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RESEARCH ARTICLE

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Industry and time specific deviations from fundamental values in a random coefficient model

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Abstract The paper analyzes the relationship between stock prices and fundamentals for a large sample of US stocks in the last 10 years using a random coefficient model. Heterogeneity and omitted variable bias are properly taken into account with model coefficients being allowed to vary across time and industries. The random coefficient model allows to track waves of reliance on analysts' forecasts and nonfundamental stock price components across time and clearly identifies the growth of the nonfundamental component in the long 1991–2000 swing.

Keywords Fundamental/price relationship · Finite mixture models · EM algorithm · Panel data

JEL Classification Numbers C140 · C230 · G120

1 Introduction

The paper aims to evaluate the behavior of investors in financial markets, considering the influence of Consensus forecasts on their investment choices. For this purpose we adopt a random coefficient approach and apply it to the constituents of the S&P 500 Composite Index whose stock prices are recorded from 1990 to 2002 on quarterly basis. Our economic purpose is to test whether a stable and significant

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relationship between stock prices and their "fundamental" discounted dividend or discounted cash flow values exists.

Starting from Shiller's seminal paper (1981) several contributions analyze the price/fundamental relationship using the net present value (NPV) approach. From an econometric point of view the question has been tackled by the existing literature alternatively in a cross-section or time series perspective. Our goal is to investigate the relationship with a panel data approach that permits to explore both dimensions at the same time.
Panel data models are generally based on the assumption that observed responses are independent conditionally upon time. This hypothesis cannot be reasonably accepted for stock prices. This is why we choose to apply a random coefficient approach which allows us to handle such problem. As we better specify in the methodological section, by doing so, we consider observations (stocks) independent, once they have been conditioned on both time (year) and space (industry) dimensions. Another advantage of our choice is that it allows to consider the effects of the fundamental component of price by taking into account the bias due to time and industry specific omitted variables.

The paper is divided into five sections (including introduction and conclusions). In section 2 we present a short survey of the literature on issues of financial market microstructure, such as financial investors reliance on fundamentals, which are relevant to the motivation and results of our inquiry. In section 3 we illustrate our random coefficient approach. Section 4 presents and comments our descriptive and econometric results. The most relevant descriptive finding is the systematic bias in analysts' forecasts, when comparing effective and expected 1 year ahead earning growth forecasts. The most interesting econometric results are the significant sensitivities of the observed prices to components related and unrelated to fundamentals and the heterogeneity of such sensitivities across time and industries.

2 Expectations and stock prices

Deviations of stock prices from their fundamental values are widely documented in the financial empirical literature. The traditional approach proposed by Shiller (1981), tackles the question by analyzing the variance of prices and of their fundamental (dividend based) net present values with variance bound ratio tests. Results from this approach lead to the formulation of the well known excess volatility puzzle in which, contrary to what expected from the theory, fundamentals vary less than observed prices. Kleidon et al. (1986) formulate the puzzle as follows: "... *dividend changes appear much smoother than those of either prices or earnings. It is conceivable that this phenomenon is the basic puzzle, and that its resolution will explain much of what remains of the apparent evidence against the present value relation.*" [1] Some authors interpret the puzzle by arguing that time varying expectations and time varying risk premia, not incorporated in fundamentals which simply discount ex post dividends, may help to understand the puzzle (see, among others, Campbell et al. 1997 for a detailed discussion on the topic). Many other contributions confirm that other factors, different from dividend based fundamentals, contribute to explain volatility in stock prices (see, for example, Campbell and

[1] For other and more recent formulations of the puzzle see West (1988) and Cochrane (1991).

Shiller 1987; Chow and Liu 1999; Mankiw et al. 1991; Campbell and Cochrane 1999; Adriani et al. 2005; Adriani and Becchetti 2004; Anderson et al. 2003). These findings stimulate a reflection on the theoretical framework of the market microstructure which may be compatible with them. Such framework is not that of fully revealing rational expectation theoretical models, which assume that private information is redundant, since the efficient market hypothesis implies the informative equivalence between private and public information. In such case, decision processes take place using information which should be exhaustively propagated on the market by the price vector (Fama 1970; Grossman 1976). As a consequence, when financial markets are characterized by perfect and symmetric information, it is impossible to make profits by trading on the basis of the publicly available information (Milgrom and Stokey 1985; Malkiel 1992; Asch et al.1982). Empirical evidence on the volume of trades and on their profits may be reconciled with financial theory by considering that, in a dynamic and uncertain world, with costly information, the classical hypothesis of fully revealing rational expectations, does not hold. If the price vector is not exhaustively informative and investors have heterogeneous information sets, we typically obtain market equilibria in which more informed agents make their investment in information profitable by trading with less informed ones (see, among others, Grossman and Stiglitz 1980; Diamond and Verrecchia 1981).

If we accept that investors have changing and heterogeneous information and expectations, forecasts on future dynamics of firm specific and economy wide variables become a critical source of knowledge for traders and a crucial factor in the formation of their fundamental value. In this framework, it becomes essential to investigate which kind of information the investors use for their trading activity and, if the information is asymmetric, which kind of relationship exists among different classes of information variables. In the next paragraph we argue that I/B/E/S earning forecasts are the main source of information used for estimating the net present value of stocks and we formulate a hypothesis on how this information is incorporated into the fundamental price which, for us, represents the benchmark for investors' trading decision.

2.1 Fundamentals and stock prices: the dividend/earning controversy

Many papers in the financial literature wonder which kind of publicly available information is valued more by asymmetrically informed investors in their buying/selling decisions. Pettit (1972), Shiller (1981), Asquith and Mullins (1983), and Bajaj and Vijh (1990), as large part of literature, have stressed that investors interpret dividends as proxies of value-relevant information. Consistently, the empirical literature finds a positive correlation between stock price changes and dividend changes around dividend announcement dates. In particular, Shiller (1981) points out that dividends (instead of cash flow) have to be used to evaluate correctly the fundamental, since dividends are what shareholders effectively cash. By following the alternative path of discounting cash flows (DCF approach), even though nondistributed dividends are reinvested with the discounted cash flow (DCF), we risk to count them twice since their variation is incorporated into earning growth forecasts.

An empirical puzzle, though, is that recent stock market values generate unreasonably low risk premia when the present value of the stocks is calculated by discounting future expected dividends. Using I/B/E/S earnings forecasts and a risk-free rate proxied by long term government bond returns, Claus and Thomas (2001) estimate the post-1985 equity premium for the US market to be of the order of 3%, much less than the historical difference between secular average yearly returns on stocks and bonds in the US market, and less than the 8% observed equity premium since 1926. The authors obtain similar findings for the equity markets of Canada, France, Germany, Japan and the United Kingdom. On the same line, Jagannathan et al. (2001) estimate negative implied risk premia for limited periods in the last two decades. Another argument in favor of the DCF approach is that the value of a stock is the net present value of cash flow in cases of a takeover which involves 100% of equity capital. Therefore, it is possible that, in periods of stock market boom, with waves of mergers and acquisitions, shareholders rationally anticipate stock values for the bidder so that fundamental values move toward DCF values.

In this paper we argue that the issue of dividends versus cash flow has much less relevance when we look at long time horizons and consider the available forecasts on earnings growth as proxies of both dividend and cash flow growth. In such case, the use of initial levels of cash flow instead of dividends should cause a bias with second order effects on the fundamental price which is mainly determined by other variables (earning growth forecasts, interest rates, terminal rate of growth, etc.). For the construction of our fundamental we therefore use and compare the two approaches (dividend and cash flow NPV) under the assumption that earnings growth expectations can be proxies of rates of growth of both variables. This restrictive assumption is justified by the fact that earnings are the only source of information systematically available for investors for a large number of companies across time. Results on the sensitivity of market prices to such measure, presented in section 4, will tell us whether our assumption captures something relevant in the behavior of stock market investors.

2.2 The model

In the formulation of our model, we do not follow the traditional financial literature which analyzes the relationship between price and its fundamental value with variance-bound tests. This is because, as pointed out by Marsh and Merton (1986), that choice does not permit to discriminate between price volatility and dividend smoothing policy. Similar difficulties in discriminating among different hypotheses exist if we use levels of dividend-price ratios. In such case we cannot distinguish between the two sources of variability unless we explicitly assume that log dividend-price ratios are cointegrated stationary (Campbell and Shiller 1988, 1989). However, even if we cannot test time stationarity and cointegration since our panel is unbalanced, we cannot reject the stationarity hypothesis when we perform these tests on the subsample on which we have complete time series.

Our assumption is that variables in levels directly allow to test the hypothesis that the price at time t for the stock i equals its fundamental value avoiding any smoothing problem related to dividend or to nondistributed earnings. Therefore, following Anderson et al. (2003), our response variable is the price level (rather than the dispersion of stock returns or indicators such as the dividend-price or earning-price ratios) and the stock price can be derived by looking at both fundamental and nonfundamental components. On this basis, the information contained in prices helps investors to select under or over priced stocks. As a first step we can therefore write the relationship between price and fundamentals as

$$p_{iItT} = F(f_{iItT}, nf_{iItT}), \tag{1}$$

where for each stock $i = 1, \ldots, n_I$, sector $I = 1, \ldots, \mathcal{I}$ and time $t = 1, \ldots, n_T$ in the year $T = 1, \ldots, \mathcal{T}$, f_{iItT} is the fundamental information determining the actual level of the stock price p_{iItT}, and nf_{iItT} represents idiosyncratic information not directly related to the fundamental value. This information can also be related to a set of "environmental" variables. Following the standard literature on market efficiency and variance-bound tests, the relationship between prices and fundamentals can be explicitly measured by decomposing the stock price into fundamental (persistent) and nonfundamental (temporary) components (see, among others, Blanchard and Quah 1989; Lee 1995). This is true if the equality in (1) holds. It is standard in this literature (which examines the problem in a time series perspective) to measure these variables as deviations from fundamental components (see, among others, Anderson et al. 2003). As better specified in section 3, our approach does not measure directly the nonfundamental part of price, while it measures the price/fundamental relationship by interpreting residual variability as determined by time and industry varying random components of the coefficient which measures the sensitivity to fundamentals. We can now introduce our model considering that, if (1) holds, then also its linear transformation

$$p_{iItT} = \alpha + \beta f_{iItT} + \varepsilon_{iItT} \tag{2}$$

must hold, where f_{iItT} is evaluated with the DCF methodology and ε_{iItT} is a residual term with variance σ_ε^2. Equation (2) describes the behavior of "fundamentalist" investors which take their trading decisions on the basis of the gap between current and fundamental values of stocks or portfolios.[2] Therefore, if financial markets are efficient and fully informative, $\varepsilon_{iItT} = 0$, while β will be close to 1 and $\alpha = 0$. In fact, if the model is correctly specified, and the information contained in the covariate is fully informative, $\hat{p}_{iItT} = \alpha + \beta f_{iItT} = f_{iItT}$, and the predicted value of p_{iItT}, will be equal to f_{iItT}. If, on the contrary, β is positive but significantly lower than one, we must argue that financial markets incorporate analysts' earnings forecasts but downweight them. This could be interpreted as a rational reaction to the fact that earnings forecasts are systematically overoptimistic (Lim 2001; Adriani et al. 2005).

To test if equation (2) is invariant across time (years) and sectors, we run, as a first approximation, an OLS regression for each combination of I and T. Regression results (not displayed here for sake of space) have shown a strong variability across sectors and time. To give an idea, the 25th and 75th percentiles of the distribution of estimates on the 428 combinations of year/sector observations are: 3.61–15.45 for the intercepts, 0.38–0.81 for the βs and 24.46–123.30 for the error variances. These results are not surprising since financial time series usually exhibit an increasing

[2] Durlauf and Phillips (1988), for example, use a similar version of the linear transformation proposed here as an equivalent form of the variance-bound tests, in order to estimate the orthogonality between the price gap and the information variables.

variability in time, which can be reduced by using a logarithmic transformation of the data. Moreover, Campbell et al. (1997) evidence that the log transformation of these series is correct (since they observe exponential growth over time) and can be used also if the linear model allows for unit roots. The strategy of the log-linear specification of (1) is normally adopted in time series as well as in cross-sectional studies and mainly in the literature on dividend-ratio models where the aim is to investigate the relationship among prices, fundamentals and related stock returns. In this respect, it should be also noted that the extreme variability of regression estimates is probably due to population heterogeneity and/or omitted environmental variables affecting the price/fundamental relationship. As better described in section 3, to take into account this variability, we employ a model specifying different error variances and regression parameters for each combination of sector and time points (years). Moreover, our model describes a linear relationship between price and fundamental value, but it allows to handle properly the miss-specification of the link function and of the response distribution through the mixture components (MacLachlan and Peel 2000; Aitkin et al. 2005). This enables us to capture the nonhomogeneous behavior of the price-fundamental relationship across sectors and time.

2.3 Specification of the fundamental

To define our fundamental we consider the following two stage "discounted divident/cash flow" approach.[3] As in Kaplan and Ruback (1995) our DCF evaluation of the fundamentals is based on I/B/E/S forecasts and has therefore the advantage of using only current net earnings (or dividends) as accounting variable. We apply a modified version of the two stage DCF model. Inside this model, we use a simple CAPM approach to estimate the expected return from an investment of comparable risk. We can specify the model by considering that, in a simplified world, the expected equity value of firm i at quarter t of the year T can be derived from (Adriani et al. 2005; Adriani and Bechetti 2004; Claus and Thomas 2001):

[3] Accounting and economic literature usually adopt at least three different approaches to calculate the fundamental value of a stock: (i) the comparison of balance sheet multiples (EBITDA, EBIT) for firms in the same sector; (ii) the residual income method; (iii) the discounted cash flow method. The first approach is highly arbitrary as, if market agents have nonhomogeneous information sets or adopt different trading strategies, the benchmark used for comparison may be overvalued or undervalued. The second problem with this method is that industry classifications become always more tricky as far as firms diversify their activities and develop new products or services which cannot be easily classified into traditional taxonomies, (Kaplan and Ruback 1995). The problem with the second approach (residual income method), which is largely used in the literature (see for example Lee et al. 1999; Frankel and Lee 1998), is that the formula for evaluating the fundamental value of a stock uses a balance sheet measure whose accuracy and capacity of incorporating changes in firm fundamental value is limited. A valuable example of this phenomenon may be given by descriptive evidence provided by Lee et al. (1999) who document the sharp up-trend in the price to book ratio which has risen three times between 1981 and 1996 for the Dow Jones Industrial Average. An interpretation for this result is that accounting methodologies lag behind in adjusting to changes in investors' market value assessments of firms whose share of intangible assets made by human and, more generally, immaterial capital is rising over time. This is the reason why, following Kaplan and Ruback (1995), we prefer to use the DCF approach.

$$f_{it} = mv^{\mathrm{e}}_{it} = cf_{it} \times \left\{ 1 + \left[\sum_{h=1}^{5} \frac{[1 + E_{t,t+4}(g_i)]}{(1+r)^h} + \frac{[1 + E_{t,t+4}(g_i)]^6}{(r_{tv} - g_n)(1+r)^6} \right] \right\}, \quad (3)$$

where mv^{e}_{it} is the expected equity market value of firm i at time t and cf_{it} represents, alternatively, current dividends or current earnings. $E_{t,t+4}$ represents at quarter t the 1 year ahead expected earnings rate of growth for firm i, according to the Consensus forecast, while r can be viewed as, either the discount rate adopted by equity investors, or the expected return from an investment of comparable risk. To evaluate r we use the standard CAPM approach, i.e., $r_{\mathrm{CAPM}} = r_f + \beta E[r_m]$, where r_f is a short term US treasury bond rate, the current beta is calculated on a sample of two year lagged weekly data and $E[r_m]$ is the risk premium. For the stock market premium we consider that our measure should be between the historical difference in the rates of return of stocks and T-bonds (between 6% and 9%) and the minimum implied risk premium for US equity markets in the sample period, which is extremely low and around 2%.[4] Both of these two extremes might be incorrect estimates for the risk premium. The former because it assumes that the long term historical premium is equal to the current premium, thereby neglecting fundamental institutional and political changes occurred in the last decades. The latter because it assumes that financial markets are correct in evaluating stocks (this is not the case in presence of a bubble or of a nonzero share of noise or liquidity traders trading with arbitrageurs of limited patience). The last part of the formula is the terminal value of the stock. We fix at the sixth year the border between the high growth and the stable growth period. Sensitivity analysis on this threshold shows nonetheless that this choice is not so crucial for the determination of the value of the stock.[5] We must in fact consider that the positive impact on the fundamental value of an additional year of high growth must be traded off with a heavier discount of the terminal value which represents a significant part of the final value. In the terminal value it is assumed that the stock cannot grow more and cannot be riskier than the rest of the economy, with g_n representing the perpetual rate of growth of the economy. We therefore assume that the discount rate in the terminal value has unit beta and calculate it as $r_{tv} = r_f + E[r_m]$.

[4] To calculate the current implied premium we use the Gordon (1962) formula in which value is equal to: expected dividends next year/(required return on stocks − expected growth rate). In the light of this formula, the extremely low implicit risk premium in the sample period may be interpreted as the availability to pay higher prices even in presence of low dividend payout. The fact that the implied risk premium is lower today than that prevailing in periods (such as the 1960s) with similar growth and inflation rates may depend for instance on political factors which may make investors' expectations more optimistic over long time horizons therefore reducing the risk of equity investment. If we just adopt the implied risk premium without weighting it for the historical risk premium, we would implicitly assume that no fundamental value exists or that the fundamental is just what investors believe in that period. In this way changes in the implied risk premium constantly update the fundamental value and the latter becomes just what investors are willing to pay for the stock.

[5] Sensitivity analysis shows that small perturbations of some selected parameters of the fundamental (risk premium, border between high growth and terminal period, risk free rate) do not change substantially results which are presented in the following sections. Evidence is omitted for reasons of space and available upon request.

3 The econometric model

To estimate (2) we use a random coefficient model in which we relax the assumption of Gaussian errors. This is because in our preliminary analysis, performed by running OLS regressions for each combination of time (year) and sector, we noted a significant variability of parameter estimates across time and sectors. Aitkin et al. (2005) stressed that a simple way to unify the different sources of model misspecification is through omitted variables. We propose to model the dependent variable through a Generalized Linear Model by adopting a semi-parametric technique based on finite mixtures, relaxing the assumption of $i.i.d.$ residuals and associating a set of random parameters to some elements of the adopted covariates set.[6] By this manipulation we explicitly adjust the estimate of model parameters for sector and time specific omitted variables which affect the relationship between prices and fundamentals (i.e., the fundamentalists'/chartists' participation rate, the forecasted interest rate term structure or time varying inflation forecasts not perfectly captured in the DCF approach). In statistical terms, by denoting with y_{iItT} the price of the stock i in sector I at quarter t of the year T, and with x_{iItT} its fundamental counterpart, we insert in our model these omitted variables by assuming that each sector has its own regression, i.e.,

$$E(y_{iItT}) = h_{iItT} = \alpha_{IT} + \beta_{IT} x_{iItT}. \tag{4}$$

Conditionally upon the regression parameters $\boldsymbol{\eta}_{IT} = [\alpha_{IT}, \beta_{IT}, \sigma^2_{IT}]'$, the probability density function of y_{iItT} is

$$f(y_{iItT}|\boldsymbol{\eta}_{IT}) = \frac{1}{\sqrt{2\pi\sigma^2_{IT}}} \exp\left[-\frac{1}{2\sigma^2_{IT}}(y_{iItT} - \alpha_{IT} - \beta_{IT} x_{iItT})^2\right] \tag{5}$$

while that of $\mathbf{y}_{IT} = [y_{1I1T}, ..., y_{n_I I n_T T}]'$ is

$$f(\mathbf{y}_{IT}|\boldsymbol{\eta}_{IT}) = \prod_{i=1}^{n_I}\prod_{t=1}^{n_T} f(y_{iItT}|\boldsymbol{\eta}_{IT}). \tag{6}$$

We assume that $\boldsymbol{\eta}_{IT}$ is a random variable with probability function g. The marginal (unconditional) distribution of $\mathbf{y}_{IT}$ is then given by the following integral

$$f(\mathbf{y}_{IT}) = \int f(\mathbf{y}_{IT}|\boldsymbol{\eta}_{IT}) g(\boldsymbol{\eta}_{IT}) \mathrm{d}\boldsymbol{\eta}_{IT}. \tag{7}$$

By assuming independence among observations belonging to different combinations of sectors and years, we can write the p.d.f. of the whole sample $\mathbf{y} = [\mathbf{y}'_{11}, ..., \mathbf{y}'_{\mathcal{I}\mathcal{T}}]'$ as

$$f(\mathbf{y}) = \prod_{I=1}^{\mathcal{I}}\prod_{T=1}^{\mathcal{T}} f(\mathbf{y}_{IT}). \tag{8}$$

[6] For a multivariate extension of the univariate semi-parametric mixture model see Alfó and Trovato (2004).

The mixture model described allows us to consider explicitly time and sector specific components of prices, thereby enabling us to capture the sector specific structure by mixtures with heterogeneous variance components. Moreover, by applying a random coefficient model, we do not need to specify other regressors which can affect the relationship between prices and the underlying fundamental, since we implement our model with random parameters which take into account the effects of these latent variables. The model, by introducing a random distribution of parameters, allows us to estimate an unbiased coefficient of the fundamental, conditional to the effects of additional unobserved environmental variables, even though these variables are not specified in the model. Summing up, the econometric model presented here allows to verify statistically the behavior of fundamental prices under the assumption that population heterogeneity affects parameters estimation. Heterogeneity has been handled by allowing parameters to vary across time (year) and industries. In the model, mixture components have time and industry varying variances. This enables us to handle missspecification due to unobserved variables or to erroneous assumptions on the link function or response distribution, such as, for example, the assumption of a linear relationship between prices and fundamentals when the true relationship is log-linear (MacLachlan and Peel 2000; Aitkin et al. 2005). Our choice to model the relationship between the price and its fundamental by finite mixture models gives us confidence about generated regressors. Indeed, by assuming a random distribution for these covariates, we are also modelling the possible bias due to the use of estimated covariated as fundamental variables in the regression (MacLachlan and Peel 2000; Aitkin et al. 2005; Aitkin and Rocci (2005)). Given the unbalanced structure of our panel, and the time gaps in our data, an additional problem may be that of the impossibility of testing for stationarity. As a solution to this problem consider that, by allowing parameters to vary also in time, without any distributional assumption on them, we can capture the structure of the data generating process also in time and not only in cross section. As it has been recalled, we do not assume any distribution for the random coefficients, since we are trying to find the best discretization of the conditional log likelihood given the data generating process of the response variable (Dempster et al. 1977; McLachlan and Krishnan 1997).

4 Results

We estimate (2) by normal mixture using a semiparametric specification (see Appendix for details). Our source of data is Datastream for stock prices and I/B/E/S for earning forecasts which are collected for the constituents of the S&P500 Composite index from 1:1990 to 12:2002 on quarterly basis. As specified before, our model assumes that observations are independent once we condition them to both sectors and time. We employ two mixture models for fundamentals, based on dividends per share (DPS) and earnings per share (EPS) respectively. The two models, expressed in GLM specifications, are

$$\text{EPS}: E(p_{iItT}) = \eta^{\mathrm{e}}_{iItT} = \alpha^{\mathrm{e}}_{IT} + \beta^{\mathrm{e}}_{IT} f\mathrm{eps}_{iItT} \tag{9}$$

$$\text{DPS}: E(p_{iItT}) = \eta^{\mathrm{d}}_{iItT} = \alpha^{\mathrm{d}}_{IT} + \beta^{\mathrm{d}}_{IT} f\mathrm{dps}_{iItT} \tag{10}$$

where $f$eps and $f$dps are the fundamentals evaluated according to (3) using as starting point earnings and dividends per share, respectively. Under the assumption of

Gaussian distribution functions for observed prices and natural link functions, η^{e}_{iItT} and η^{d}_{iItT} represent the linear predictors for the two models. The models have the standard statistical property of the mixed models evaluated by finite mixtures (for details see MacLachlan and Peel 2000; Aitkin et al. 2005; Alfó and Trovato 2004). Parameter estimates are computed by implementing the EM algorithm described in Appendix, using a code written in Matlab R11. To overcome the local optima problem, a common feature of all iterative algorithms, we started several times our program by using different initializations and chose the solution which yields the maximum value of the likelihood. The starting points, i.e., the initial parameter values, have been selected randomly or by grouping the results of the OLS regressions ran for each combination of sector and year. This procedure has been repeated for different numbers of mixture components ranging from 2 to 25. The correct number of components has been finally chosen by using the BIC criterion (Kerbin 2000).

It is trivial to observe that in our model the intercept captures components unrelated to the fundamentals. By just looking at descriptive statistics of the dependent and independent variables we find that the volatility of the fundamental is higher than that of the observed price (Table 1). The relatively higher volatility of the fundamental is confirmed when we compare sector averages of individual stock standard deviations in each industry (Figure 1). The problem of this first descriptive finding is that we do not decompose price and fundamental volatilities into their cross sectional and time series components, and therefore do not extract the (time series) relevant from the (cross-sectional) largely irrelevant one which depends on distances between stock prices. To do so, we compute the time series standard deviations of the fundamental and of the observed price for each stock. The ratio of the standard deviation of the fundamental to the standard deviation of the price, both averaged across stocks, has mean and median above one (Figure 2), confirming that fundamentals are more volatile than prices for more than half of stocks in our sample portfolio. In Table 2 we extend our descriptive evidence on this indicator to its industry breakdown (column 3), reported together with the average industry fundamental/price ratio (column 1). Once again, we observe that the time series standard deviation of the fundamental is above that of prices in almost all industries. When estimating our econometric model we find that the estimated expected values of the β coefficients are 0.571 and 0.588 for the earning based and for the dividend based fundamental, respectively (Table 3). The significance of these parameters is confirmed by the confidence interval (at 95%) and likelihood ratio tests (LRTs). In both models $E(\beta)$ is between 0 and 1, since the LRT rejects, at 99.9%, for both the two null hypotheses ($H_0 : E(\beta) = 1$ and $H_0 : E(\beta) = 0$).[7]

These results suggest that investors are highly sensitive to fundamentals based on analysts forecasts, even though they slightly downweight them. This attitude may be considered not irrational if we take into account, by looking at Figure 2, that financial analysts systematically overestimate earnings throughout all the considered period. Another interesting finding is that the intercept, i.e., the coefficient measuring the market price component which is unrelated to the fundamental, is significant and positive. We may therefore argue that prices incorporate a component

[7] The p-values are obtained by comparing the maximum likelihoods of the full and constrained models. The latter is obtained by estimating the model under the constraint $E(\beta) = \sum_k \beta_k \pi_k = c$, where c can be 0 or 1.

Table 1 Stock prices and fundamentals

	Descriptive Statistics			
	Mean	SD	Skewness	Kurtosis
p	27.563	18.163	1.387	8.017
$f$eps	29.932	24.541	2.328	12.570
$f$dps	29.156	24.023	2.364	12.959
Obs	10826			

$f$eps Fundamental value of the stock based on discounted earnings, $f$dps fundamental value of the stock based on discounted dividends

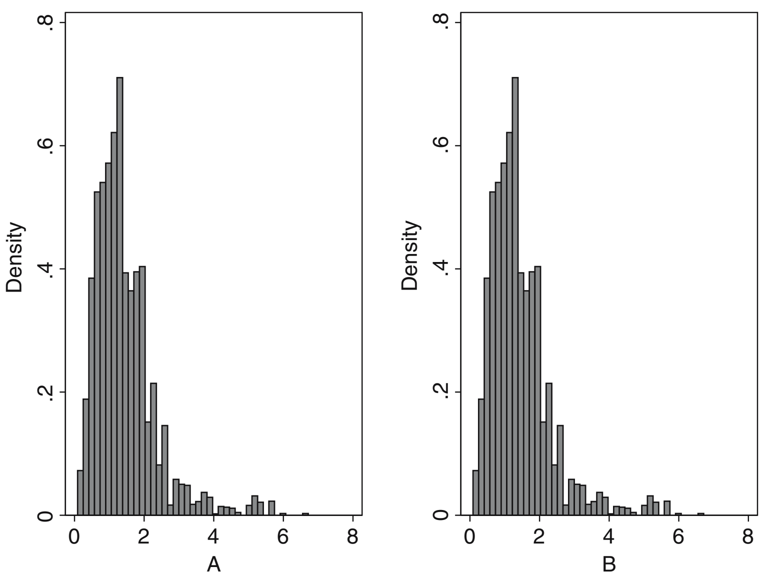

Fig. 1 Densities of the ratio of the (time series) standard deviation of the fundamental to the standard deviation of price averaged across stocks. **a** Kernel density estimate of the ratio of the sd of $f$eps (earning based fundamental) on the sd of p. **b** Kernel density estimate of the ratio of the sd of $f$dps (dividend based fundamental) on the sd of p

of time varying euphoria unrelated to forecasts of fundamentals. In Table 4 we find that estimated mean locations for α and β in both specifications are similar. Looking at the locations of the mixture components, we do not observe significant differences in the distributions of αs and βs, (Table 4). When we examine the industry breakdown we observe that confidence on analysts' forecasts is higher in sectors with well known companies, such as diversified industries, or in those in which stocks are more heavily traded, as in high-tech or financial industries (see Table 5). If we examine the variation in time of the $\hat{\alpha}_{IT}$ and $\hat{\beta}_{IT}$ coefficients (Figures 3 and 4 for fundamentals evaluated by earnings and dividends, respectively) we find that the weight of the intercept (stock value unrelated to fundamentals)

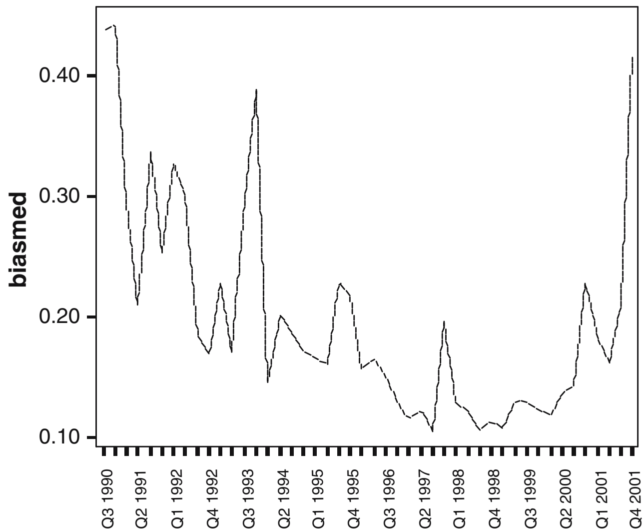

Fig. 2 Dynamics of the average earning forecast bias, where: $\text{bias}_{jt} = \frac{E_t[\text{eps}_{jt+1}]-\text{eps}_{jt}}{p_{jt}}$

gradually but slowly grows, dramatically accelerating in proximity of the peak of the stock bubble, while the sensitivity of the earning and dividend based fundamentals starts to fall before the bubble. Since our fundamental is calculated on the basis of the historical risk premium, we may consider it as a proxy of the implied risk premium and therefore argue that, before we reach the proximity of the peak of the stock bubble, we observe a negative correlation between reliance on analysts' forecasts and implied risk premium. In the proximity of the peak the correlation becomes positive since the reliance on fundamentals falls, while the sensitivity to nonfundamental components keeps on rising. After the peak, the sensitivity to nonfundamental components falls dramatically, while the sensitivity to fundamentals keeps on falling.

Remembering that our model allows to capture, through time and industry specific coefficients, unobserved (time and industry specific) factors affecting the relationship between our variables and prices, a plausible interpretation of our results is that changes in our coefficients proxy time (and industry specific) participation rates of chartists and fundamentalists to the stock market. This would explain the dynamics of the nonfundamental component around the peak of the stock bubble, with fundamentalists anticipating the fall and leaving the market before chartists. An alternative plausible interpretation of persistence and autocorrelation of short term intercept deviations from their historical average values may be provided by the point developed by Chow and Liu (1999) who argue that long stock market (dividend) swings positively affect investors' evaluation of future stock market perspectives. In their model investors have rational expectations and try "ride the wave" by updating their model and learning about the length of the cyclical swing based on its past duration. These ingredients may produce the coefficient dynamics we estimated in our sample period.

Table 2 Industry breakdown of the fundamental/price ratio and of the ratio of the (time series) SD of fundamental to the SD of price averaged across stocks

	Mean ($f$eps$/p$)	SD($f$eps$/p$)	sd($f$eps)/sd(p)
Mining	1.29	0.39	1.35
Oil and gas	1.43	1.02	2.04
Chemicals	1.15	1.19	1.34
Construction and building materials	0.92	0.44	1.08
Forestry and paper	1.07	0.45	1.17
Steel and other metals	1.4	0.55	2.13
Aerospace and defence	1.39	0.69	1.51
Diversified industrials	1.17	0.55	1.37
Electronic and electrical	1.54	1.48	1.46
Engineering and machinery	1.26	0.54	1.25
Automobiles and parts	1.34	0.83	1.51
Household goods and textiles	1.16	0.69	1.77
Beverages	1.04	0.44	1.23
Food producers and processors	1.14	0.52	1.88
Health	1.07	0.45	1.65
Personal care and household products	1.1	0.49	1.29
Pharmaceutical and biotechnology	1.1	0.57	1.39
Tobacco	1.4	0.39	2.39
Retailers, general	1.07	0.62	1.28
Leisure and hotels	1.06	0.4	1.59
Media and entertainment	0.94	0.47	0.96
Support services	0.97	0.48	1.18
Transport	1.43	1.3	1.41
Food and drug retailers	1.17	0.55	1.25
Telecom services	1.11	0.61	1.14
Electricity	1.24	0.58	2.01
Utilities, other	1.23	0.46	1.31
Banks	1.17	0.5	1.59
Insurance	1.25	0.46	1.61
Life assurance	1.3	0.67	1.85
Real estate	1.05	0.45	1.54
Speciality and other finance	0.98	0.52	1.44
Information technology hardware	0.95	0.44	0.95
Software computer services	1.16	1.16	1.22
Total	1.15	0.71	1.45

$mean(f\text{eps}/p)$: Average of $f$eps on observed price, $SD(f\text{eps}/p)$ standard deviation of $f$eps on observed price, $sdf\text{eps}/s\text{dp}$ standard error of $f$eps on standard error of observed price

5 Conclusions

Hope in the future is the fundamental virtue on which prosperity of real and financial markets is based. When we look at stock prices we find that hope in the future concretely and positively affects prices by reducing current implied risk premia. Production of hope in the future may be viewed in the short run as a positive sum game as it creates advantages for both analysts (in terms of increased investors participation) and investors (in terms of increasing capital gains). The risk of the game is that hope is a psychological variable which is highly volatile. The higher the current level of hope, the higher the costs of its sharp fall on financial values and the higher the risk that negative shocks induce investors to deem their hopes as unrealistic, given the current levels of prices.

Table 3 Average intercept and beta coefficients of the price–fundamental equation

	Estimated Parameters									
	$\hat{E}(\alpha)$	95% CI		$\hat{E}(\beta)$	95% CI		$\hat{V}(\alpha)$	$\hat{V}(\beta)$	$\hat{E}(\sigma^2)$	n_k
EPS	11.698	11.450	11.950	0.571	0.564	0.576	97.421	0.058	116.690	15
DPS	11.647	11.400	11.900	0.588	0.582	0.594	95.718	0.062	117.290	14
	$H_0 : E(\beta^{\mathrm{e}}) = 1$	$p -$ value $= 0.000$								
	$H_0 : E(\beta^{\mathrm{d}}) = 1$	$p -$ value $= 0.000$								

The two estimated models are: EPS: $E(p_{iI_tT}) = \eta^{\mathrm{e}}_{iI_tT} = \alpha^{\mathrm{e}}_{IT} + \beta^{\mathrm{e}}_{IT} feps_{iI_tT}$, DPS: $E(p_{iI_tT}) = \eta^{\mathrm{d}}_{iI_tT} = \alpha^{\mathrm{d}}_{IT} + \beta^{\mathrm{d}}_{IT} f\mathrm{dps}_{iI_tT}$. In the EPS the fundamental value of the stock is based on discounted earnings, in the DPS model the fundamental value of the stock is based on discounted dividends; $E(\alpha)$ and $V(\alpha)$ are mean and variance of the random intercept; $E(\beta)$ and $V(\beta)$ are mean and variance of the random regression coefficient; n_k identifies the number of mixture components which have been selected by using the BIC criteria

Table 4 Locations and prior probabilities of mixtures' components

	EPS				DPS			
k	α_k	β_k	π_k	σ^2_k	α_k	β_k	π_k	σ^2_k
1	15.139	0.124	0.025	60.5	50.358	0.122	0.016	1379.0
2	50.008	0.130	0.016	1382.8	15.147	0.123	0.024	60.6
3	29.056	0.239	0.059	207.7	25.177	0.301	0.091	179.7
4	16.068	0.305	0.066	149.2	16.608	0.303	0.067	150.6
5	20.017	0.383	0.056	120.1	28.875	0.385	0.094	324.6
6	28.382	0.388	0.086	328.5	5.766	0.444	0.066	12.1
7	5.553	0.444	0.067	11.7	7.792	0.458	0.083	72.3
8	7.659	0.451	0.079	70.9	9.115	0.585	0.085	45.1
9	9.575	0.559	0.074	44.3	4.679	0.614	0.138	28.1
10	4.762	0.600	0.141	29.0	9.425	0.782	0.111	106.0
11	8.834	0.779	0.102	108.1	4.103	0.865	0.068	46.9
12	4.2797	0.828	0.072	48.0	2.086	0.870	0.069	9.1
13	2.0843	0.840	0.071	9.4	3.526	1.028	0.052	39.0
14	3.407	1.003	0.052	39.1	7.484	1.078	0.035	140.7
15	7.711	1.038	0.032	144.5				

k Number of mixture components selected by penalized criteria, σ^2_k locations' standard errors, α_k and β_k local regression parameters, π_k prior probabilities to belonging to that local area

These considerations may help to interpret our results and justify the fact that: (i) analysts overestimates are systematic and constant in the last 20 years; (ii) the number of analyst forecasts is larger and confidence on analysts' forecasts is higher in sectors with well known companies, such as diversified industries, or in those in which stocks are more heavily traded, such as in high-tech or financial industries; (iii) the creation of hope reaches its maximum in particular periods and prepares conditions for its sharp fall. The signs of this are (iiia) a dramatic rise in the component which is unrelated to expectations on marketwide and firm specific financial variables and (iiib) a price sensitivity to fundamentals which anticipates price sensitivity to nonfundamentals around the stock market peak, suggesting that significant changes in fundamentalists/nonfundamentalists stock market participation occurred before the stock market downfall in the year 2000.

Table 5 Industry specific sensitivity to fundamentals

Sectors	INDC	EPS	DPS
		β^{e}	β^{d}
Mining	4	0.4382	0.4492
Oil and gas	7	0.2484	0.2607
Chemicals	11	0.6325	0.6667
Construction and building materials	13	0.6148	0.6331
Forestry and paper	15	0.5684	0.5724
Steel and other metals	18	0.4816	0.4955
Aerospace and defence	21	0.4884	0.5087
Diversified industrials	24	0.7148	0.7441
Electronic and electrical	25	0.3422	0.3514
Engineering and machinery	26	0.5743	0.5902
Automobiles and parts	31	0.528	0.541
Household goods and textiles	34	0.6514	0.6661
Beverages	41	0.481	0.5084
Food producers and processors	43	0.698	0.7167
Health	44	0.6224	0.63
Personal care and household products	47	0.5153	0.5377
Pharmaceutical and biotechnology	48	0.4278	0.4495
Tobacco	49	0.5284	0.5424
Retailers, general	52	0.61	0.6259
Leisure and hotels	53	0.6769	0.7036
Media and entertainment	54	0.5821	0.5833
Support services	58	0.6365	0.67
Transport	59	0.6134	0.6254
Food and drug retailers	63	0.6584	0.6753
Telecom services	67	0.6089	0.6337
Electricity	72	0.5205	0.5552
Utilities, other	77	0.6513	0.6614
Banks	81	0.6259	0.6302
Insurance	83	0.5984	0.613
Life assurance	84	0.666	0.6846
Real estate	86	0.6128	0.6315
Speciality and other finance	87	0.6612	0.6935
Information technology hardware	93	0.6801	0.6951
Software computer services	97	0.4327	0.431

The opportunity of extending our investigation to the dynamics of sensitivities to the fundamental and nonfundamental components across time is made possible by the adoption of a random effect approach in which the vector of regression parameters (intercept, regression coefficient and error variance) is considered as a vector random variable, independently and identically distributed across the different combinations of sectors and years. For this vector, we relax the standard normality assumption (see, among others, Baltagi 2001) by estimating its conjoint distribution with a non-parametric approach based on mixture modelling. The mean of this vector is estimated and tested. We also predict the realized values of this vector by computing the posterior means for each regression.

However, the model introduces some simplifications of the reality. In fact, we assume that two observations are dependent if they belong to the same combination of sector and year, but independent if they belong to different regressions,without

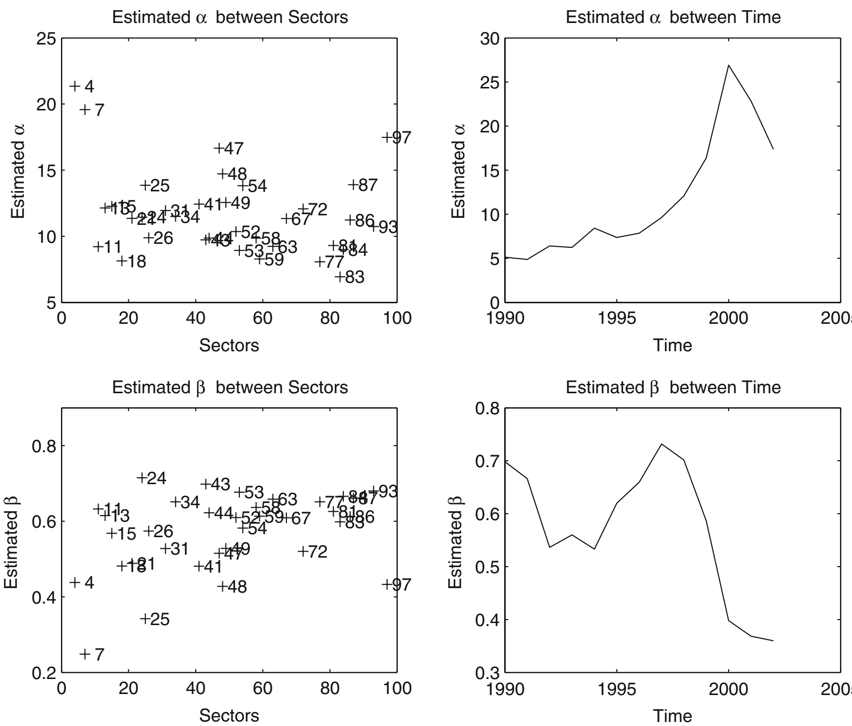

Fig. 3 Time and industry varying sensitivities to fundamental and non fundamental components (fundamental evaluated by discounting earnings)

taking care of a possible serial correlation among observations related to the same firm in different years. Nevertheless, we could not test the presence of this correlation because the panel is unbalanced and with some missing data (supposed to be "at random") even if we suspect its existence. In spite of these limits, we think that the model has been able to capture the essential information present in the data.

Appendix: Parameters estimation

The parameters of our model are estimated by adopting a non- parametric maximum likelihood (NPML) approach (Laird 1978) and relaxing the usual assumption of normality which is very frequent in panel data modeling. In particular, we do not assume any specification for the p.d.f. g but estimate it together with the other parameters. Following this approach, the mixture (7) is estimated by a finite mixture of the form

$$f(\mathbf{y}_{IT}) = \sum_{k=1}^{K} \pi_k \prod_{i=1}^{n_I} \prod_{t=1}^{n_T} f(y_{iItT} | \boldsymbol{\eta}_k). \tag{11}$$

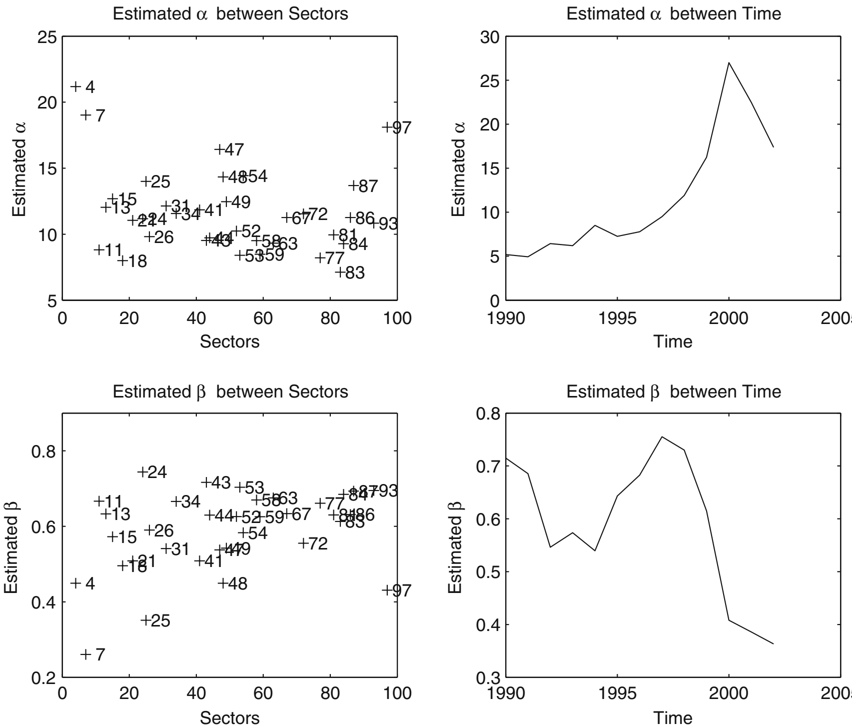

Fig. 4 Time and industry varying sensitivities to fundamental and nonfundamental components (fundamental evaluated by discounting dividends)

The likelihood of the sample is then

$$L(\boldsymbol{\vartheta}|\mathbf{y}) = f(\mathbf{y}) \tag{12}$$

$$= \prod_{I=1}^{\mathcal{I}} \prod_{T=1}^{\mathcal{T}} f(\mathbf{y}_{IT}) \tag{13}$$

$$= \prod_{I=1}^{\mathcal{I}} \prod_{T=1}^{\mathcal{T}} \left(\sum_{k=1}^{K} \pi_k \prod_{i=1}^{n_I} \prod_{t=1}^{n_T} f(y_{iItT}|\boldsymbol{\eta}_k) \right). \tag{14}$$

The maximum likelihood estimates of model parameters are computed by using an EM algorithm (Dempster et al. 1977).[8]

The algorithm is based on the maximization of the complete likelihood

$$L_c(\boldsymbol{\vartheta}|\mathbf{y}) = \prod_{I=1}^{\mathcal{I}} \prod_{T=1}^{\mathcal{T}} \prod_{k=1}^{K} \left(\pi_k \prod_{i=1}^{n_I} \prod_{t=1}^{n_T} f(y_{iItT}|\boldsymbol{\eta}_k) \right)^{z_{ITk}}, \tag{15}$$

where z_{ITk} is 1, if the observation $\mathbf{y}_{IT}$ has been sampled from the kth component of the mixture, and 0 otherwise. The z's are not directly observed and are therefore treated as missing data, i.e., they are estimated on the basis of their expectations

[8] For a detailed survey on the topic see McLachlan and Krishnan (1997).

$$\hat{z}_{ITk} = \frac{\pi_k f(\mathbf{y}_{IT}|\boldsymbol{\eta}_k)}{\sum_{k=1}^{K} \pi_k f(\mathbf{y}_{IT}|\boldsymbol{\eta}_k)}. \tag{16}$$

The algorithm simply maximizes the complete likelihood (step M) given a set of z's estimates (step M) and then recalculates by (16) the z's estimates (step E). It can be shown that, at each E or M step, the likelihood (14) increases. The algorithm starts from initial estimates of the parameters, iterates the two steps and stops when the likelihood increment between two iterations is less than a given threshold.

In our approach the M step is partitioned into three sub-steps where the complete likelihood is maximized with respect to a sub-set of parameters given the current values of the others. The three sub-steps can be described as follows.
In the first sub-step the log of the complete likelihood

$$\ell_c(\boldsymbol{\vartheta}|\mathbf{y}) = \sum_{I=1}^{\mathcal{I}} \sum_{T=1}^{\mathcal{T}} \sum_{k=1}^{K} \hat{z}_{ITk} \left(\log(\pi_k) + \sum_{i,t} \log(f(y_{iItT}|\boldsymbol{\eta}_k)) \right) \tag{17}$$

is maximized with respect to the π's. It is simple to show that, by rewriting (17) as

$$\ell_c(\boldsymbol{\vartheta}|\mathbf{y}) = \sum_{ITk} \hat{z}_{ITk} \log(\pi_k) + c, \tag{18}$$

where c is a constant term independent from the parameters of interest, the log-complete likelihood attains a maximum when

$$\pi_k = \frac{1}{\mathcal{I}\mathcal{T}} \sum_{IT} \hat{z}_{ITk}. \tag{19}$$

In the second sub-step we maximize (17) with respect to $\sigma_1^2, \sigma_2^2, \ldots, \sigma_K^2$ conditionally upon the other parameters. By rewriting (17) as

$$\ell_c(\boldsymbol{\vartheta}|\mathbf{y}) = \sum_{I,T,k,i,t} -\hat{z}_{ITk} \frac{1}{2} \left(\log\left(\sigma_k^2\right) + \frac{1}{\sigma_k^2} (y_{iItT} - \alpha_k - \beta_k x_{iItT})^2 \right) + c, \tag{20}$$

we see that the problem corresponds to K different independent maximizations, each of them having as solution

$$\sigma_k^2 = \frac{1}{\sum_{I,T,i,t} \hat{z}_{ITk}} \sum_{I,T,i,t} \hat{z}_{ITk} (y_{iItT} - \alpha_k - \beta_k x_{iItT})^2. \tag{21}$$

In the last sub-step, the log-complete likelihood (17) is maximized with respect to the regression coefficients. As in the previous sub-step, we note that this corresponds to the solution of K independent maximization problems, one for each (α, β) couple. This can be easily solved by noting that, by rewriting (17) as

$$\ell_c(\boldsymbol{\vartheta}|\mathbf{y}) = -\sum_{I,T,i,t} \hat{z}_{ITk} \frac{1}{2\sigma_k^2} (y_{iItT} - \alpha_k - \beta_k x_{iItT})^2 + c \tag{22}$$

it follows that

$$\beta_k = \frac{\sum_{I,T,i,t} \hat{z}_{ITk} y_{iItT}(x_{iItT} - \bar{x}_k)}{\sum_{I,T,i,t} \hat{z}_{ITk}(x_{iItT} - \bar{x}_k)^2}, \tag{23}$$

$$\alpha_k = \bar{y}_k - \beta_k \bar{x}_k, \tag{24}$$

where

$$\bar{x}_k = \frac{1}{\sum_{I,T,i,t} \hat{z}_{ITk}} \sum_{I,T,i,t} \hat{z}_{ITk} x_{iItT}, \tag{25}$$

$$\bar{y}_k = \frac{1}{\sum_{I,T,i,t} \hat{z}_{ITk}} \sum_{I,T,i,t} \hat{z}_{ITk} y_{iItT}. \tag{26}$$

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