Returns Premia on Company Fundamentals *

Kateryna Shapovalova † Alexander Subbotin ‡
Thierry Chauveau §

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Abstract

This paper studies the excess returns on stocks, associated to various company fundamentals on a panel of US stocks from 1979 to 2008. The returns premia are measured using a random coefficient panel data model on the individual stock level. We show that the HML and SMB factors in the Fama and French model probably have no particular economic meaning as sources of systematic risk other than being proxies for the impact of the book-to-price and size characteristics. While the book-to-price ratio, market capitalization, past year sales growth and the share of reinvested profits generate significant premia, earnings history and forecasts are of little predictive power. We statistically confirm the time-varying nature of the style premia but find no strong evidence for the value and growth momentum in a multivariate setting when the systematic risk is controlled for. Some of the premia are positively correlated with the market return and between each other, while others seem to be unrelated. Variations in premia associated with companies' high internal growth and growth of sales are positively correlated between each other, with the market return and with the value premium. Variations of the size premium are probably driven by different factors.

Keywords: Stock returns, company fundamentals, asset pricing, three-factor model, style momentum

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†University of Paris-1 (CES/CNRS) and Renaissance Finance. Corresponding author:
9, chemin Pierre de Ronsard, 92400 Courbevoie, tel: +33 1 80 88 70 80, fax: +33 1 80 88 70 81,
kateryna.shapovalova@renaissance-finance.eu

‡University of Paris-1 (CES/CNRS), Renaissance Finance and Natixis,
alexander.subbotin@natixis.com

§University of Paris-1 (CES/CNRS), thierry.chaveau@univ-paris1.fr

1 Introduction

For describing the link between stock returns and company fundamentals, the Fama and French (1993) three-factor model is the first reference. Among various extensions of the capital asset pricing model (CAPM) by Sharpe (1964), it has so far been the most successful as of its empirical performance and influence on the financial industry. It represents the equity premium as a sum of three components: the traditional CAPM market beta, and the betas to two specially designed factors, HML (High Minus Low) and SMB (Small Minus Big). The HML factor is the difference in returns on portfolios including high book-to-price (BtP) stocks, also called "value stocks", and low BtP stocks, also called "growth" stocks. SMB is the difference in returns on portfolios, including low and high market capitalization (MCAP) stocks. In practitioners' world, value and size are often referred to as investment style factors.

The lack of theoretical underpinnings for the Fama and French artificial risk factors stimulated intensive research over the last two decades. The effort is mainly concentrated on finding fundamental economic factors, to which HML and SMB are proxies. This would fit the three-factor model within framework of the intertemporal CAPM by Merton (1973), which explains equity returns by unpredictable shifts in the investment opportunity set. Both dynamic and cross-sectional properties of the style factors are explored in literature. Some time series evidence in favor of their ICAPM interpretation is provided in Guo et al. (2009). In dynamic cross-section analysis, Hahn and Lee (2006) and Petkova (2006) demonstrate that the Fama and French factors can be replaced by a series of ICAPM predictors (notably, the term spread and the credit spread). However, Lioui and Poncet (2010) show that these results are, to a big extent, due to statistical artifacts. There is no widely accepted consensus on the origin of the style premia, meaning that the value and size puzzles still stand.

So, why yet another paper on this topic? We believe that the "mechanics" of the three factor model itself is not explored enough, both from the statistical and economic viewpoints. SMB and HML are artificial constructions, based on the fundamental characteristics of companies. An early paper by Fama and French (1996) claims that pricing anomalies related to the link between average future returns and stocks characteristics (earnings-to-price, cash flow-to-price, past sales growth, long term and short-term past earnings and others) are all eliminated by including HML and SMB factors in a CAPM. The stocks in a sample are first classified into a set of portfolios according to a characteristic in question and then their returns are regressed on the three factors. This time-series regression smooths out all variations from average returns that are observed unconditionally (constant terms in all ranked portfolios are approximately equal). So the additional return, computed over many years, is small for the stocks ranking high/low according to this characteristic.

We think that such evidence is insufficient because the statistical procedure, used to obtain it, is too restrictive. One reason is that the three-factor model tests are favorably biased due to the factor structure, induced by the construction of the set of the characteristics-based portfolios, as shown in a recent paper by Lewellen et al. (2010). Another reason is that the impact of fundamentals, significant in cross-section, can vary in time, so that the overall effect, recorded over many years, could be insignificant if outperformance and underperformance periods offset each other.

The goal of this paper is to explore the impact of company fundamentals on stock returns. We study whether company fundamentals generate returns premia, once the conventional systematic risk factors are accounted for, and if so, if these premia are constant in time and what are the corresponding dynamic patterns. Here we do not attempt to explain the nature of excess returns associated to the fundamentals.

Doubts on the relevance of the HML and SMB factors were raised, among others, by Daniel and Titman (1997), who argued that the loadings on the style factors are no more than proxies for the loadings on the company characteristics themselves, and the latter have possibly nothing to do with the systematic risk. Namely, it is the characteristic (high book-to-market) rather than the covariance (high sensitivity to HML) that is associated with high expected returns. Their arguments were subject to further empirical investigations in (Daniel et al., 2001, Davis et al., 2000) with contradictory results. Daniel and Titman's critics is based on the statistical evidence from the excess returns on the portfolios, obtained by the multi-way sorts on various fundamental characteristics. This approach imposes important restrictions on the number of accounting variables, whose impact on returns can be studied simultaneously, and it suffers from the two drawbacks, mentioned above in the discussion of the Fama and French (1996) tests.

In this paper we adopt an alternative approach, based on the panel data regressions on the individual stocks level. Previous literature argued, though without any analytical or empirical proof, that using portfolios instead of stock reduces the specific risk and yields more precise estimates of factor loadings and risk premia. But the loss of precision due to possible errors in the estimates of individual betas, which is the main Fama and French's argument for using portfolios rather than stocks, can be compensated by a large number of stocks and periods in our sample and by the absence of test biases due to the factor structure in portfolio construction. In a recent paper Ang et al. (2009) show analytically and confirm empirically that the more efficient estimates of betas from creating portfolios do not lead to lower asymptotic variances of factor risk premia estimates. On the contrary, shrinking the dispersion of betas leads to higher asymptotic variance of these estimates.

Besides, looking at individual stocks is natural when dealing with the accounting fundamentals that are only available on the company level. Despite measurement errors in individual betas, the three-factor model, if it were true, should perform reasonably well on the disaggregated level, compared to the alternative characteristics model. Finally, explaining and predicting individual stock returns is by itself an important problem, arising in financial management fare applications, such as estimating the cost of capital (see Bartholdy and Peare, 2005).

As we are working with panel data, we have to develop adequate statistical tools for estimating time-varying premia. Our statistical inference is based on a random coefficient panel data model with Kalman filtering, close to the ones proposed in Cooley and Prescott (1976) and Harvey (1978). To our knowledge, this is the first attempt to apply such models to stock market data and to large samples of rotating data. One of the advantages of our approach is the possibility to asses the premia on fundamentals in a multivariate setting, i.e. when all other factors are kept constant. We develop our definitions of returns premia on fundamentals ("style premia") suitable for the stock level setting and asses these premia.

We find that on the individual stock level the loadings on the SMB and HML factor are largely due to the cross-sectional correlations between betas and characteristics and the three-factor model is not capable of consistently explaining the pricing anomalies, associated with various accounting fundamentals. Several accounting fundamentals do generate significant return premia, regardless of whether the sensitivities to the conventional systematic risk factors and price momentum are controlled for or not. Testing a large set of accounting fundamentals, we find that the book-to-price ratio, company size, past year sales growth and the amount of reinvested return on equity ("internal growth") have the most pronounced impact on returns. Surprisingly, indicators related to earnings and their growth and analysts' forecasts have relatively small impact. Besides, indicators computed over the past year contain more information than the long-term averages.

We explore the properties of the return premia, associated to the retained factors, and show that they are variable in time, though almost no evidence for statistically significant style momentum is found. Some of the premia are positively correlated with the market return and between each other, while others seem to be unrelated. Companies with high internal growth perform well in good times and at the same periods as the stocks with high sales growth and the value stocks do. The variations of the size premium are probably due to different factors, so that they are unrelated to the premia on the other fundamentals.

The rest of the paper is organized as follows. Section 2 discusses the data used in our study. Section 3 describes our model and sets up the testable hypotheses. In Section 4 we compare Fama and French (1993) and Daniel and Titman (1997) models for the expected excess returns. In Section 5 we estimate the time-varying style premia, associated with different fundamentals, perform various tests related to their dynamics and discuss the results. Finally, Section 6 summarizes the main findings.

2 Data

Our data includes all stocks, quoted on the New York Stock Exchange from 1979 to 2008 and available in the Datastream database. Overall, the sample includes 9,363 stocks, for which prices and market capitalizations are collected on the monthly basis. Monthly returns are used for pre-estimation of various sensitivities to factors (betas), while asset pricing models are tested and premia are estimated on quarterly data. We also performed some test and estimations of asset pricing models on the monthly data, but as explained further the dimension of the problem becomes too high and the estimation methods had to be simplified due to the computation burden. Besides, many explicative variables (accounting fundamentals) are available only at quarterly basis, so monthly estimates do not make much sense.

The sample includes the securities that were delisted, thus the survival bias is avoided. The dependent variable is the total return, i.e. the sum of the capital gain and the dividend yield during a given time period. If stock price does not change for more than three weeks, the returns for that period, extended by one week before and after, are excluded, because the trade for that stock is considered inactive and the stock itself illiquid.

The total return (including dividends) on the S&P500 Index is used as a proxy for the market portfolio. Monthly returns on the 3-months US Treasury bills are used as risk-free rates of returns. SMB and HML factors are constructed according to the Fama and French procedure of independent sorts from the top and the bottom of the distribution of BtP and MCAP. Unlike many other authors, we do not use the data for SMB and HML portfolios available on Kenneth French's website but compute them ourselves in order to obtain factors representative of our sample.

Accounting characteristics of the issuers come from the same data provider and are collected at the highest frequency available for each case (monthly, quarterly or yearly). We do not require that the same companies have data for all characteristics. The raw indicators are used to compute the fundamental factors that potentially have explanatory power for future returns. Our choice of factors is motivated both by the evidence in the academic literature, by common market practice and by common sense that hints us that some of them can be helpful to predict future cash flows and/or to proxy the sensitivity to risk factors.

The set of explicative variables includes a group of ratios of price to fundamental accounting characteristics, measuring companies' performance: book-to-price value (BtP), earnings-to-price (EtP), sales-to-price (StP) and cash flow-to-price (CFtP). Accompanied by the dividend yield (DY), they form a set of "value" factors, commonly used by both researchers and market practitioners. The size factor is as usually captured by the market capitalization (MCAP).

We also use direct measures of growth, computed over 1, 3 and 5 years: growth of sales-per-share (gSpS, gSpS_3, gSpS_5) and growth of earnings-per-share (gEpS, gEpS_3, gEpS_5). Motivated by the market practice, we add a set of forecasts, representing the consensus of financial analysts over future companies' performance: forecast of growth of earnings-per-share over one year (fgEpS), forecast of long term growth of earnings-per-share (fgEpS_5) and projected earnings-to-price (fEtP). All forecasts come from IBES. We also use the indicator of internal growth (IG, IG_5), which is the reinvested part of the return-on-equity (ROE). This indicator is used by many index providers and characterizes the level of companies' investment activity. It is computed as (1-PR)×ROE, where PR is the dividend payout ratio. For IG_5 a five-years average is taken.

From the practical viewpoint, it is important to analyze the variables that are used in financial industry as benchmarks of style investment. Table 1 reports the lists of such variables, used by global style index providers. It is noteworthy that index providers define separate dimensions for value and growth (except DJ STOXX), i.e. different sets of indicators are used to construct value and growth portfolios. On the contrary Fama and French (1993, 1996) and Lakonishok et al. (1994) refer to the growth stocks as those, which are not value (i.e. high BtP for value and low BtP for growth). The rationale for this approach is that the high market value relative to fundamentals implies high future growth rate, projected by rational investors.

Table 1: Accounting Fundamentals used as Style Factors

Indicator	Notation	Used by Index Providers
Price to Book ratio	PtB	DJ, FTSE, MSCI, S&P
Projected Price to Earnings	fPtE	DJ, MSCI
Price to Earnings	PtE	DJ
Price to Sales	PtS	FTSE, S&P
Price to Cash Flow	PtCF	FTSE, S&P
Dividend Yield	DY	DJ, FTSE, MSCI, S&P
Projected Growth of Earnings per Share	fgEpS	DJ, FTSE, MSCI
Growth of Earnings per Share	gEpS	DJ, FTSE, MSCI, S&P
Growth of Sales per Share	gSpS	FTSE, MSCI, S&P
Projected Growth of Sales per Share	fgSpS	FTSE
Internal Growth	IG	FTSE, MSCI
Market Capitalization	MCAP	DJ, FTSE, MSCI, S&P

Growth variables can be computed over different time horizons, as explained in the text.

Finally, we use past returns over one month, one quarter and one year to represent the so-called price momentum (PM_1m, PM_1q, PM_1y). There is much empirical evidence in favor of the predictive power of momentum variables. Jegadeesh (1990) evidence for the mean-reversion in monthly returns returns and thus profitability of short-term contrarian strategies. Jegadeesh and Titman (1993) find outperformance for portfolios of stocks with high historical 3-month and yearly returns. Carhart (1997) add one-year momentum as a risk factor in the Fama and French framework to construct a four-factor model. Though momentum has nothing to do with the accounting fundamentals, we include it in the analysis along with the value and growth factors mainly in order to see, whether its effect is persistent, once these factors are controlled for.

For robustness purposes all factors are pre-processed using a probability integral transform, which enables mapping characteristics to a range from zero to one. So we do not consider absolute values of indicators, but only the relative ranking of stocks. This secures that the impact of outliers on the results is minimal. We carried out the same estimation procedure with the unprocessed values of company characteristics and found roughly similar results.

For the factors that use accounting data in their definitions (e.g. book-to-price ratio, earnings-per-share) we apply a 3-month lag when including them into regressions in order to ensure that the corresponding indicators are publicly available at the date when they are supposed to be used for returns prediction. For the factors, depending on market data only (e.g. market betas, price momentum) no lags are needed.

The actual number of stocks available depends on the availability of the data for particular periods and for various indicators. It ranges from 408 for the long term historical growth of indicators in the early 80'es to about 1,200 for most variables in the recent years. For panel data modeling we need to construct rotating samples with a fixed number of observations per unit of time. In such samples, stock are replaced randomly in a fixed proportion. More details on these techniques are given in Section 3.

3 A Model for the Panel of Individual Stock Returns

Let us first introduce some formalism, necessary to represent different asset pricing models in the setting of the individual stocks panel data. Denote $r_{i,t}$ the total return (capital gain and dividend yield) on stock i, $i \in \{1, \ldots, N\}$, over period t, $t \in \{1, \ldots, T\}$ and r_t^f the risk-free rate of return over period t. Our model assumes that the excess returns are explained by a set of different factors that can be of different nature: companies' fundamentals directly or the sensitivities of each stock to systematic risk factors, denoted as "betas". In the latter case we describe the setting of the classic asset pricing models, such as CAPM or the three-factor model. This can be written:

$$r_{i,t} - r_t^f = c_t + \sum_{j=1}^{K} \gamma_t^j \, \theta_{i,t}^j + \nu_{i,t} \qquad (1)$$

with $\theta_{i,t}^j$ the value of factor j, $j \in \{1, \ldots, K\}$, for company i at date t, γ_t^j the return premia associated in period t with a unitary increase in the value of the factor. In a general setting, the term $\nu_{i,t}$ can be represented by the equation:

$$\nu_{i,t} = \bar{\nu} + \nu_t + \nu_i + \widetilde{\nu}_{i,t}, \tag{2}$$

whose terms are a constant, a time effect, an individual effect and an error term. We further assume the absence of individual effects, which is consistent with no arbitrage. In other words, no stock is supposed to systematically generate excess returns, unexplained by the model factors. Starting with a model including individual effects and then testing their absence might seem more appropriate, but this is extremely complex in our context of time-varying premia and rotating sample. The absence of individual effects is crucial for being able to carry out the estimation procedures. We also suppose that $\widetilde{\nu}_{i,t}$ is a Gaussian zero-mean noise, *iid* in time and space.

The Fama and French (1993) three-factor model is a particular case of (1) and can be represented by:

$$r_{i,t} - r_t^f = \gamma_t^M \ \beta_{i,t}^M + \gamma_t^{\mathrm{HML}} \ \beta_{i,t}^{\mathrm{HML}} + \gamma_t^{\mathrm{SMB}} \ \beta_{i,t}^{\mathrm{SMB}} + \nu_{i,t} \tag{3}$$

with γ_t^M, γ_t^{HML} and γ_t^{SMB} the time-varying premia on the HML and SMB factors. They measure how much the expected return of a stock varies, when its loading $\beta_{i,t}^{\mathrm{HML}}$ or $\beta_{i,t}^{\mathrm{SMB}}$, measuring the sensitivity of stock i returns to each of the factors, increases by one.

The alternative stock characteristics model in Daniel and Titman (1997) suggests that:

$$r_{i,t} - r_t^f = \gamma_t^M \ \beta_{i,t}^M + \gamma_t^{\mathrm{BtP}} \ \mathrm{BtP}_{i,t-l} + \gamma_t^{\mathrm{MCAP}} \ \mathrm{MCAP}_{i,t-l} + \upsilon_{i,t} \tag{4}$$

with γ_t^{BtP} and γ_t^{MCAP} measuring the return premia, generated by companies' characteristics $\mathrm{BtP}_{i,t-l}$ and $\mathrm{MCAP}_{i,t-l}$ at the past period, taken with lag l equal to 3 months.

In (3) the loadings $\beta_{i,t}^j$ to the three factors have to be measured from N time series regressions for each stock. The classical Fama and MacBeth (1973) procedure suggests estimating them from 4-years long rolling windows. To this end we use a three-factor time series model for each stock i, defined over a historic period $[t-L; t]$, $L = 4$ years. It is given by the following equation, verified at each date $t-l$, $l \in \{1, \ldots, L\}$:

$$r_{i,t-l} - r_{t-l}^f = \gamma_{t-l}^M \, \beta_i^M + \gamma_{t-l}^{\mathrm{BtP}} \, \beta_i^{\mathrm{BtP}} + \gamma_{t-l}^{\mathrm{MCAP}} \, \beta_i^{\mathrm{MCAP}} + \omega_{i,t-l} \tag{5}$$

with $\omega_{i,t-l}$ a Gaussian white noise and all other notations unchanged. Then estimates $\hat{\beta}_{i,t}^j$ can be used in T cross-sectional regressions to estimate γ_t^j [1].

[1] In principle, time-varying betas can be estimated in many alternative ways: by Flexible Least Squares (FLS) method of Tesfatsion and Veitch (1990) or by Kalman filtering, supposing that the coefficient is a random walk. We implemented these alternative methods and our findings were generally

The estimation of the model (1) may depend on the dynamic structure of γ_t^j. We describe it by an autoregressive random coefficient model of the form:

$$\gamma_t^j = c^j + \phi^j \, \gamma_{t-1}^j + \varepsilon_t^j \tag{6}$$

with c^j and ϕ^j coefficients, $|\phi^j| \leq 1$, and ε_t^j a random innovation term. If all ϕ^j are strictly smaller than one, the model describes a stationary process that corresponds to the "return to normality", first used in Harvey (1978). The case $\phi^j = 1$ correspond to the random walk model of Cooley and Prescott (1976). The case $\phi^j = 0$ corresponds to the case when the premium is a white noise.

Together equations (1) and (6) describe a random coefficient panel data model. We estimate it by the maximum likelihood method, inspired by Hsiao (2003, p. 158-161). The maximum likelihood function is constructed for the prediction errors from the Kalman filter, designed for (6). The stocks for which data is available are not the same at different dates, so the estimation is done for a rotating sample. Due to the absence of individual effects, we can substitute stocks without any consequences. The number of stocks with available data increases dramatically in 1999 (from about 500 to about 1000, the exact number depending on model specification), so we choose to define two subsamples: before Q1-99 and after Q1-99 with a fixed number of stocks in each of them. As the maximum likelihood function is additive in time, we simply decompose it into two terms, corresponding to each subsample. The outcome of the Kalman filter for the first subsample are used as initial values for the second subsample to ensure consistency. The estimation procedure is described in details in Appendix A.

As general goodness-of-fit measures we use the log-likelihood tests, computed for the naive null model, in which all premia to factors are equal to zero, and for a model in which there are no explicative factors except the time-specific constant. We systematically report the p-values (denoted p_1 and p_2), based on the χ^2-statistics with the number degrees of freedom, corresponding to the difference in the dimensionality of the full and restricted models, which is $3(K+1)-1$ and $3(K+1)-3$ for the two tests respectively. Besides, for illustration purpose, we report the ratio of the sum of the squared errors to the total sum of squares, resulting from the preliminary OLS estimates of premia, obtained by running cross-sectional regressions for each date (sum of squares are aggregated over all time periods both in the numerator and the denominator). We call the resulting indicator R^2, because it corresponds to a weighted average coefficient of determination, with the weights being the portion of each period in the total sum of squares. The reader must note that in the context of models on individual stock level with returns as dependent variable only a small portion of variance can be explained by

similar to those we obtained with the rolling windows procedure. These results are not reported here and are available from the authors on request.

the regressors, whatever they are. Explaining about 5% - 15% of the total variance of returns in cross-section is already a relative succes.

For assessing the significance of coefficients and other specific hypotheses, two approaches are possible. The first is based on likelihood ratio tests, when the likelihood function is constrained to the parameter values corresponding to the null hypothesis. The second approach is based on bootstrapping the distribution of parameters and testing whether the confidence intervals include zero. For specific tests, distributions of parameters under the null hypothesis must be simulated. We obtained very similar results with both approaches and report the results obtained from the bootstraps procedures, because they allow to obtain straightforward measures for the standard deviations of parameters.

The errors in coefficient estimates are estimated by a two-step bootstrap algorithm. First, the dynamics of risk premia is simulated from K equations (6) by bootstrapping (resampling residuals) from the distribution of estimated innovations in these equations. Then the stock returns are simulated by bootstrapping from the estimated errors in (1). We compared the results obtained with resampling from raw residuals and from studentized residuals and found no significant differences. The results reported correspond to resampling from raw residuals. As our sample sizes are always rather significant ($T \times N$ with $T > 50$ and, in most cases, $N > 100$), the problems associated to "over-optimistic" confidence intervals from bootstrap in small samples are not relevant (see Schenker, 1985). Design of specific tests, based on the bootstrapping procedures, is described in the following sections.

4 Model Specification: Characteristics *vs* Betas

Before exploring the properties of return premia, related to fundamentals, we need to solve the general specification problem, i.e. to chose the most appropriate way of modelling the impact of companies fundamentals on the returns. We can rather use the model in form of the sensitivities to factor portfolios, like in (3), or a model where returns are directly explained by company characteristics, like in (4).

The arbitrage between the two models is subtle. For the Fama and French model (3) to make sense, some relation similar to the Daniel and Titman model (4) must hold. Indeed, recall the definition of HML and SMB factors. They are constructed as return differentials for portfolios of stocks with high and low BtP and MCAP characteristics. For the factors to be meaningful, these characteristics must have some discriminative power over returns. So the real question is not whether (4) holds, but whether (3) is a relevant explanation of expected returns by loadings to systematic risk factors. In our view, the answer would be positive if loadings on HML and SMB factors explain expected returns significantly even if characteristics and loadings do not match (say, some stock having high loading on HML and low BtP should have higher expected return than a stock with low loading on HML and high BtP).

A negative answer to this question would suggest that the Fama and French factors are only proxies for stock characteristics and, whenever the latter are available, one should privilege their direct usage. Note that the practical use of (4) is somewhat simpler, allowing for the prediction of stock returns and building style arbitrage strategies, since returns at period t depend on the observable characteristics, known at $t-1$. The use of (3) is less direct, because it requires the estimation of unobservable loadings. However, this does not undermine the utility of (3) for portfolio style analysis. To explain excess returns in a manager's portfolio when the characteristics of stocks in the portfolio are unobservable, we would have to rely on the loadings to HMB and SML that can be valid proxies for characteristics.

The above-mentioned model choice criterion is not straightforward to implement because the characteristics and betas to the corresponding factors are significantly correlated in cross-section. We need to detect whether the Fama and French historical betas have predictive power on returns because they are correlated to companies fundamentals or they are significant by themselves. To design a statistical test, we construct a special subsample of stocks, whose betas and characteristics do not match. A reduced sample for testing the mechanism of the impact of the BtP ratio includes, at each period, 30% of all stocks that have most important differences in ranking according to BtP and β_i^{HML}. By analogy, another sample is constructed for the stocks, having most important differences in ranking according to MCAP and β_i^{SMB}. The model that behaves in the same way when estimated for the full and for the reduced sample is deemed to be the true model, while the other can be considered as a proxy model. In all cases the independent variables are converted to ranks by the probability integral transform.

In Table 2 we report the results of comparison of two alternative specifications: company characteristics BtP and MCAP as factors (a, the left panel of the table) and covariances with HML and SMB portfolios as factors (b, the right panel of the table). Each model is estimated with the random coefficient panel data approach in three different samples: full sample, including all time periods available (the upper block of the table), reduced sample based on BtP ranking (the middle block of the table) and reduced sample, based on MCAP ranking (the bottom block of the table).

In columns (1a,b) - (3a,b), for illustration purpose, we report the portion of time periods when the cross-section estimate of γ_t^j is significant at 0.9 confidence level, and then the portion of positive and negative premia among those that are significant. Columns (4a,b) contain the estimates of the average quarterly premia $\bar{\gamma}^j$, associated to a unitary increase in the independent variable. For example, the value 0.0182 of the premium in the characteristics model, estimated in the full sample, means that, all other thing equal, expected quarterly log-return on the stock with the highest BtP ratio is by 1.82% higher than the expected log-return on the lowest BtP ratio stock (7.28% in annualized terms). In other words, the premium for a one-centile increase in BtP ratio is about 2bp quarterly and 7bp annually. Below the average premia estimates we report their bootstrapped standard deviations (in brackets) and the p-values of the significance test.

Our results unambiguously evidence in favor of the characteristics model. In the full sample, as expected, both specifications behave in a similar way. Betas to HML and SMB as well as BtP and small MCAP characteristics generate positive premia. However, we note that the characteristics model has better explicative power in terms of the explained portion of the returns variation. The premium on the BtP characteristics is almost the same as on the beta to HML (about 1.8% quarterly). The premium on the MCAP characteristics is slightluy higher than on the beta to SMB (1.7% against 1.2% quarterly).

Table 2: Characteristics *vs* Covariances⋆

	(1a)	(2a)	(3a)	(4a)		(1b)	(2b)	(3b)	(4b)
Characteristics, Full Sample					**Covariances, Full Sample**				
M	58	60	40	0.0065	M	52	51	49	0.0042
				(0.0037)					(0.0038)
				0.029					0.114
BtP	50	65	35	0.0182	HML	48	70	30	0.0177
				(0.0073)					(0.0089)
				0.003					0.0190
MCAP	48	63	37	0.0172	SMB	43	62	38	0.0116
				(0.0095)					(0.0107)
				0.039					0.128
Const	56	62	38	0.0127	Const	65	68	32	0.0243
				(0.0075)					(0.0137)
				0.041					0.007
p_1=0.008, p_2=0.012, R^2=0.0506; T_1=68, N_1=440 (Q1-82:Q4-98) / T_2=40, N_2=959 (Q1-99:Q4-08)					p_1=0.0154, p_2=0.0282, R^2=0.0395; T_1=68, N_1=421 (Q1-82:Q4-98) / T_2=40, N_2=906 (Q1-99:Q4-08)				
Characteristics, BtP Sample					**Covariances, BtP Sample**				
M	35	71	29	0.0126	M	16	45	55	0.0027
				(0.0054)					(0.0063)
				0.004					0.291
BtP	32	71	29	0.0286	HML	20	31	69	-0.0277
				(0.0112)					(0.0151)
				0.008					0.042
MCAP	24	58	42	0.0151	SMB	27	59	41	0.0179

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	(1a)	(2a)	(3a)	(4a)		(1b)	(2b)	(3b)	(4b)
				(0.0134)					(0.0212)
				0.157					0.193
Const	30	55	45	0.0046	Const	35	81	19	0.0750
				(0.0106)					(0.0257)
				0.330					0.001
p_1=0, p_2=0.003, R^2=0.1044; T_1=68, N_1=111 (Q1-82::Q4-98) / T_2=40, N_2=252 (Q1-99:Q4-08)					p_1=0, p_2=0.004, R^2=0.1002; T_1=68, N_1=123 (Q1-82:Q4-98) / T_2=40, N_2=259 (Q1-99:Q4-08)				
Characteristics, MCAP Sample					**Covariances, MCAP Sample**				
M	34	55	45	0.0031	M	31	81	19	0.0165
				(0.0054)					(0.0062)
				0.247					0.0040
BtP	34	58	42	0.0156	HML	27	56	44	0.0157
				(0.0118)					(0.0107)
				0.065					0.1670
MCAP	42	56	44	0.0167	SMB	33	35	65	-0.0391
				(0.0144)					(0.0305)
				0.146					0.1190
Const	37	64	36	0.0214	Const	49	88	12	0.0785
				(0.0088)					(0.0241)
				0.008					0
p_1=0, p_2=0.009,R^2=0.0905; T_1=68, N=112 (Q1-82:Q4-98) / T_2=40, N=255 (Q1-99:Q4-08)					p_1=0, p_2=0.001, R^2=0.1166; T_1=68, N_1=138 (Q1-82:Q4-98) / T_2=40, N_2=286 (Q1-99:Q4-08)				

* a - model with characteristics as factors, b - model with covariances as factors; (1) periods when variable is significant, % of all periods; (2),(3) positive and negative impact, % of periods when variable is significant; (4) average premium in quarterly log-return, its standard deviation and p-value of the significance test. p_1 and p_2 are p-values of two likelihood ratio tests, described in Section 3. R^2 is the percentage of variance, explained by the model. T and N are reported separately for two subsamples before and after 1999.

On the reduced samples the models behave in the way that the characteristics and not the factor loadings predict: the sign of premia reverses to negative values for both the HML and SMB betas in the reduced samples. So, for the beta to the HML factor the premium in the full sample was estimated at about 1.8% in the full sample and at -2.7% in the reduced sample, based on the BtP. This happens because, by contruction of the sample, stocks with higher sensitivity to HML have lower BtP. For the beta to SMB the change is even more spectacular: the premium slides from 1.1% to -3.9%. For the characteristics models we record no changes in the directions of the the premia estimates across the samples, though the significance of estimates decreases in the reduced samples due to the smaller number of stocks included in it.

5 Exploring the Return Premia

In this section we study the properties of return premia on a broader set of company fundamentals, than just the BtP ratio and company size. Besides the main question of which characteristics generate significant average excess return over time, we study the dynamics of these excess returns in more detail. For each characteristics we formulate and test a series of hypotheses, described below.

H1: Positive expected premium. The characteristics generates an average return premium above zero, i.e. buying stocks with high (or low) value of characteristics generates expected return higher than on average, all other characteristics being equal. To assess this assumption, we simply test the significance of the average premium, computed over time, as we did in the previous section. The null hypothesis is that the expected premium is equal to zero: $\gamma_t^j = 0$.

H2: Positive expected premium at any date. Buying stocks with high (or low) value of characteristics generates non-negative expected excess return at any period. The null hypothesis is that $\min_t\{\gamma_t^j\} > 0$ and to asses it we need to bootstrap the distribution of $\min_t\{\gamma_t^j\}$.

H3: Negative expected premium at any date. Buying stocks with high (or low) value of characteristics generates negative expected excess return at any period. The null hypothesis is that $\max_t\{\gamma_t^j\} < 0$ and it is assessed in the same way as the previous hypothesis by bootstrapping.

H4: The premium is constant in time. Buying stocks with high (or low) value of characteristics generates expected excess return $\gamma_t^j = \bar{\gamma}^j$ at any period. Here we need to test if the differences in the estimates of the premia for different periods are due to estimation errors or there really are some patterns. We bootstrap the distribution of the time volatility of the estimated expected premium $v = \sqrt{\mathrm{Var}\{\widehat{\gamma}_t^j\}}$ under the null hypothesis. To get this distribution we replace the estimated values of the premia by their time average and simulate (1) by bootstrapping from the residuals. The null assumption is rejected when the observed standard deviation of premia is higher than it is probable in the case when the time differences are only due to statistical error.

H5: Positive (negative) autocorrelation in expected premia. The null hypothesis is that the subsequent changes in expected premia are linearly uncorrelated. We test the significance of the first order autocorrelations.

We studied a wide set of variables, listed in Table 1. We report in Table 3 the results for a model that contains market beta, four company fundamentals that were found to generate positive expected premium at 0.9 confidence level and a time effect variable (constant in cross-section). This model includes two traditional "value" (BtP) and "small" (MCAP) variables and two growth variables: the one-year historical Growth of Sales per Share (gSpS) and the Internal Growth (IG), equal to the product of the

Return one Equity (ROE) and the portion of reinvested profits, i.e. one minus the Payout Ratio (PR). Estimation results for several other combinations of factors are presented in Appendix B and more results are available from the authors on request.

Before discussing the results of the tests, described above, let us comment on the list of the retained factors. Several observations regarding this list of factors deserve special comments. First, among all the ratios of company performance indicators to market price, i.e. Book-to-Price (BtP), Earnings-to-Price (EtP), Sales-to-Price (StP), Cash Flow-to-Price (CFtP), Dividend Yield (DY), the BtP ratio seems to be the most discriminating, which is consistent with the previous literature on the Fama and French model. However, one should keep in mind that all these five factors are highly correlated in cross-section, so that including any of them as a value factor yields rather similar results. However, when trying to include BtP and EtP in the same regression, we obtain slightly negative loadings on EtP (see Table 4 in Appendix B). Among companies that have low growth prospects, as rendered by their high BtP ratio, those that have lower than average earnings yield higher expected premia. In Fama and French terms, such companies are in "double distress". Similar results are obtained for CFtP, while for StP and DY we get statistically insignificant positive premia, when the BtP ratio is controlled for.

Second, notice the absence of the Earnings-per-Share (EpS) among the retained growth indicators, regardless of whether the forecasts or the historical values are taken and whatever the time horizon. On the contrary, the growth of Sales-per-Share and portion of reinvested profits generate positive premia. The latter are less direct measures of future invested opportunities than the EpS is. One possible explanation, consistent with the behavioral finance, may be that these indicators are underlooked by analysts and investors, compared to the realized earnings. So the information they contain is integrated in prices more slowly. The logic described for the past earnings can also apply to the publicly available earnings forecasts. In Table 6 of Appendix B we report the results for a model, including the short-term and long-term consensus forecasts of the EpS growth, demonstrating the absence of any significant impact of the latter on the returns. If these forecasts are of any value, our regression with a 4-month lag may simply be not enough reactive to reflect their impact. Another explanation within the risk paradigm could be that growth prospects of companies with growing sales and high reinvested profits are also more risky. Here we do not dispose of the elements necessary to discriminate between these competing paradigms an leave the question open.

Third, we find that for the indicators of sales and earnings, last year growth works better than the long-term average. In the model reported in Table 5 of Appendix B we replaced the last-year historical measures of growth by five-year averages and recorded a decrease in the magnitude and significance of the premia. This finding is consistent with the idea that the information related to distant years is already conveyed in the market prices, while this is not necessarily true for the recent growth.

Our observations help to understand why the two indicators, retained in the three-factor model literature, are BtP and MCAP and not, for example, IG and gSPS, though in terms of the generated expected premia they are quite similar. Probably the answer lies in the specification of the model, in which factors are constructed as historical returns sensitivities to HML and SMB portfolios. Under particular conditions measuring styles directly by characteristics and by sensitivity to artificially constructed portfolio returns might give similar results. This is the case when, for instance, the returns on the low BtP stocks are highly correlated with the HML portfolio (in other words, stocks with high BtP and high betas to HML are the same stocks). This situation can arise if characteristics do not change too rapidly (because covariances in HML betas are estimated from historical data), and if the returns of the high BtP stocks had other common factors in the past, e.g. related to the same economic sector. If these conditions are verified, one can expect that the HML portfolio will be a good substitute to represent the impact of the BtP characteristic. The HML portfolio can go up and down relative to the market and mirror the periods when the characteristic has positive and negative impact.

The logic above would not work for characteristics that change rather rapidly (e.g. last year's growth of sales). If we construct portfolios, mimicking the returns of securities, classified according to such characteristics, and compute the returns differentials *à la* Fama and French, betas to this factor will either have no meaning at all, of will have a completely different meaning from that of the characteristics'. So, in the example with sales' growth, estimating beta over four or five years means picking up the stocks, which in the past had returns profiles, similar to those of companies with currently growing sales, but not companies with growing sales themselves. At best, we will pick the stocks whose sales were growing over past years, but we found that only the last year's growth matters. Henceforth, computing "betas" to such factors does not make sense. They do not fit in the Fama and French framework. This observation also suggests that the nature of the premia on "value" and "growth" factors may not be the same: in the case of BtP ratio and MCAP we can *a priori* exclude the hypothesis of positive information, not yet incorporated in prices.

We can now turn to the discussion of the results reported in Table 3. Columns (1)-(3) are included for illustrative purposes and contain the percentage of time periods when each factor is significant and among those periods, the percentage of positive and negative premia. Columns (4)-(6) contain the average, minimum and maximum premia with standard deviations and p-values of the tests H1-H3 respectively. In column (7) we report the volatility of premia in time, its standard deviation and the p-value of test H4. Finally, column (8) reports the autocorrelation of the variations in premia, its standard deviation and p-value of the significance test H5.

Table 3: Return Premia on Company Fundamentals*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M	47	49	51	0.0020	0.1821	-0.1160	0.0439	-0.2016
				(0.0040)	(0.0314)	(0.0201)	(0.0044)	(0.0981)
				0.285	0	0	0	0.039
BtP	46	72	28	0.0329	0.2703	-0.1808	0.0759	0.0826
				(0.0088)	(0.0444)	(0.0361)	(0.0062)	(0.0979)
				0	0	0	0	0.2700
MCAP	44	70	30	0.0183	0.2084	-0.1312	0.0700	0.209
				(0.0090)	(0.0376)	(0.0314)	(0.0058)	(0.0946)
				0.019	0	0	0	0.055
gSpS	23	72	28	0.0140	0.1214	-0.2265	0.0508	-0.0056
				(0.0060)	(0.0310)	(0.0555)	(0.0060)	(0.0990)
				0.008	0	0	0	0.4430
IG	32	83	17	0.0300	0.1964	-0.1637	0.0628	0.007
				(0.0076)	(0.0345)	(0.0408)	(0.0056)	(0.0960)
				0	0	0	0	0.517
Const	34	43	57	-0.0121	0.1362	-0.2253	0.0681	-0.1381
				(0.0068)	(0.0391)	(0.0479)	(0.0054)	(0.0974)
				0.046	0	0	0	0.150
p_1=0, p_2=0.009, R^2=0.0973;								
T_1=68, N_1=220 (Q1-82:Q4-98) / T_2=40, N_2=529 (Q1-99:Q4-08)								

* (1) periods when variable is significant, % of all periods; (2),(3) positive and negative impact, % of periods when variable is significant; (4) average premium in quarterly log-return, its standard deviation and the p-value of the significance test H1; (5),(6) maximum and minimum premium over time, its standard deviation and p-values of the H2 and H3 tests; (7) volatility (standard deviation) of the premium in time, its standard deviation and the p-value of the H4 test; (8) first-order autocorrelation in variations of the premium, its standard deviation an the p-value of the H5 test. p_1 and p_2 are p-values of two likelihood ratio tests, described in Section 3. R^2 is the percentage of variance, explained by the model. T and N are reported separately for two subsamples before and after 1999.

Notice that high market beta is not associated with higher expected return, contrarily to what could be expected from the CAPM perspectives. However, it is still helpful to explain the cross-section of stock returns in almost half of the periods. The BtP ratio generates the most important average premium of 3.3% quarterly, which is significant at 0.9 confidence level in almost half of the observation periods. The premium for being small is more modest at only 1.8% quarterly. Growth characteristics gSpS and IG on average yield 1.4% and 3.0% respectively.

The results of the tests H2 and H3 indicate that whatever the factor, there are periods when stocks with characteristics, corresponding to positive average premia, systematically downperform. The worst negative premia is of the same magnitude for all factors (between -18 and -23%), except for the MCAP whee the loss is limited to -13.1%. On the other side, the BtP has the highest maximum premium of 27.0% whilet the gSpS has the lowest at 12.1%. We reject the hypothesis of the constancy of the premia (H4) at 0.99 confidence level for all independent variables.

The dynamics of quarterly premia on all four factors are illustrated on Figure 1 in comparison with the market total return (capital gain and dividend yield on a wide Russel 3000 stock index) for the same time periods. Grey lines on the figure correspond to confidence intervals at 0.95 level, obtained from the first-step cross-sectional OLS regressions. We notice high variability of all premia in time and absence of evident time patterns. During the periods of particularly stressed market (1982, 1987, 1991, 1998, 2000-2002 and 2008) the confidence intervals for all premia estimates widen, but there is no common behavior neither from one crisis to another nor across different fundamentals. Thus, in the most recent crisis small companies tend to outperform, while other factors generate negative excess returns. In 2001 value and growth factors outperform spectacularly, while small stocks downperform.

Figure 2 plots the premia against market returns. Notice that for value and small premia the relation to the market return is almost inexistent, while growth indicators do better in good times, especially for the IG, the premium on which shows a significant correlation of 0.3 with the market total return. The two plots at the bottom of the figure correspond to the premium on market beta and the time effect (shock to the average return, unexplained by the market beta and other fundamentals). By construction, these variables are strongly correlated with the market (0.6 for the premium on beta).

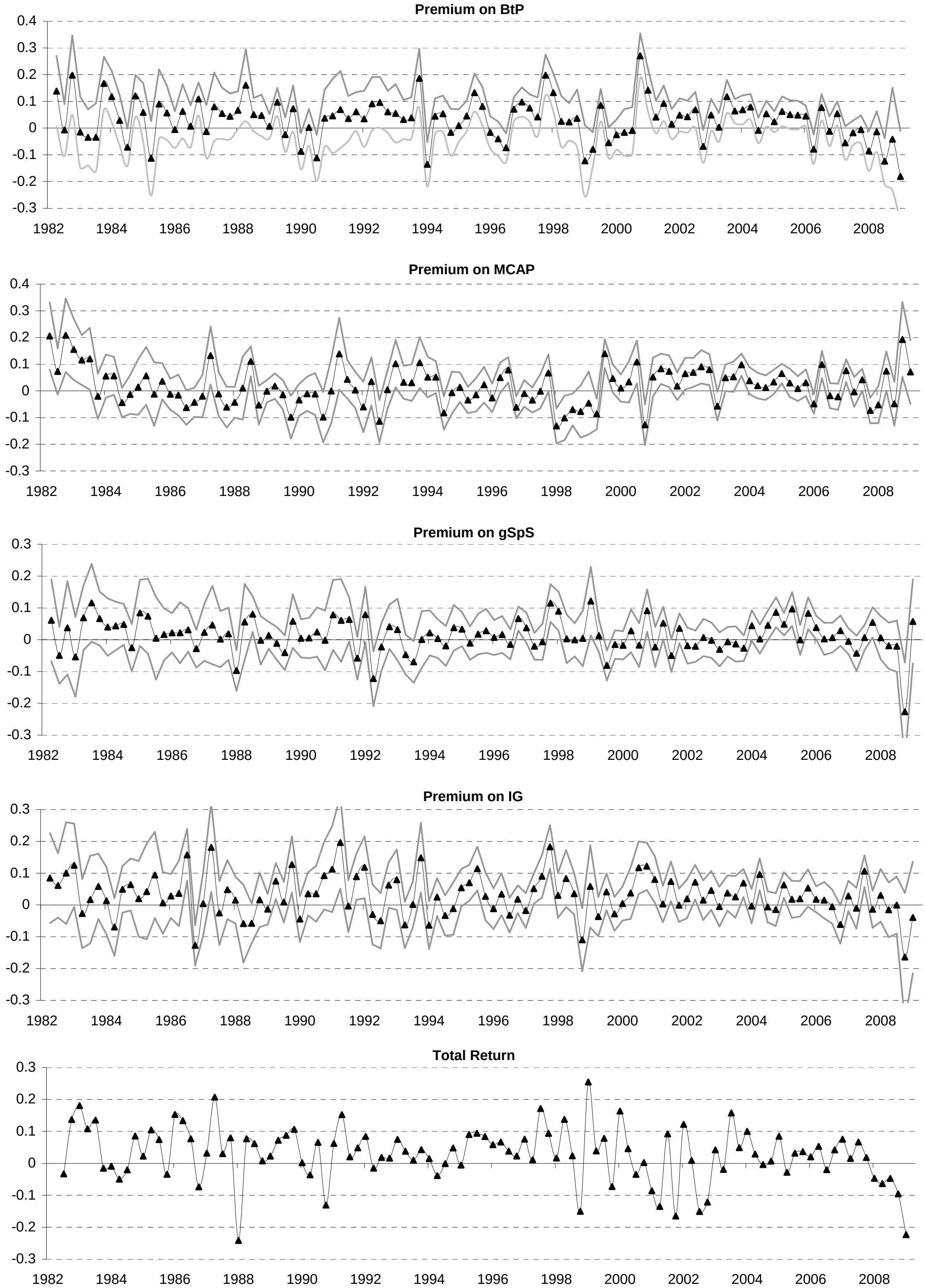
The premia are further explored on Figure 3, where they are plotted against each other. We find that that there is no clear relationship between value and small premia. The latter seems also to be unrelated to the growth indicators. The two growth indicators tend to perform well simultaneously. The IG performance is also correlated to the value premium.

What can be the intuition underpinning the relationships between the growth premia and other variables? Companies with high internal growth and fast growing sales are those that have investment opportunities and use them. In good times (when market does well), investment projects are more often successful, hence the positive correlation with the market. It turns out that value stocks, whose growth prospects are possibly undervalued by the market, tend do better at the same time, which is less intuitive.

As regards the momentum in the premia, associated to the company fundamentals, it can be seen in column (8) of Table 3 that the autocorrelations are not significantly different from zero (test H5) for all factors except the company size, so that equation (6) can be simplified to:

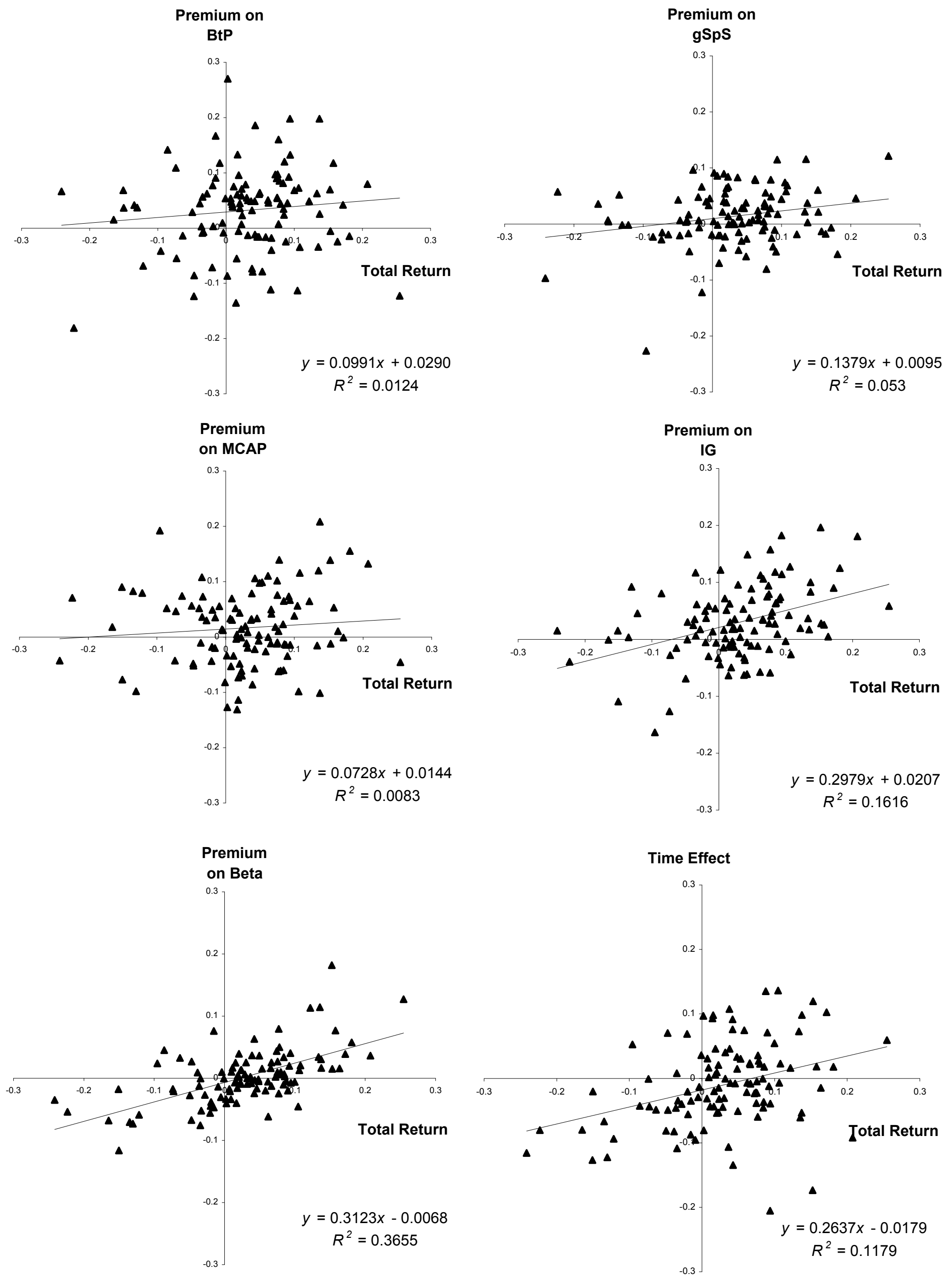
$$\gamma_t^j = \bar{\gamma}^j + \varepsilon_t^j. \tag{7}$$

Figure 1: Dynamics of Premia on Company Fundamentals



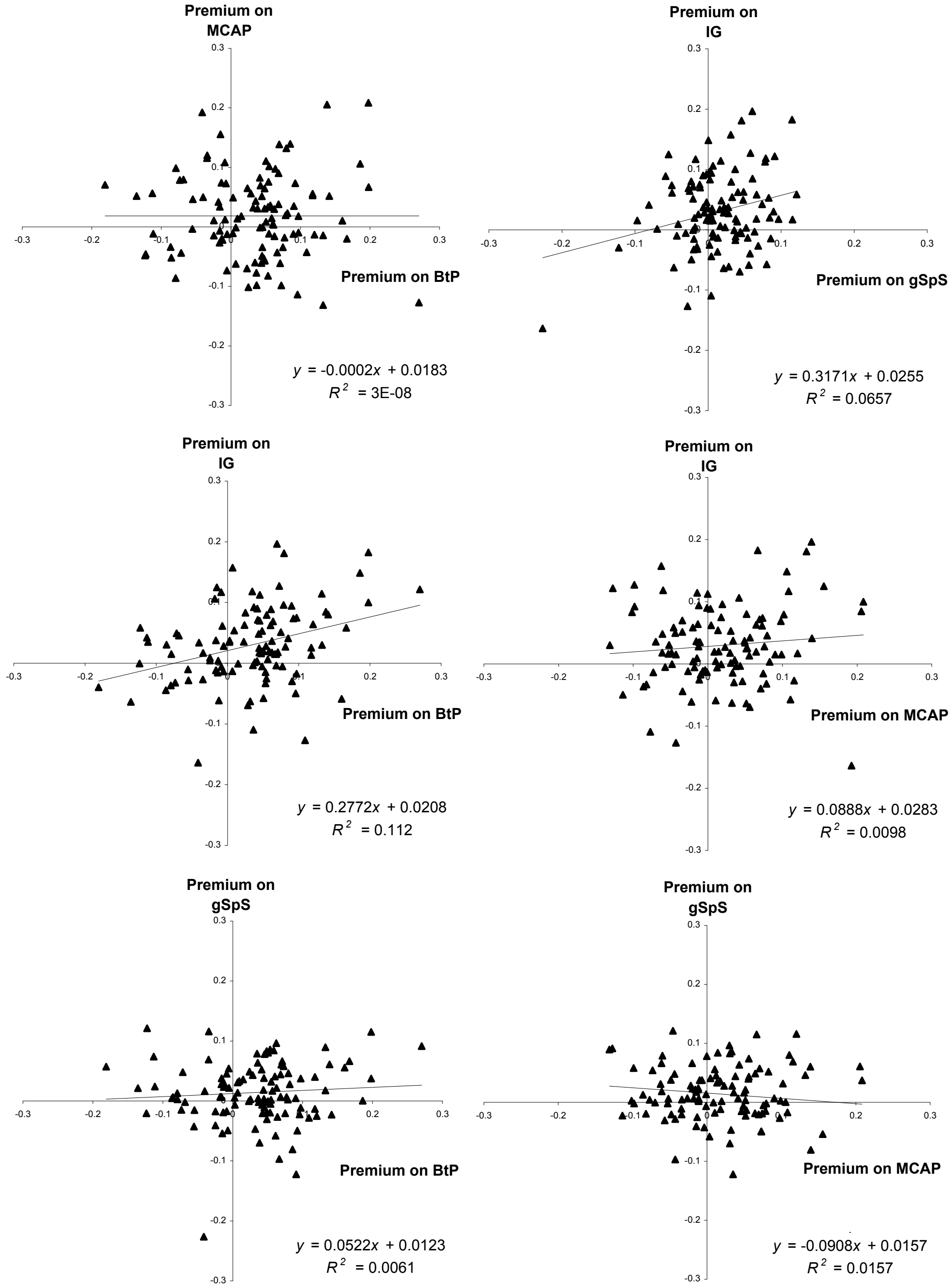
The upper four plots on the figure repesent the estimates of the time-varying premia $\widehat{\gamma}_t^j$ on the company fundamentals retained in the model reported in Table 3, j =BtP, MCAP, IG, gSpS. Grey lines represent 0.95 level confidence intervals. The plot in the bottom of the figure represents the total return on the Russel 3000 Index used as a proxy for the market portfolio yield.

Figure 2: Premia on Company Fundamentals *vs* Market Total Return



The scatter plots illustrate the dependence in time between the premia $\widehat{\gamma}_t^j$ (Y-axis) and the total return on the Russel 3000 Index used as a proxy for the market portfolio yield (X-axis). The solid line represents the OLS estimate of the linear regression of the premia on the market return, reported in the right bottom corner of each plot.

Figure 3: Interdependences between Premia on Company Fundamentals



The scatter plots illustrate the dependence in time between different pairs of premia $\{\widehat{\gamma}_t^i, \widehat{\gamma}_t^j\}$. The solid line represents the OLS estimate of the corresponding linear regression, reported in the right bottom corner of each plot.

For MCAP we find an autocorrelation value of 0.20, which is significant at 0.9 but not at 0.95 confidence level. This result is of special importance because it demonstrates the absence of auto-predictability in the variations of excess returns, associated to most company fundamentals, which is sometimes called "style momentum". This contradicts the evidence in Lucas et al. (2002), Chen and De Bondt (2004), Aarts and Lehnert (2005) and other voluminous literature stock-picking that describes the benefits of style rotation. Note that our results are in accordance with the conclusion in Chen and De Bondt (2004) that the style premia are time-varying, but we find that previously observed higher (lower) than average premia do not significantly increase the expected premia at the subsequent quarter.

What can be at the origin of this discrepancy in conclusions? Previous literature defines style premia through the return differentials on style-based portfolios, thus not controlling for the market betas and the other fundamentals. We define style premia in the multivariate setting. We also estimated BtP and MCAP premia excluding betas to the market portfolio (see Table 7 in Appendix B) and managed to reproduce the style momentum on the value premium, associated to the BtP indicator (autocorrelation of 0.17 significant at 0.9 confidence level). This indicates that value momentum returns probably come at the expense of higher systematic risk. This is not true for the size momentum, which is robust to the controlling for market betas. The question of why the value momentum vanishes when betas are controlled and it is not so for the size momentum can be added to the list of puzzles, related to the nature of style premia.

Given that in our model the value factor (BtP) is a ratio with the market price in the denominator and that the size factor (MCAP) is directly related to the stock price, it is interesting to check if the premia on them are affected by including the price momentum variables in the regression. Though momentum factors cannot be seen as company fundamentals, its is common since Carhart (1997) to include these variables in the models explaining stock returns along with the Fama and French factors. For the premia on momentum factors we find the results consistent with Jegadeesh and Titman (1993), i.e. significant negative impact of the returns over the past quarter (mean reversion), and positive but less significant impact of the returns over the previous year (see Table 8 in Appendix B). Contrary to what one could expect, adding momentum to the model does not reduce the premia on BtP, MCAP and the growth variables. All the main findings related to the magnitude and dynamics of the return premia remain unchanged.

6 Conclusion

Breaking with the tradition of the style analysis literature, where value and growth premia are defined as return differentials on factor-based portfolios, we redefine the premia on company fundamentals in a multivariate framework on the individual stock level. This framework allowed us to look at various factors simultaneously and to study each of them other things equal. We develop a random coefficient panel data framework that allows for the time-varying returns premia on company fundamentals.

After testing alternative model specifications, we chose to model the impact of the fundamentals on returns directly rather than through the past returns sensitivities to the artificially constructed risk factors, as in the Fama and French model. Our results show that the HML and SMB factors probably have no particular economic meaning other than being proxies for the impact of the book-to-price and size characteristics, as it was earlier suggested by Daniel and Titman (1997).

The main findings can be summarized in two categories. The first group of results relates to the choice of fundamentals that are relevant for predicting the cross-section of the individual stock returns. The practical importance of such studies is self-evident, given the direct link with the stock-picking investment strategies. We confirm the importance of the traditional variable used in academic literature on style analysis and in the business practice (book-to-price ratio, market capitalization, sales growth and internal growth), while rejecting others often used by market practitioners (like earnings forecasts).

The second group of results concerns the dynamics of the premia. We confirm the commonly accepted view that the latter are time-varying but find little evidence for style momentum when the systematic risk is controlled for, at least for the value premium. Nevertheless, we cannot claim that the variations in style premia are serially independent: the underlying dynamic structure could be more complicated and not linear than our methodology could be able to detect. We also identify several dependency patterns between the premia on fundamentals and market returns and between different style premia. While value and size premia variations seem to be unrelated, the premia on the growth variables (internal growth and growth of sales) tend to vary simultaneously and are related to the market. Controlling for the price momentum does not significantly impact the estimates of the premia on the company fundamentals, though the momentum variables come out significant.

While focusing on the modeling and estimation methodology and providing empirical evidence, in this paper we do not attempt to solve the fundamental questions of the economic nature of the premia associated with the economic factors. In particular, we do not try to test whether the excess returns are related to additional systematic risk not captured by the market bets. This analysis is an area of further research.

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A Estimation of a Random Coefficient Panel Data Model

For simplicity, we illustrate the estimation procedure on an example of a model with three factors: market betas and two company fundamenetals, BtP and MCAP. It can readily be extended to arbitrary number of factors. The system of equations (4) and (6) forms a model for the panel of stock returns. Let us rewrite it in matrix terms, which are easier to manipulate when the estimation procedure is described. Let Y_t be an $N \times 1$ vector of returns at each date and X_t the $k \times N$ vector of regressors, including the constant. In our case $k = 4$ and $X_t = [I, \beta_t^M \,\mathrm{BtP}_t, \mathrm{MCAP}_t]^T$. Also denote B_t a $k \times 1$ diagonal matrix of random dynamic coefficients, measuring the premia, $B_t = [\gamma_t^I, \gamma_t^M, \gamma_t^{\mathrm{BtP}}, \gamma_t^{\mathrm{MCAP}}]^T$ and υ_t the $N \times 1$ vector of errors. Equation (4) can be written:

$$Y_t = X_t^T \, B_t + \upsilon_t. \tag{8}$$

If $|\phi^j| < 1$, equation (6) for the coefficients dynamics can be written as:

$$\gamma_t^j - \bar{\gamma}^j = (\gamma_{t-1}^j - \bar{\gamma}^j)\phi^j + \varepsilon_t^j \tag{9}$$

with $\bar{\gamma}^j = \frac{c^j}{1-\phi^j}$ the mean value of the return premium on characteristic j. To cast our model in a state-space form, we define $\bar{\gamma}_t \equiv \bar{\gamma}$, the $k \times 1$ vector of mean premia for all characteristics; $\delta_t = \gamma_t - \bar{\gamma}$, a $k \times 1$ vector of deviations from these mean values; $\Phi = \mathrm{diag}[\phi^I, \phi^{\mathrm{BtP}}, \phi^{\mathrm{MCAP}}]$, the $k \times k$ diagonal matrix of coefficients; and ε_t, a $k \times 1$ vector of innovations to the premia. This gives:

$$\begin{bmatrix} \bar{\gamma}_t \\ \delta_t \end{bmatrix} = \begin{bmatrix} I_k & 0 \\ 0 & \Phi \end{bmatrix} \begin{bmatrix} \bar{\gamma}_{t-1} \\ \delta_{t-1} \end{bmatrix} + \begin{bmatrix} 0 \\ I_k \end{bmatrix} \varepsilon_t, \tag{10}$$

or with a parsimonious notation:

$$\alpha_t = S \, \alpha_{t-1} + R \, \varepsilon_t, \tag{11}$$

The associated measurement equation can be obtained from (8) by introducing a new $N \times 2k$ vector of independent variables $Z_t \equiv [X_t^T, X_t^T]$. This yields:

$$Y_t = Z_t \, \alpha_t + \upsilon_t. \tag{12}$$

In order to make statistical inference, based on this model, we will need to make further assumptions on the stochastic innovations to the style premia (ε_t) and the measurement equation (υ_t). We suppose that ε_t is a k-dimensional *iid* Gaussian process with independent components, $\varepsilon_t \sim N(0, Q)$ with:

$$Q = \mathrm{E}\left[\varepsilon_t\ \varepsilon_t^T\right] = \begin{bmatrix} q_1 & 0 & 0 \\ 0 & q_2 & 0 \\ 0 & 0 & q_3 \end{bmatrix}. \tag{13}$$

The measurement error is supposed be normal and identically distributed over time and space, that is for all t, $\upsilon_t \sim N(0, H)$ with

$$H = \mathrm{E}\left[\upsilon_t\ \upsilon_t^T\right] = \sigma_\upsilon^2 I_N. \tag{14}$$

We also assume that the measurement error and innovations to the state equations are independent.

When S, R, Q and H are all known, we can design a Kalman filter to obtain a GLS estimator of $\bar{\gamma}_t$. Let $\widehat{\alpha}_t$ denote the minimum mean square (MMSE) estimator of α_t, conditionally to the observations $Y_1, \ldots, Y_t$ up to period t and $\widehat{\alpha}_{t/t-1}$ the estimate, conditional on the observations up to period $t-1$. Denote P_t and $P_{t/t-1}$ the $k \times k$ covariance matrices of the errors of these estimates. The one-step forward estimate and its error can be obtained from prediction equations:

$$\widehat{\alpha}_{t/t-1} = S\widehat{\alpha}_{t-1} \tag{15}$$

$$P_{t/t-1} = S\ P_{t-1}\ S^T + R\ QR^T. \tag{16}$$

Denote ν_t the $N \times 1$ vector of errors, obtained from this prediction:

$$\nu_t = Y_t - Z_t\ \widehat{\alpha}_{t/t-1}. \tag{17}$$

It can be shown that this error is normally distributed, $\nu_t \sim N(0, F_t)$ with

$$F_t = H + Z_t\ P_{t/t-1}\ Z_t^T. \tag{18}$$

When observation of time t arrives, the new estimates $\widehat{\alpha}_t$ and P_t are obtained by the updating (or filtering) equations:

$$\widehat{\alpha}_t = \widehat{\alpha}_{t/t-1} + P_{t/t-1}\ Z_t^T\ F_t^{-1}\ (Y_t - Z_t\widehat{\alpha}_{t/t-1}) \tag{19}$$

$$P_t = P_{t/t-1} - P_{t/t-1}\ Z_t^T\ F_t^{-1}\ Z_t\ P_{t/t-1}. \tag{20}$$

The proof of these classical results for the Kalman filter is based on the properties of the joint normal distribution and can be found, for example, in Hsiao (2003, p. 158-161).

To obtain the GLS estimate of $\bar{\gamma}_t$ with this filter, we need to give a prior distribution of α_1, $\alpha_1 \sim N(\widehat{\alpha}_1, P_1)$. We set $\widehat{\delta}_1 = 0$ and infer $\bar{\gamma}_1$ by OLS from the cross-sectional data of the first period, so the estimate of the initial state vector becomes:

$$\widehat{\alpha}_1 = \begin{bmatrix} (X_1\, X_1^T)^{-1}\, X_1\, Y_1 \\ 0 \end{bmatrix}. \tag{21}$$

Denote Γ the covariance matrix of δ_t:

$$\Gamma = \begin{bmatrix} \frac{q_1}{1-(\phi^I)^2} & 0 & 0 \\ 0 & \frac{q_2}{1-(\phi^{\mathrm{BtP}})^2} & 0 \\ 0 & 0 & \frac{q_3}{1-(\phi^{\mathrm{MCAP}})^2} \end{bmatrix}. \tag{22}$$

The error of the estimate $\widehat{\alpha}_1$ can be decomposed in the measurement error and the error of the identification of the system state:

$$\begin{gathered} P_1 = \begin{bmatrix} \mathrm{E}\,\{(\widehat{\bar{\gamma}}_1 - \bar{\gamma})(\widehat{\bar{\gamma}}_1 - \bar{\gamma})^T\} & \mathrm{E}\,\{(\widehat{\bar{\gamma}}_1 - \bar{\gamma})(\widehat{\delta}_1 - \delta_1))^T\} \\ \mathrm{E}\,\{(\widehat{\delta}_1 - \delta_1)(\widehat{\bar{\gamma}}_1 - \bar{\gamma})^T\} & \mathrm{E}\,\{(\widehat{\delta}_1 - \delta_1)(\widehat{\delta}_1 - \delta_1)^T\} \end{bmatrix} = \\ \begin{bmatrix} \mathrm{E}\,\{(\widehat{\bar{\gamma}}_1 - \gamma_1 + \delta_1)(\widehat{\bar{\gamma}}_1 - \gamma_1 + \delta_1)^T\} & -\mathrm{E}\,\{(\widehat{\bar{\gamma}}_1 - \gamma_1 + \delta_1)\, \delta_1^T\} \\ -\mathrm{E}\,\{\delta_1\, (\widehat{\bar{\gamma}}_1 - \gamma_1 + \delta_1)^T\} & \mathrm{E}\,\{\delta_1\, \delta_1^T\} \end{bmatrix}. \end{gathered} \tag{23}$$

Notice that $\widehat{\bar{\gamma}}_1$ is OLS estimator of γ_1, so its covariance matrix reads:

$$\mathrm{E}\,\{(\widehat{\bar{\gamma}}_1 - \gamma_1)(\widehat{\bar{\gamma}}_1 - \gamma_1)^T\} = (X_1 H^{-1} X_1^T)^{-1} = (X_1\, X_1^T)^{-1} \sigma_\upsilon^2. \tag{24}$$

The independence of the state equation innovations and the measurement error gives:

$$\mathrm{E}\,\{(\widehat{\bar{\gamma}}_1 - \gamma_1)\, \delta_1^T\} = 0. \tag{25}$$

P_1 thus simplifies to:

$$P_1 = \begin{bmatrix} (X_1\, X_1^T)^{-1}\sigma_\upsilon^2 + \Gamma & -\Gamma \\ -\Gamma & \Gamma \end{bmatrix}. \tag{26}$$

Now the estimate $\widehat{\bar{\gamma}}$ can be obtained as the upper block of $\widehat{\alpha}_T$ by recursively applying equations (15) -(20) for $t = 1, \ldots, T$.

The estimate $\widehat{\bar{\gamma}}$ known, we can define a new zero-mean observation process $\widetilde{Y}_t$:

$$\widetilde{Y}_t = Y_t - X_t^T \widehat{\bar{\gamma}}, \tag{27}$$

We can now re-run the Kalman filter to get new predictions and prediction errors, conditional to $\bar{\gamma} = \widehat{\bar{\gamma}}$. The new measurement equation reads:

$$\widetilde{Y}_t = X_t^T\, \widetilde{\delta}_t + \widetilde{\upsilon}_t \tag{28}$$

with $\widetilde{\delta} = \gamma_t - \widehat{\widetilde{\gamma}}$. The state equation becomes:

$$\widetilde{\delta}_t = \Phi\, \widetilde{\delta}_{t-1} + \widetilde{\varepsilon}_t. \tag{29}$$

The Kalman filter prediction equations can be written:

$$\widehat{\widetilde{\delta}}_{t/t-1} = \Phi\, \widetilde{\delta}_{t-1}, \tag{30}$$
$$\widetilde{P}_{t/t-1} = \Phi\, \widetilde{P}_{t-1}\, \Phi^T + Q. \tag{31}$$

The prediction errors are:

$$\widetilde{\nu}_t = \widetilde{Y}_t - X_t^T\, \widehat{\widetilde{\delta}}_{t/t-1} \tag{32}$$

and their covariance matrix:

$$\widetilde{F}_t = H + X_t^T\, \widetilde{P}_{t/t-1}\, X_t. \tag{33}$$

Finally, the filtering equations become:

$$\widehat{\widetilde{\delta}}_t = \widehat{\widetilde{\delta}}_{t/t-1} + \widetilde{P}_{t/t-1}\, X_t\, \widetilde{F}_t^{-1}\, (\widetilde{Y}_t - X_t^T \widehat{\widetilde{\delta}}_{t/t-1}) \tag{34}$$
$$\widetilde{P}_t = \widetilde{P}_{t/t-1} - \widetilde{P}_{t/t-1}\, X_t\, \widetilde{F}_t^{-1}\, X_t^T\, \widetilde{P}_{t/t-1}. \tag{35}$$

The filter can be initialized by an OLS estimate $\widehat{\widetilde{\delta}}_1$ from the first-period cross-sectional data:

$$\widehat{\widetilde{\delta}}_1 = (X_1 X_1^T)^{-1}\, X_1\, \widetilde{Y}_1. \tag{36}$$

The initial prediction error is:

$$\widetilde{P}_1 = \mathrm{E}\,\{(\widehat{\widetilde{\delta}}_1 - \widetilde{\delta}_1)(\widehat{\widetilde{\delta}}_1 - \widetilde{\delta}_1)^T\} = (X_1\, X_1^T)^{-1} \sigma_\upsilon^2. \tag{37}$$

Up to now we supposed that Φ, Q and σ_υ^2 are known. In practice we need to estimate them from the $N \times T$ matrix of observations Y. For this end, we implement the maximum likelihood method. The likelihood function of Y can be represented in terms of the $N\,T \times 1$ vector of prediction errors $\widetilde{\nu} = [\widetilde{\nu}_1^T, \ldots, \widetilde{\nu}_T^T]$. It is normally distributed with $N\,T \times N\,T$ covariance matrix $\widetilde{V}$. The log-likelihood function reads:

$$L(Y; \bar{\gamma}, \Phi, Q, \sigma_\upsilon^2) = \text{const} - \frac{1}{2} \log |\widetilde{V}| - \frac{1}{2} \widetilde{\upsilon}\, \widetilde{V}^{-1}\, \widetilde{\upsilon}^T \tag{38}$$

Notice that $\widetilde{V}$ is block-diagonal since elements of the prediction error vectors at different periods $\widetilde{\upsilon}_i$ and $\widetilde{\upsilon}_j$ are uncorrelated, $i \neq j$. So the log-likelihood can be decomposed "period by period". For each t, the two Kalman filter recursions yield GLS estimates of $\bar{\gamma}$ and the prediction error covariance matrix, $\widetilde{F}_t$, conditional to Φ, Q, σ_υ^2. These estimates can be used to form a concentrated log-likelihood function:

$$L_c(Y; \Phi, Q, \sigma_v^2) =$$

$$\text{const} -\frac{1}{2}\sum_{t=1}^{T} \log|\widetilde{F}_t| - \frac{1}{2}(Y_1 - X_1^T\widehat{\widehat{\delta}}_1)\ H^{-1}\ (Y_1 - X_1^T\widehat{\widehat{\delta}}_1)^T - \frac{1}{2}\sum_{t=2}^{T} \widetilde{v}_t^T\ \widetilde{F}_t^{-1}\ \widetilde{v}_t \tag{39}$$

In our case the stocks for which data is available are not the same for each date. Due to the absence of individual effects, we can without any consequences substitute stocks in the sample. The number of of stocks with available data increases dramatically in 1999 (from about 500 to about 1000, the exact number depending on model specification), so we choose to define two subsamples: before Q1-99 and after Q1-99 with a fixed number of stocks in each of them. As the maximum likelihood function is additive in time, we simply decompose it into two terms, corresponding to each subsample. The outcome of the Kalman filter for the first subsample are used as initial values for the second subsample to ensure consistency.

In each subsample, we ensure random rotation of stocks. The procedure is as follows. We start with all stocks available at the first date, at the next period we replace the stock for which some data is missing by randomly picked stocks for which data at this date are present, and so on. If we are not able to replace all stocks, we restart the procedure with a smaller number of stocks at the first period. Thus we constitute the samples with maximum possible number of stocks. Since generally the number of stocks tends to increase in time, the number of stocks retained is close to the number of stocks at the initial date of each subsample.

The minimization of the negative log-likelihood is carried out numerically around the initial estimates, obtained by a two-step OLS procedure. First, for each date we run cross-sectional regressions to obtain $\widehat{B}_t^{OLS}$ and then estimate AR(1) models for each of its components to get $\widehat{\Phi}^{OLS}$,$\widehat{Q}^{OLS}$,$\widehat{\sigma}_\nu^{OLS}$.

The errors in coefficient estimates are estimated by a two-step bootstrap algorithm. At the first stage, the time varying premia are simulated using (6) by bootstrapping from the distribution of errors $\widehat{\varepsilon}_t^j$, estimated from the Kalman filter with the parameters $\widehat{\Phi}^{ML}$, $\widehat{Q}^{ML}$,$\widehat{\sigma}_\nu^{ML}$. At the second stage, we simulate equation (8) by bootstrapping from the distribution of $\widetilde{v}_t$ at each date.

B Additional Tables

Table 4: A Model Including BtP and EtP Simultaneously*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AM	44	50	50	0.0005	0.1861	-0.107	0.044	-0.2028
				(0.0039)	(0.0336)	(0.0172)	(0.0042)	(0.0925)
				0.403	0	0	0	0.028
PtB	37	83	17	0.0396	0.3182	-0.191	0.08	0.1287
				(0.0095)	(0.0502)	(0.0449)	(0.0072)	(0.0978)
				0	0	0	0	0.188
EtP	35	45	55	-0.0112	0.1826	-0.2233	0.0725	0.1865
				(0.0095)	(0.0381)	(0.0430)	(0.0062)	(0.0954)
				0.135	0	0	0	0.117
MCAP	44	67	33	0.018	0.1959	-0.142	0.0683	0.1846
				(0.0088)	(0.0383)	(0.0336)	(0.0053)	(0.1012)
				0.017	0	0	0	0.082
gSpS	26	79	21	0.0132	0.1229	-0.1883	0.0509	0.0123
				(0.0063)	(0.0341)	(0.0423)	(0.0050)	(0.0977)
				0.014	0	0	0.001	0.484
IG	32	83	17	0.0352	0.2551	-0.2064	0.0704	0.0375
				(0.0080)	(0.0416)	(0.0491)	(0.0064)	(0.0984)
				0	0	0	0	0.438
Const	28	43	57	-0.0113	0.1594	-0.2141	0.0693	-0.1293
				(0.0071)	(0.0395)	(0.0453)	(0.0059)	(0.0942)
				0.064	0	0	0	0.142
p_1=0,p_2=0.002, R^2=0.1010;								
T_1=68, N_1=216 (Q1-82:Q4-98) / T_2=40, N_2=503 (Q1-99:Q4-2008)								

* (1) periods when variable is significant, % of all periods; (2),(3) positive and negative impact, % of periods when variable is significant; (4) average premium in quarterly log-return, its standard deviation and the p-value of the significance test H1; (5),(6) maximum and minimum premium over time, its standard deviation and p-values of the H2 and H3 tests; (7) volatility (standard deviation) of the premium in time, its standard deviation and the p-value of the H4 test; (8) first-order autocorrelation in variations of the premium, its standard deviation an the p-value of the H5 test. p_1 and p_2 are p-values of two likelihood ratio tests, described in section 3. R^2 is the percentage of variance, explained by the model. T and N are reported separately for two subsamples before and after 1999.

Table 5: A Model Including Earnings Forecasts*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AM	40	51	49	0.0052	0.1289	-0.0837	0.0375	-0.1846
				(0.0033)	(0.0185)	(0.0160)	(0.0037)	(0.0946)
				0.044	0	0	0	0.044
BtP	32	71	29	0.0133	0.2281	-0.2033	0.0706	-0.0227
				(0.0076)	(0.0391)	(0.0398)	(0.0064)	(0.0945)
				0.035	0	0	0	0.393
MCAP	36	66	34	0.0128	0.1384	-0.1775	0.0624	0.1618
				(0.0081)	(0.0278)	(0.0350)	(0.0050)	(0.0956)
				0.052	0	0	0	0.127
LTG	40	49	51	-0.0007	0.2545	-0.2288	0.0772	-0.2415
				(0.0071)	(0.0492)	(0.0451)	(0.0068)	(0.0956)
				0.463	0	0	0	0.02
fgEPS	22	58	42	0.0015	0.1291	-0.1298	0.0479	0.1528
				(0.0063)	(0.0291)	(0.0312)	(0.0043)	(0.0974)
				0.444	0	0	0.003	0.205
Const	36	68	32	0.0155	0.1941	-0.1693	0.0726	0.1188
				(0.0088)	(0.0400)	(0.0376)	(0.0062)	(0.0993)
				0.044	0	0	0	0.251

p_1=0.002,p_2=0.013, R^2=0.0787;

T_1=68, N_1=337 (Q1-82:Q4-98) / T_2=40, N_2=735 (Q1-99:Q4-2008)

* see comments to Table 4.

Table 6: A Model Using Long-Term Historical Growth Measures*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AM	38	64	36	0.0034	0.1593	-0.122	0.0409	-0.2532
				(0.0037)	(0.0236)	(0.0202)	(0.0039)	(0.0992)
				0.164	0	0	0	0.012
BtP	44	69	31	0.0204	0.2456	-0.3065	0.0760	0.1774
				(0.0103)	(0.0481)	(0.0724)	(0.0079)	(0.1023)
				0.017	0	0	0	0.096
MCAP	39	59	41	0.007	0.1698	-0.1492	0.0646	0.0428
				(0.0079)	(0.0319)	(0.0294)	(0.0053)	(0.1043)
				0.187	0	0	0	0.435
gSpS5	20	58	42	0.001	0.119	-0.2183	0.0550	0.0185
				(0.0067)	(0.0306)	(0.0474)	(0.0061)	(0.1009)
				0.394	0	0	0	0.493
IG5	29	64	36	0.0143	0.2523	-0.2026	0.0741	0.2072
				(0.0105)	(0.0450)	(0.0404)	(0.0074)	(0.1048)
				0.072	0	0	0	0.094
Const	32	60	40	0.0084	0.1627	-0.1185	0.0621	0.1275
				(0.0085)	(0.0350)	(0.0345)	(0.0052)	(0.0983)
				0.158	0	0	0	0.232

p_1=0, p_2=0.011, R^2=0.0869;

T_1=60, N_1=224 (Q1-84:Q4-98) / T_2=40, N_2=603 (Q1-99:Q4-2008)

* see comments to Table 4.

Table 7: Return Premia on Company Fundamentals*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PtB	54	71	29	0.0267	0.4656	-0.2771	0.0912	0.1742
				(0.0104)	(0.1677)	(0.1566)	(0.0153)	(0.0868)
				0.002	0	0	0.033	0.091
MCAP	48	65	35	0.034	0.6307	-0.1753	0.104	0.1867
				(0.0115)	(0.1952)	(0.1791)	(0.0177)	(0.0818)
				0	0	0	0.016	0.065
Const	68	62	38	0.0146	0.3007	-0.2871	0.0975	-0.0208
				(0.0092)	(0.0974)	(0.0564)	(0.0087)	(0.0921)
				0.051	0	0	0.001	0.384

p_1=0.010, p_2=0.037, R^2=0.0371;

T_1=68, N_1=521 (Q1-82:Q4-98) / T_2=40, N_2=1302 (Q1-99:Q4-2008)

* see comments to Table 4.

Table 8: Return Premia on Company Fundamentals and Price Momentum*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AM	38	54	46	-0.0001	0.1769	-0.1208	0.0405	-0.0060
				(0.0042)	(0.0358)	(0.0228)	(0.0045)	(0.0983)
				0.4970	0	0	0	0.4470
PtB	46	80	20	0.0355	0.2988	-0.1652	0.0729	0.0873
				(0.0084)	(0.0543)	(0.0364)	(0.0066)	(0.0969)
				0.0000	0	0	0	0.2800
MCAP	44	66	34	0.0176	0.2010	-0.1356	0.0687	0.2605
				(0.0087)	(0.0400)	(0.0335)	(0.0054)	(0.0939)
				0.0210	0	0	0	0.0210
gSpS	29	74	26	0.0160	0.1390	-0.1345	0.0488	0.0983
				(0.0061)	(0.0305)	(0.0329)	(0.0048)	(0.0994)
				0.0070	0	0	0	0.2860
IG	31	88	12	0.0308	0.2055	-0.1173	0.0622	0.0093
				(0.0076)	(0.0365)	(0.0369)	(0.0056)	(0.0977)
				0.0000	0	0	0	0.4970
Pmom1q	37	18	82	-0.0217	0.2251	-0.1914	0.0693	0.0597
				(0.0078)	(0.0482)	(0.0358)	(0.0058)	(0.1022)
				0.0030	0	0	0	0.3880
Pmom1y	31	52	48	0.0087	0.3253	-0.1434	0.0785	-0.2532
				(0.0074)	(0.0494)	(0.0414)	(0.0080)	(0.0949)
				0.1040	0	0	0	0.0230
Const	39	52	48	-0.0063	0.2492	-0.2197	0.0834	-0.1831
				(0.0078)	(0.0512)	(0.0490)	(0.0068)	(0.0996)
				0.2540	0	0	0	0.0930
p_1=0,p_2=0.0097, R^2=0.0973;								
T_1=68, N_1=220 (Q3-84:Q4-98) / T_2=40, N_2=529 (Q1-99:Q4-2008)								

* see comments to Table 4.