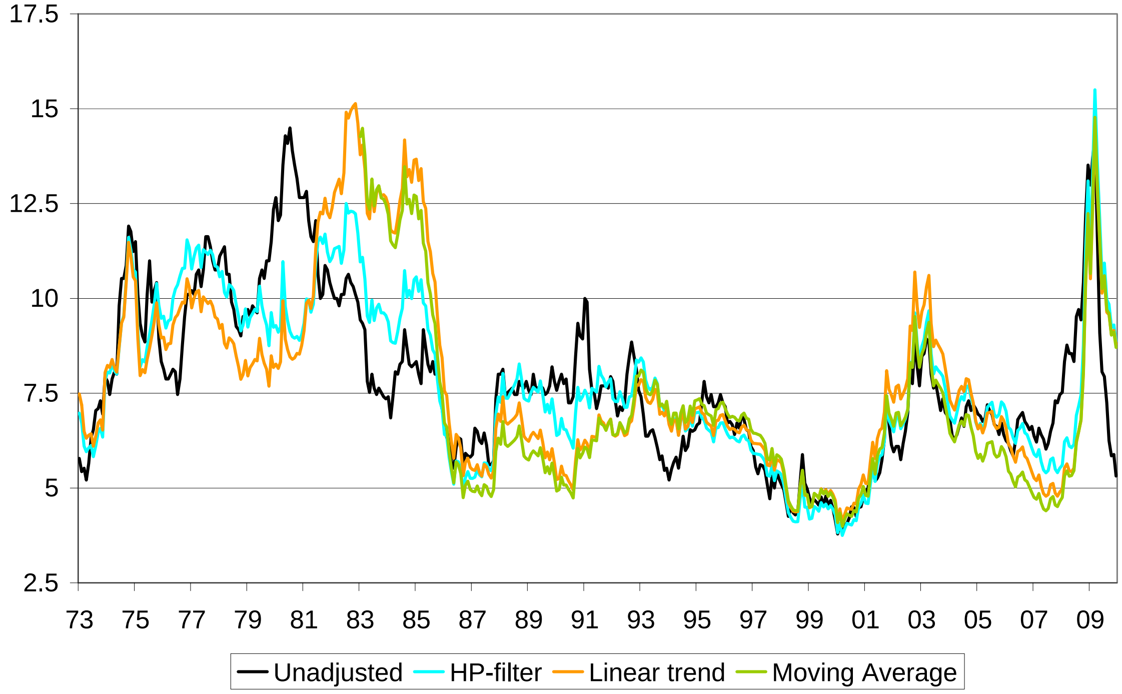
[18]The table reports the results of a specification analysis aimed at comparing the baseline model used in this paper with other popular models (alternatives 1, 2 and 3 described in the Appendix). The column entitled MSE reports the mean squared prediction error of the out-of-sample forecasts produced by the models. The column entitled 'Posterior odds' reports the posterior odds ratios, computed as follows: the numerator is the marginal likelihood of the data under the baseline model, while the denominator is the marginal likelihood of the data under the alternative model (the prior odds ratio is assumed to be equal to 1). So, for example, the baseline model is 12,36 times more likely than Alternative model 2.

Figure 1 – The cyclical component of earnings



The figure plots three estimates of the cyclical component of corporate earnings. *Log-linear trend*: the cyclical component is calculated as the natural logarithm of earnings minus its linear trend (fitted by OLS). *HP filter*: the cyclical component is obtained HP-filtering the natural logarithm of earnings (the frequency parameter is 129,600). *State space*: the cyclical component is the transitory component of the state-space model introduced in Section 2 (the median and the 5th and 95th percentiles of the posterior distribution are reported). The sample period is from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

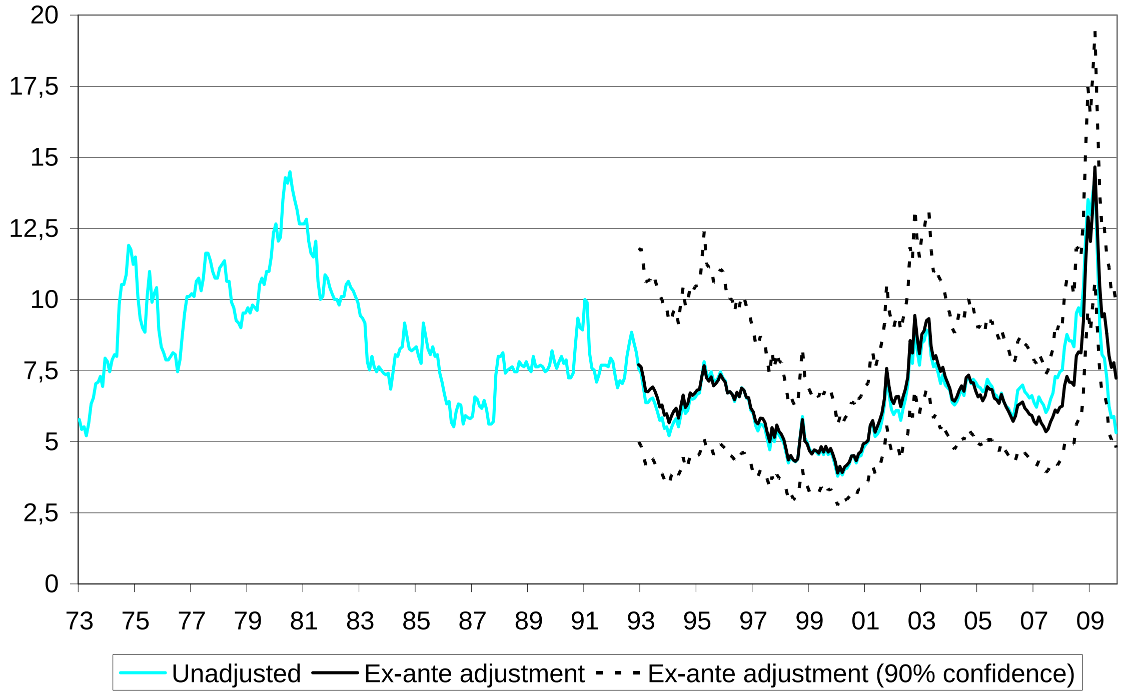
Figure 2 – Earnings/price ratio – Adjusted and unadjusted



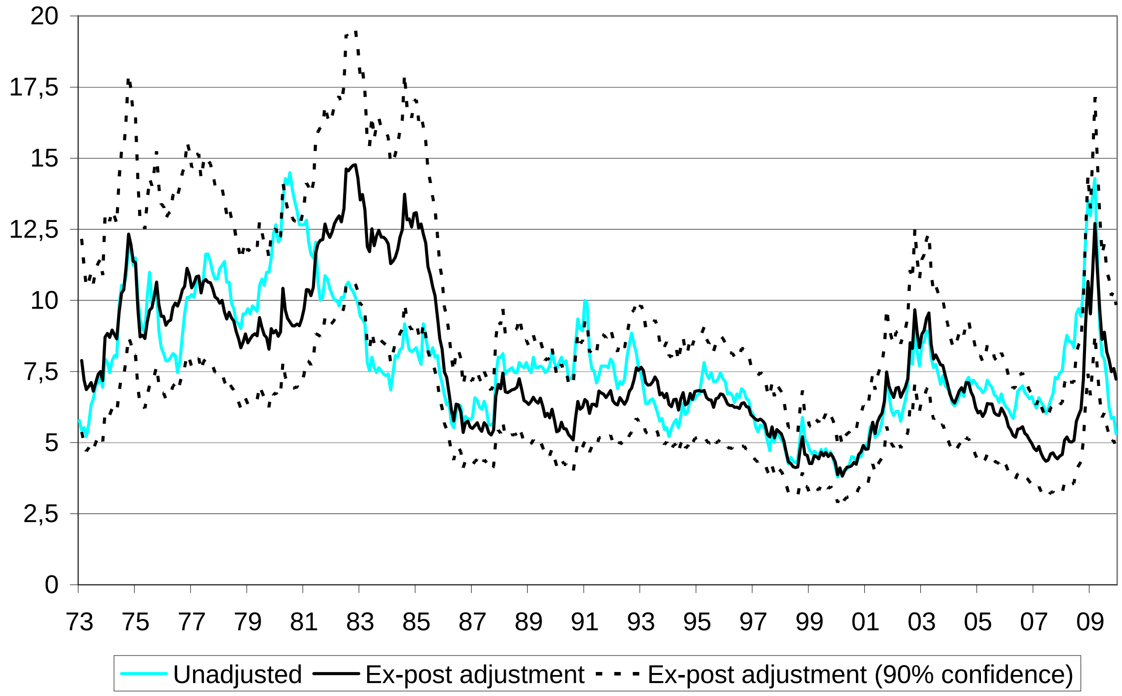
The figure plots the adjusted and the unadjusted earnings/price ratios. The adjusted ratios are obtained dividing the filtered time series of earnings by the stock price. In the time series labelled 'HP filter', the cyclical component of earnings is removed by HP-filtering the natural logartithm of earnings (the frequency parameter is 129,600). In the time series labelled 'Linear trend', the cyclical component of earnings is removed by fitting a linear trend to the natural logartithm of earnings. In the time series labelled 'Moving Average', the cyclical component of earnings is removed by taking 10-year moving averages of earnings, and then rescaling the series so that the sample mean of the filtered series coincides with the sample mean of the original series. The sample period goes from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

Figure 3 – Earnings/price ratio – State-space model adjustment

Panel A – Ex-ante adjustment

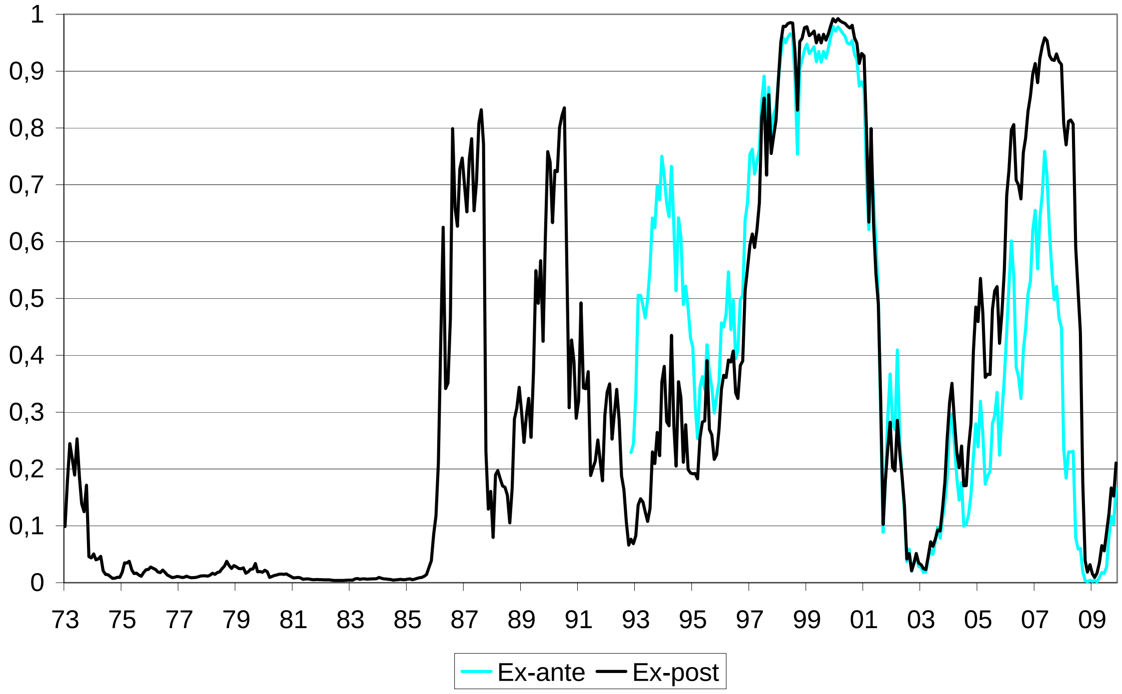


Panel B – Ex-post adjustment



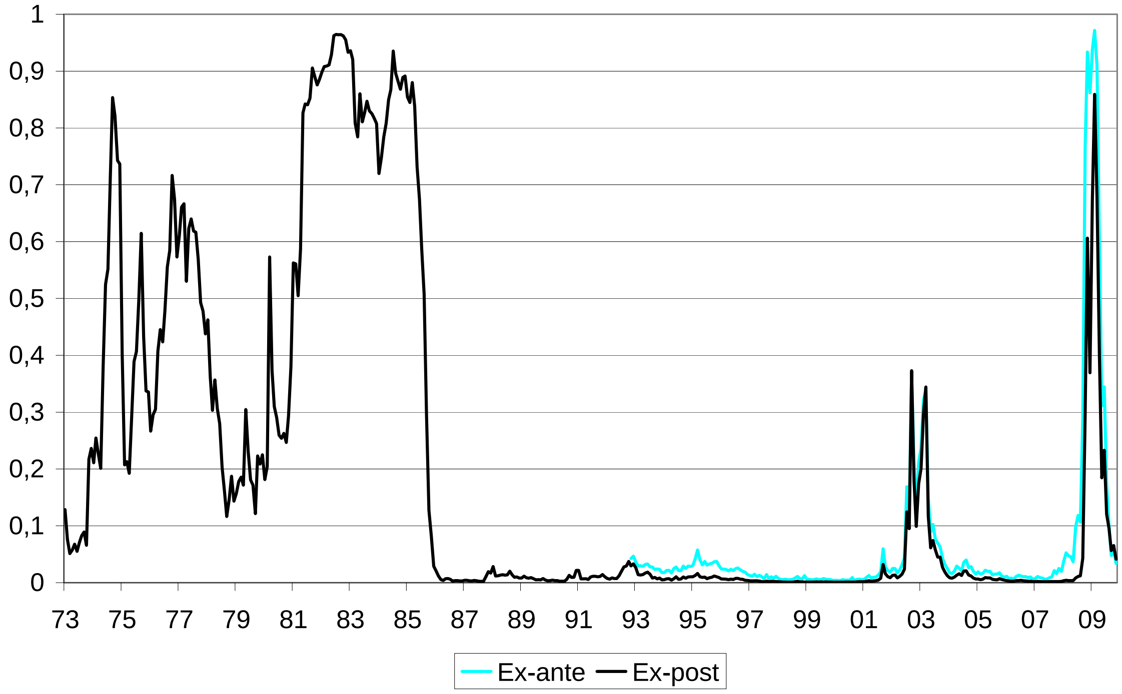
The figures plot the adjusted and the unadjusted earnings/price ratios. In the adjusted ratio, the numerator is the permanent component of earnings, as estimated by the state-space model. In Panel A, the adjustment is *ex-ante*, in the sense that the permanent component of earnings in any one period is estimated using only information available up to that same period. In Panel B, the adjustment is *ex-post*, i.e. the permanent component of earnings in any one period is estimated using also information available after that same period. The solid black line represents the median of the posterior distribution of the adjusted ratio, while the dotted lines represent the 5th and 95th percentiles of the same distribution. The confidence bands reflect both the uncertainty related to the estimation of the parameters of the model and the uncertainty related to the estimation of the unobservable states of the model. In panel A, the *ex-ante* estimation begins only after 20 years of data become available. The sample period goes from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

Figure 4 – Probability that the stock market is 30%-over-valued



The figure plots the *ex-ante* and *ex-post* probabilities that the stock market is 30%-over-valued. The stock market is 30%-over-valued if the adjusted earnings/price ratio is more than 30% below its long-run mean. The *ex-ante* probability in any one period is estimated using only information available up to that same period. The *ex-ante* probability starts to be estimated only after 20 years of data become available. The *ex-post* probability is estimated using all the information received up to the end of the sample. The sample period goes from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

Figure 5 – Probability that the stock market is 30%-under-valued



The figure plots the *ex-ante* and *ex-post* probabilities that the stock market is 30%-under-valued. The stock market is 30%-under-valued if the adjusted earnings/price ratio is more than 30% above its long-run mean. The *ex-ante* probability in any one period is estimated using only information available up to that same period. The *ex-ante* probability starts to be estimated only after 20 years of data become available. The *ex-post* probability is estimated using all the information received up to the end of the sample. The sample period is from January 1st, 1973 to December 1st, 2009, for a total of 444 monthly observations.

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