Panel Data Models for Stock Returns: the Importance of Industries

Rob Bauer
ABP Investments and Limburg Institute of Financial Economics

Borislav Pavlov
Limburg Institute of Financial Economics and ABP Investments

Peter C. Schotman
Limburg Institute of Financial Economics and CEPR

March 3, 2004

Abstract: We study the predictability of stock returns in a panel of individual stocks. Our econometric models can deal with unbalanced panel data, cross sectional correlation among prediction errors and industry specific time effects. We perform misspecification tests related to the cross industry heterogeneity and poolability. For a panel of 1216 US firms for the period 1985–2002 we find that industry effects are significant and interact with firm characteristics like size and momentum. This conclusion is robust to the estimation method, the data and the forecasting horizon. High expected returns are mostly related to the cash flow-to-price ratio and the analyst earnings revisions, somewhat to the momentum, but hardly to most valuation ratios. In-sample portfolio construction results in long-short portfolios with substantial abnormal returns.

Keywords: Stock Returns, Forecasting, Panel data, Industry effects, Individual effects, Time effects.

JEL codes: C23, G12.

Correspondence address: LIFE
University of Maastricht
P.O. Box 616
6200 MD Maastricht
Netherlands
E-Mail: R.Bauer@berfin.unimaas.NL
B.Pavlov@berfin.unimaas.NL
P.Schotman@berfin.unimaas.NL

* We are obliged to Franz Palm, Luis Viceira and Pieter-Jelle van der Sluis for useful comments and to ABP Investments for providing the data. The expressed views do not necessarily reflect those of ABP Investments.

1 Introduction

Various firm characteristics seem to have predictive power for future stock returns. Prominent candidate predictors are size, price ratios (book-to-market, price-earnings, dividend yield), analyst earnings predictions and past returns.[1] In addition returns are related to industries and countries.[2] Many of these effects are correlated and sometimes interact.

The typical statistical procedure for documenting return predictability starts with the construction of portfolios. Stocks are sorted according to a particular characteristic and allocated to a small number of portfolios. If the average returns of the portfolios are significantly different, the characteristic has predictive power. With multiple characteristics the stocks are sorted along different dimensions. Well known two-dimensional sorts are the 25 Fama-French portfolios, sorted with respect to five size and five book-to-market categories[3]. Another example are country-industry portfolios, see for example Cavaglia and Moroz (2002). With only one or two characteristics this methodology is simple and has proven to be very powerful.

The number of portfolios grows, however, exponentially with the number of characteristics. With ten different characteristics, and just two categories per characteristic, we would already need at least 2^{10} different portfolios. Adding a possible industry effect multiplies the number of portfolios with another factor of about 20, depending on the number of industries. When the number of explanatory variables grows, the portfolio formation methodology is bound to become problematic, since many portfolios will contain none or few stocks.

With multiple explanatory variables it becomes fruitful to look at data for individual stocks. In this paper we construct a prediction model for stock returns. We apply panel data analysis and use a sample of 1216 US stocks over a period of 17 years. Using the panel we aim at answering questions that can not be addressed with the portfolio method.

[1] The literature is so huge that it will be impossible to cite more than a few empirical studies. Some book references are Bodie, Kane and Marcus (2002, ch 12, 13), Cochrane (2001, ch 20), Haugen (1999, 2001, 2002), Campbell et al (1997). Empirical studies include Fama and French (1992, 1996), Davis et al (2000), Jegadeesh and Titman (1993, 2001), DeBondt and Thaler (1985), Lewellen (2002).

[2] See Heston and Rouwenhorst (1994), Rouwenhorst and Heston (1995), Haugen and Baker (1996), Moskowitz and Grinblatt (1999), Fama and French (1997), Cavaglia, Brightman and Aked (2000), Lewellen (1999), Cohen and Polk (1998).

[3] The returns of these portfolios are used in many empirical studies. A subsample of this literature is Fama and French (1996), Hodrick and Zhang (2001), Campbell and Vuolteenaho (2002).

We focus on model selection in a panel data framework that involves a number of issues.

The first issue that we are interested in is the amount of cross sectional heterogeneity in average stock returns. How much of the cross sectional variation in returns is explained by the characteristics and industry effects and how much cross sectional variation remains? This requires testing for individual effects. Important heterogeneity on the level of individual firms could be interpreted as missing predictive variables.

The second issue is the effect of industries. Practitioners often consider industries to be the first level of diversification. We investigate the alleged importance of industries by testing for industry specific effects. More important, we test whether the parameters of the characteristics are identical in all industries. Can industries be pooled or do we need a separate model for each industry?

A third issue concerns the most effective way to construct portfolios with a large dispersion in average returns. From the panel study we obtain expected returns for each stock in every time period. Sorting directly on expected returns we can compare the typical characteristics of portfolios with high and low average returns.

Panel data models for individual stock returns are scarce. Cavaglia and Moroz (2002) apply a panel to study the stock allocation across countries and industries. They use panel data at the industry level and do not include individual company effects in their model specifications. Other examples are discussed in Haugen and Baker (1996), Grinold and Kahn (1999) and Brennan et al (1998). All empirical studies with individual firms rely on the estimator of Fama and MacBeth (1973), which estimates the structural parameters cross sectionally for every time period. Such methods have difficulty with typical panel features like individual effects that are firm specific rather than time specific.

There are good reasons why the analysis of portfolio returns has been much more popular than working with panels of individual stock returns. First of all, panels of individual data are inherently unbalanced, since companies come, merge and go. In addition, well diversified portfolios are less noisy than individual firm data. The explanatory variables for individual firms are sometimes even more noisy than the returns. Especially financial ratios like earnings-to-price contain huge (negative) outliers that can be influential. Portfolio formation strategies are usually robust against outliers in the explanatory variables. For example, all firms with negative earnings will end up in the same portfolio, and the exact value of the price-earnings ratio will not matter. In a regression analysis all outliers in the explanatory variables must be closely inspected prior to running any regressions.

Most challenging for statistical testing in panels of individual stocks are the contemporaneous covariances among the errors. Even after including time effects much cross correlation remains. Estimating a full cross sectional covariance matrix will be infeasible given the large number of individual stocks. To get around this problem many studies have used the Fama and MacBeth (1973) estimator. This estimator will not be feasible, however, when firm specific individual effects are introduced. On the other hand, pooled OLS with individual effects and time effects will be consistent in most cases. For the standard errors we rely on the spatially consistent estimator of the standard errors proposed by Driscoll and Kraay (1998). A limitation of our study is an assumption on the linearity of the interaction between expected return and characteristics.

An econometric problem that arises in model selection tests is that with individual fixed effects the number of parameters increases with the number of firms N, while with fixed time effects the number of parameters is of order T. When both N and T are large, as in a panel of stocks returns, standard asymptotic tests for inclusion of either individual or time effects become unreliable. We decide on inclusion of these effects using the Schwartz information criterion. As shown by Bai and Ng (2002) model selection criteria are consistent with the appropriate choice of the penalty function provided that the cross sectional correlations are not too strong. To evaluate the robustness of the explanatory variables we compare parameter estimates of the characteristics under various assumptions about the panel structure of the errors.

In the empirical analysis we consider a set of predictive variables that have been widely used in previous studies. The predictive variables are size, various valuation ratios and alternative momentum indicators. We find that in a pooled panel model only few variables have any predictive power. But when firm characteristics and industry dummies are allowed to interact results improve considerably. When we construct portfolios based on expected returns, we find that good and bad portfolios have very distinctive characteristics. Optimal portfolios are not in the extremes on one particular predictive variable, but score well on many attributes. Increasing the forecasting horizon sharply decreases the portfolio turnover and does not deteriorate returns. After correcting for the standard four risk factors (market, size, value, momentum), significant outperformance remains. Moreover, optimal portfolios are very stable over time. Only about five percent of the top 30% highest expected return stocks differ from month to month. Finally, the results appear robust to alternative estimation procedures.

The remainder of the paper is organized as follows. Section 2 discusses the specification of the panel model, the model selection criterion and hypothesis testing. Section 3 describes the data and how the raw data are transformed to regressors in the panel model. Section 4 presents the empirical results. Section 5 considers the implications for portfolios that are constructed by sorting stocks on expected returns. Section 6 concludes.

2 Methods

2.1 Specification

Our interest is in predicting returns y_{it} of individual stocks using a K-vector of firm characteristics x_{it}, known at the beginning of period t, and L industry dummies $D_{i\ell}$ that indicate in which industry firm i is active. Return data are observed for T months. The most general model we consider is a two-way error component model with industry specific parameters,

$$y_{it} = \mu_i + \sum_{\ell=1}^{L} D_{i\ell} \left(x_{it}' \beta_\ell + \lambda_{\ell t} \right) + e_{it}, \tag{1}$$

where μ_i is a stock specific effect, β_ℓ is a K-vector of coefficients for industry ℓ, $\lambda_{\ell t}$ is a time effect for industry ℓ in period t, and e_{it} is an error term. The errors have mean zero and are assumed to be uncorrelated with the regressors, i.e. $\mathsf{E}[x_{jt} e_{it}] = 0$. In each period complete data for returns and characteristics are observed for N_t firms. The total number of data points is $n = \sum N_t$. Not all parameters in the general model are identified. For example, with individual effects μ_i included, the industry specific time effects $\lambda_{\ell t}$ must be normalized in some way. In the general model we have a panel model for each industry. Pooling restrictions on either $\lambda_{\ell t}$ or β_ℓ lead to predictability across industries.

The purpose of the model is to forecast stock returns based on their characteristics. The time effects $\lambda_{\ell t}$ will be fully unrestricted fixed effects. Since at the beginning of period t we can not predict $\lambda_{\ell t}$, absolute forecasts can not be made with this model. Instead, the model is designed for making relative forecasts. With industry specific time effects $\lambda_{\ell t}$ it can predict which firm in a particular industry will have the higher return in the next month compared to all other firms in that industry. When the time effect is common to all firms ($\lambda_{\ell t} = \lambda_t$), the model will predict the relative returns of all stocks.

It is important to understand the differences between the panel specification and the portfolio formation strategies. Much of the empirical literature follows a non-parametric approach by sorting stocks in different portfolios. Each of the K characteristics would be classified in N categories. Adding the L different *Industries* would lead to LN^K portfolios and as many parameters. Clearly, this full generality is infeasible if the potential number of characteristics K is more than 2 or 3, since we would quickly exhaust all degrees of freedom. In this paper we will include $K = 9$ characteristics and $L = 22$ industries. With the typical choice of $N = 5$ different classes per characteristic we would need more than 40 million parameters, many more than we have observations.

The following example with a double sort on *size* and *value* illustrates the relation between the panel (1) and the portfolio construction method. *Size* is measured as the market capitalization of a firm and *value* as some accounting ratio like earnings-to-price. Suppose there are N classes for *size* and *value*. Define the dummy variables

$$D_{ijkt} = \begin{cases} 1 & \text{if firm } i \text{ belongs to portfolio } (j,k) \text{ in period } t, \\ 0 & \text{otherwise,} \end{cases} \tag{2}$$

where portfolio (j,k) includes all stocks that belong to the j^{th} *size* class and to the k^{th} *value* class. Classes are defined by breakpoints $\tilde{S}_{1t} < \ldots < \tilde{S}_{N-1,t}$ for *size* and an analogous set of breakpoints $\tilde{V}_{kt}$ for *value*. A typical choice for the breakpoints are the $1/N^{th}$ quantiles of the cross sectional distribution of each characteristic. Average returns are estimated in the "panel"

$$y_{it} = \sum_{j=1}^{N} \sum_{k=1}^{N} \beta_{jk} D_{ijkt} + \epsilon_{it}, \tag{3}$$

which has N^2 parameters. The panel model (1) imposes two restrictions on (3). The first is the separability restriction $\beta_{jk} = \beta_{Sj} + \beta_{Vk}$. This reduces the number of parameters to $2N - 1$ and leads to the model[4]

$$y_{it} = \sum_{j=1}^{N} \beta_{Sj} D^S_{ijt} + \sum_{k=1}^{N} \beta_{Vk} D^V_{ikt} + \epsilon_{it}, \tag{4}$$

[4] The number of parameters is $2N - 1$, since both sets of dummies add to one, thus creating a singularity in the set of explanatory variables.

where $D_{ijt}^S = \sum_k D_{ijkt}$ and $D_{ikt}^V = \sum_j D_{ijkt}$.

Second, the step functions in (4) are replaced by a monotone linear approximation. For *size* the approximation is

$$\sum_j \beta_{Sj} D_{ijt}^S \approx \beta_{0S} + \beta_S \left(S_{it}/\bar{S}_t \right), \tag{5}$$

with S_{it} the market capitalization of firm i at the beginning of period t and $\bar{S}_t$ the cross sectional average. The effect is defined in terms of the scaled variable $S_{it}/\bar{S}_t$ to be consistent with the quantile breakpoints $\tilde{S}_{jt}$ that are typically used in the portfolio construction methods. The analogous approximation for the value characteristic is

$$\sum_k \beta_{Vj} D_{ikt}^S \approx \beta_{0V} + \beta_V \left(V_{it} - \bar{V}_t \right). \tag{6}$$

The value ratio V_{it} is expressed in deviation of the cross sectional average.[5] In line with the cross sectional nature of the model we subtracted the cross sectional average. With the approximation the number of parameters is reduced to three: β_S, β_V and the intercept $\beta_{0S} + \beta_{0V}$.

The assumptions for separability and linearity enable the introduction of a larger number of explanatory variables. Most of the characteristics in x_{it} are valuation ratios that are the result of the transformation (6). Apart from *size* and *value* the third type of characteristic is *momentum*. *Momentum* variables are functions of lagged returns y_{it}. Portfolio sorting procedures often use a formation period of three to six months. In the panel this corresponds to explanatory variables that are defined as the cumulative returns over three or six months in deviation of the cross sectional average.

Instead of a fixed intercept the actual panel model (1) includes time effects $\lambda_{\ell t}$, which can possibly be pooled across industries ($\lambda_{\ell t} = \lambda_t$).[6] Estimating the panel with time effects implies that all variables are automatically taken in deviation of their cross sectional mean. With a variable like earnings-to-price this implies that we only consider the cross sectional effect whether firms with higher earnings tend to generate higher returns compared to other firms. A possible effect of a historically

[5] Other transformations are of course possible. For example, a closely related alternative for *size* is the transformation $\ln S_{it} - \ln \bar{S}_t$. For *value* we could also further normalise by the cross sectional standard deviation of V_{it}. This would lead to different results when the cross sectional distribution of a ratio like earnings-to-price fluctuates a lot over time.

[6] Still an intercept may be estimated by imposing the identification condition that the average time effect is zero.

low earnings-to-price ratio on the market (industry) wide level of stocks returns is captured by the time effect λ_t ($\lambda_{\ell t}$), but is not taken into account for predicting. Time effects also take out a large common noise component from the returns, and thus reduce the cross-sectional correlation of the errors, which in turn will enhance estimation efficiency.

The only interaction effects that we examine are between the industries and the characteristics. For this reason the slope parameters β_ℓ in (1) depend on the industry. This enables tests of hypotheses on the interaction between industries and firm characteristics. For example, Moskowitz and Grinblatt (1999) find that the momentum effect is in essence an industry effect. Their empirical results imply that momentum does not help predict the relative returns of individual firms, but rather the relative performance of an entire industry. Momentum should disappear once we correct for industry wide effects. If their hypothesis is correct, and we estimate the panel with industry specific time effects, we should expect that momentum variables are not significant. For if they are, we would be able to predict the relative returns within the same industry and thus have individual momentum.

The final element in the specification of (1) are the individual effects μ_i. These are only introduced as a diagnostic, as one would hope that they can be omitted. With individual effects in the model the relative return of stocks i and j depends on the difference $\mu_i - \mu_j$. In searching for stocks with high expected returns, we would then need to take into account the estimates of μ_i. These are likely to be poorly estimated, as information on them can only come from the time series dimension of the data. Firms without a long history will have especially poorly determined individual effects. Furthermore, individual firm returns are very noisy — that is exactly what motivates portfolio formation — and the forecasting performance of the model will be negatively affected by the noisy estimates of μ_i. On the other hand, the cross sectional variation in μ_i does tell us a lot about the unmodelled systematic cross-sectional variation in the data, and thus about the goodness of fit. When the individual effects μ_i turn out to be significant, much of the cross sectional variation in expected returns remains unexplained.

The effect of some explanatory variables is related to the individual effects. Taking again the example of momentum, a function of the lagged dependent variable, it is easy to mistakenly conclude that momentum is significant when instead an individual effect should have been included. As a diagnostic of omitted individual effects we therefore compare the estimates of β_ℓ in models with and without individual effects.

The importance of the individual effects depends on the cross sectional variation of average returns. Jegadeesh and Titman (2002) argue that this cross sectional variation is small and negligible relative to the potential gains of a momentum trading strategy. Because of the possible interaction between the individual effects and the explanatory variables, we will treat the μ_i as fixed effects and not as random effects. From the panel data literature it is known that random effects estimation is inconsistent if μ_i and x_{it} are correlated.

So far we have not been explicit about the horizon of the returns y_{it}. The empirical literature on predicting stock returns usually considers holding periods of varying lengths. For example, in testing momentum strategies, the usual holding period ranges from one to six months. Sorting on Book-to-Market often takes place once a year, and the resulting portfolios are held for one year. In the panel regressions the holding period will therefore be an important choice. If we wish to test prediction over a horizon of M months, we construct y_{it} as the cumulative return over M months. Though the explanatory variables x_{it} remain the same, different values of M give rise to different dependent variables. Obviously, parameter estimates, model selection, and predictive power will depend on M. For example, Book-to-Market may be an important predictive variable for medium length periods like six months, but have no explanatory power for one-month returns. When returns are measured over a horizon longer than the sampling interval, e.g. three-months returns with monthly data, the panel regression uses overlapping data and we must take the resulting autocorrelation in account. Details about estimation and inference are discussed in the following subsection.

2.2 Estimation and Testing

Estimation and testing are affected by a number of issues that are typical for panels with stocks returns. First, the panel is inherently unbalanced since stocks come, merge and go. Second, both N and T are large. In our application the cross sectional dimension N_t ranges between 600 and 1100 companies, whereas $T = 200$ months. Third, the errors e_{it} are likely to be strongly cross sectionally correlated even after including the time effects $\lambda_{\ell t}$. Because of the large cross sectional dimension, it will be infeasible, however, to estimate the cross sectional error covariance matrix. As a consequence we can not derive an optimal efficient estimator and we must be careful in estimating the parameter standard errors.

Instead of the infeasible optimal GMM estimator we estimate the parameters by OLS. The time effects cause the characteristics to be in deviation of the cross sectional average, either the full cross section of all N_t stocks, or an industry specific average when $\lambda_{\ell t} = \lambda_t$. In addition, when individual effects are also included, the estimator for β corrects for both the cross sectional as well as the time series average of y_{it} and x_{it}. The computational details of the data transformations in an unbalanced panel with two-way effects can be found in Baltagi (2001, ch 9) and Wansbeek and Kapteyn (1989). Estimators of fixed effects in unbalanced panels are derived in the Appendix.

Other panel studies, for example Haugen and Baker (1996) and Brennan, Chordia and Subrahmanyam (1998), estimate the parameters by the Fama and MacBeth (1973) procedure. The estimator is defined as the time series average of a series of T cross sectional regressions, ignoring the individual effects,

$$\hat{\mathbf{b}}_{FM} = \frac{1}{T}\sum_t \hat{\mathbf{b}}_t \tag{7}$$

$$\hat{\mathbf{b}}_t = \left(X_t' Q_t X_t\right)^{-1} X_t' Q_t y_t, \tag{8}$$

where y_t is the N_t-vector containing the returns in period t, X_t is an $(N_t \times KL)$ matrix containing the explanatory variables, $\mathbf{b}$ the KL-dimensional vector of parameters containing β_ℓ, $(\ell = 1, \ldots, L)$ and

$$Q_t = I - J_t(J_t' J_t)^{-1} J_t \tag{9}$$

is an $(N_t \times N_t)$ matrix that eliminates the time effects in which J_t is the $(N_t \times L)$ matrix of industry dummies $D_{i\ell}$ for the stocks that are in the panel at time t. For comparison, the standard OLS estimator for $\mathbf{b}$ in a model without individual effects is a matrix weighted average of the Fama-MacBeth cross-sectional $\hat{\mathbf{b}}_t$,

$$\hat{\mathbf{b}}_{OLS} = \left(\sum_t X_t' Q_t X_t\right)^{-1} \sum_t X_t' Q_t X_t \hat{\mathbf{b}}_t, \tag{10}$$

The OLS estimator gives equal weight to each data point instead of equal weight to each time period. This means that periods with much cross sectional dispersion in characteristics will be more influential. Likewise, months with larger cross sections will be more influential for estimating $\mathbf{b}$. Since the number of stocks in the panel has grown over time, the more recent periods have a relatively large weight in the estimator compared to the Fama-MacBeth estimator. Without individual effects both estimators are consistent, but not necessarily efficient. In a two-way panel with individual effects the Fama-MacBeth estimator suffers from omitted variables bias if individual effects are correlated with the explanatory variables.

Another variation of the least squares estimator is weighted least squares in which time periods are weighted by their residual variance. If $\hat{\sigma}_t^2$ is the residual variance,

$$\hat{\sigma}_t^2 = \frac{1}{N_t}\hat{e}_t'\hat{e}_t, \tag{11}$$

with $\hat{e}_t$ the residuals from the OLS estimator, then the WLS estimator is defined as

$$\hat{\mathrm{b}}_{WLS} = \left(\sum_t \frac{1}{\hat{\sigma}_t^2} X_t' Q_t X_t\right)^{-1} \left(\sum_t \frac{1}{\hat{\sigma}_t^2} X_t' Q_t y_t\right), \tag{12}$$

We check the robustness of our estimation results by applying WLS and Fama-Macbeth methods to estimate the panel models, and comparing these results with the OLS results.

A further complication are the lagged returns among the predictive variables. It is well-known that lagged dependent variables cause biases in a dynamic panel data model. The bias arises from the elimination of the individual effects by subtracting the time series average of each stock. The bias disappears when T is large, as we assume, or if the individual effects μ_i are absent.

Prior to inference on the predictive characteristics x_{it} we must decide on the inclusion of individual effects and (industry specific) time effects. The number of individual and time effects grows as N or T becomes large. This implies that restrictions imposed on the individual or time effects cannot be tested reliably with standard test statistics. For model selection we therefore use the Schwartz information criterion (SC), defined as

$$SC = \ln s^2 + \frac{k}{n}\ln n, \tag{13}$$

where s^2 is the residual sum of squares of the estimated model, n is the total number of observations in the panel and k is the total number of parameters including all individual and time effects.[7] In the application we have more than 1100 firms and 200

[7] It is unknown however whether SC is a consistent model selection criterion in this panel. Bai and Ng (2002) provide some theoretical guidance on this question. Like us they consider a panel with large N and T. Their assumptions on the error terms are also appropriate for our panel. Most critical is the bound on the cross sectional covariance stating that the sum over all $\mathsf{E}[e_{it}e_{jt}]$ is at most of order N. They consider a factor model for which the number of parameters is of order $M(T+N)$ with M denoting the number of unobserved factors. Their interest is in estimating M. In our model the number of parameters is of order $N + LT$ and our interest is in whether we can exclude N of them that represent individual firm effects. A further interest is in whether we can exclude $(L-1)T$ parameters that represent industry specific time effects.

months of data. Allowing for missing values about 90,000 data points are available. With these values of N, T and n, and K fixed and small, the SC criterion will select a model with individual effects if the residual sum of squares is reduced by 14%. For comparison, the classical F-test will already be significant at the 1% level if the sum of squared residuals falls by less than 1%. The critical value of the F-test is misleading though, since the errors in (1) are very likely cross sectionally correlated, even after allowing for time effects $\lambda_{\ell t}$. The Schwartz criterion will be more conservative than the F-test.

The main interest is in the parameters β_ℓ, which determine the predictability of returns. The number of elements in β_ℓ does not change if N or T grows. Hypotheses on these slope parameters are tested using a Wald test. Since the errors exhibit cross sectional correlation, we use a robust estimator of the covariance matrix of $\hat{\beta}_\ell$ proposed by Driscoll and Kraay (1998) that only relies on large T. For the asymptotic variance we can not estimate the cross sectional error covariance matrix and must therefore rely on a time series estimator. As in Driscoll and Kraaij (1998) we use that

$$\text{Var}(\sqrt{T}(\hat{\mathbf{b}} - \mathbf{b_0})) = B^{-1}SB^{-1}, \tag{14}$$

where $B = \text{plim } \frac{1}{T}\sum_t X_t' Q_t X_t$,

$$S = N\mathsf{E}\left[\sum_{s=-M}^{M} h_{t-s}h_t'\right], \tag{15}$$

in which the time series of KL-vectors h_t are defined as

$$h_t = \frac{1}{\sqrt{N_t}} Z_t' Q_t e_t, \tag{16}$$

and N is the average cross sectional sample size. We estimate S using the Newey-West weights on the autocorrelations,

$$\hat{S} = \frac{N}{T}\sum_{s=-M}^{M}\left(1 - \frac{|s|}{M+1}\right)\sum_t \hat{h}_{t-s}\hat{h}_t', \tag{17}$$

where $\hat{h}_t$ uses the estimated residuals $\hat{e}_t$. Both the estimator $\hat{\mathbf{b}}$ and the covariance matrix estimator is straightforwardly modified for when some elements in $\mathbf{b}$ are pooled, or when individual effects are included. For the WLS estimator we divide y_t and X_t everywhere by $\hat{\sigma}_t$. In the absence of autocorrelation in the errors the estimator reduces to just the term with $s = 0$ in (17).

As additional evidence on the importance of individual effects we consider their cross sectional distribution and the cross sectional distribution of the t-statistics for each effect μ_i. Although we can estimate the individual t-statistics for $\hat{\mu}_i$, we can not estimate the $N \times N$ covariance matrix of all individual effects to perform a Wald test.

3 Data

The data set that we use is the US MSCI data universe. It covers the investable universe for most institutional investors since it contains relatively few small stocks. Because of this the size effect might not appear in the data. MSCI data are widely used in both academics (see for example Rouwenhorst (1998)) and in the investment profession. For firms followed by MSCI we also observe most characteristics, which implies that there are only few missing data. To be included in the MSCI data universe, firms must either be part of the MSCI index or must be actively followed by MSCI. The MSCI index covers about 70% of the stock market capitalization. With the additional followed firms we have a fairly complete picture of the US market capitalization. The sample period ranges from November 1984 until June 2002. The raw data set covers 1216 large companies. Each of the companies belongs to a specific industry. The total number of industries is 22.

Figure 1 shows the return from equally weighted and value weighted portfolios including all stocks from the data set. For comparison we plot the Fama-French value weighted index. The two series differ at only a few data points. Thus the MSCI data universe seems to be representative for the US market.

The number of company characteristics (regressors) used to predict stock returns varies a lot in different empirical studies. We have chosen nine regressors that have been common in the literature for ten years or more, have proved to contribute to the prediction of stock returns and capture different characteristics of the company. The nine explanatory variables fall into three groups:

Size: Size (MV) is measured as the relative market value of firm i as a percentage of all companies in the panel at time t.

Valuation ratios: We include the ratios book-to-price (BP), earnings-to-price (EP), dividends-to-price (DP), cash flow-to-price (CP) and sales-to-price (SP). These ratios capture the well known value effect.

Momentum: We introduce two groups of momentum variables. Price momentum includes the cumulative returns of the last 12 months (*RET12*) and over the last six months (*RET6*). Earnings momentum (analysts earnings revisions) is denoted as *CFY1* and captures the expectation revisions of financial analysts about next year's earnings of the stock. It is computed as the number of positive revisions minus the number of negative revisions, divided by the total number of revisions. The original source of the data is I/B/E/S.

Examples of each of the variables in the empirical literature are Fama and French (1992), Rosenberg, Reid and Lanstein (1985), Lakonishok, Shleifer and Vishny (1994), and Daniel and Titman (1997) for *MV*, *BP*, *EP* and *CP*, while momentum variables are used in Rouwenhorst (1998), and Jegadeesh and Titman (1993). Frankel and Lee (1998) focus on earnings momentum using I/B/E/S data. Chan et al (1996) discuss earnings momentum and price momentum using I/B/E/S data as well. Cochrane (2001) discusses the use of price ratios like *SP* and *DP* for prediction of stock returns. Chang et al (2002) find that an investment strategy based on *CFY1* yields positive abnormal returns in emerging markets, and negative abnormal returns in developed markets. Peterson and Peterson (1995) claim that near-term forecast revisions are significantly related to stock returns at the time of recommendation.

Fama and French (1997) focus on the industry costs of equity. A number of studies focus on the interaction between firm characteristics and industries and on the impact of this relation on cross-sectional stock return volatility. Dempsey et al (1993) find a significant relation between industry and dividend payout and thus between industry and *DP*. Moskowitz and Grinblatt (1999) claim that industry momentum strategies outperform momentum investment strategies after controlling for firm characteristics. Nijman et al (2002) discuss whether industries drive the momentum in Europe. Finally, Fama and French (1992) study the interaction between firm characteristics.

The number of companies per industry in the data set are reported in table 1. Some industries[8] only contain a few firms, indicating that we should be careful in defining industry specific parameters for these industries. Panel A of table 2 reports descriptive statistics of the data set. For the econometric analysis we delete all data points that contain either incomplete or missing data. This leads to a data set that contains 1165 companies and 95,136 data points which amounts to 36.3% of the

[8] These industries are Power Producers, Data Processing and Computer Service. The low number of firms in the last two industries can be explained with the high number of firms in the industry Technology Hardware.

number of data points for a complete panel, and to 90.2% of the number of data points for which the monthly return (RET) is observed.[9]

Descriptive statistics of the complete data are reported in panel B of table 2. Some characteristics like the valuation ratios have outliers. The outliers are milder compared to the ones in Panel A due to the deletion of incomplete data points. After inspection of the worst outliers we concluded that the outliers are real and not due to systematic deficiencies of the data or the companies. Since outliers in the valuation ratios have a strong influence on the regression results, we trimmed all outliers to the lower and upper 1% tail of the distribution.

As a preliminary test for predictability of the individual characteristics we form portfolios that are sorted on a single characteristic. Table 3 reports summary statistics for portfolios formed on each of the characteristics separately. At the beginning of each period we form a long and a short portfolio. For the characteristic x_{it} the long portfolio includes stocks for which x_{it} is above the cross sectional average $\bar{x}_t$, or above the cross sectional median value of x_t. The portfolio is either equally weighted or weighted by the characteristic x. Table 3 shows a statistically insignificant size effect. Price momentum is significant at the 10% level. The strongest predictive variable is *CFY1* capturing the analyst earnings revisions. Surprising is the very low predictability of all valuation ratios. In general, the signs of the t-statistics are as expected, but the only significant variable is *CFY1*.

We inspect whether the low predicting power of the valuation ratios and the price momentum is possibly due to industry effects. It is possible that the t-statistics in table 3 are insignificant because of the industry heterogeneity. Within each industry we construct equally weighted and characteristic weighted portfolios based on deviation from the average value, as described in the previous paragraph. Then each month we calculate the return from an equally weighted composite portfolio that includes returns from all equally weighted industry portfolios. Further, we calculate the monthly returns from a value weighted composite portfolio that includes returns from all value weighted industry portfolios. The industry portfolios are weighted according to the total market value of the respective industry. Panel C of table 3 reports the results from this industry neutral portfolio construction. Valuation ratios have higher t-statistics than the ones in panel A. In contrast to the strategy that

[9] Deletion of incomplete data points leads to a loss of information. Imputation methods, reviewed in Kofman and Sharpe (2003), could increase the efficiency of the estimator. Since only 9.8% of the data is incomplete we have not pursued the imputation estimator.

does not correct for industry effects (panel A of table 3) the characteristics *CP* and *RET12* are significant at the 5% level. This simple analysis shows the importance of the industry effects and motivates us to focus on the possibility of capturing these effects in a panel data model.[10]

4 Results

We have estimated the general specification (1) and several restricted versions. The models have been estimated both with the full panel and a number of smaller panels that excludes all firms with less than 60 observations. An overview of the results is presented in table 4. Parameter estimates for models with pooled β's are reported in table 5. Other results are presented in a series of graphs and additional tables.

4.1 Individual Effects

We compare the Schwartz criterion (SC) for a group of models that are similar except for the intercept. The first model in each group contains individual effects, the second model only has industry specific intercepts, the third only has a pooled time effect. The model specifications to be compared are different with respect to whether the time effects $\lambda_{\ell t}$ are pooled over industries. Further, some model specifications do not include any time effects. The coefficients β_ℓ are not pooled over industries.

The left panel of table 4 reports values of the SC for all models that predict monthly returns. In all cases the Schwartz criterion prefers the model without individual effects to the same model with individual effects μ_i.[11] Figure 2 shows histograms of the estimated individual effects of firms belonging to twelve sectors. The histograms of the rest eight sectors are not much more different and are available upon request.

For the 5% largest estimates (in absolute value) we checked on how many observations the estimate of the individual effect was based. Figure 3 shows the histogram

[10] We checked the possibility of monthly firm characteristics to forecast cumulative returns over three and six months. Using three and six month returns instead of monthly returns we repeated the analysis that is shown in table 3. In general the t-statistics are similar. The earnings momentum *CFY1* is insignificant in portfolios that are not industry neutral. The price momentum *RET6* is significant in industry neutral portfolios. Details on all results with longer forecasting horizon are available upon request.

[11] Alternatively we estimated all models using data for all companies that were included in the US S&P index from January 1990 until January 2002. The ranking of the models is identical to the one shown in table 4. Detailed results are available upon request.

of the number of observations per outlier, and compares it with the histogram of the number of observations per company for the entire data set. It appears that most of the large individual effects correspond to companies for which we have only few observations. We therefore redid the model selection after deleting all firms with less than 60 observations (5 years). The estimation results are reported in panel B of table 4. Although the number of firms is reduced by about 400, none of the results changes. The Schwartz criterion still prefers the models without individual effects. We conclude that individual effects are not important, consistent with the findings of Jegadeesh and Titman (2002).

The middle and right panels of table 4 report values of the SC for all models that predict three month returns and six month returns, respectively. The panels show that the SC-ranking and our finding that individual effects are not important are robust to the forecasting horizon. This is also confirmed by the SC-ranking of models with pooled coefficients (not reported here).

4.2 Industry Effects

Table 4 shows that the Schwartz criterion always prefers the model with pooled time effects λ_t compared to the same model with industry specific time effects $\lambda_{\ell t}$. Further, since the Schwartz criterion always prefers the model with industry effects compared to the same model with individual effects, we focus on models without individual effects.

We test whether the coefficients and the intercepts are industry specific or can be pooled. The overall null hypothesis is that $\beta_\ell = \beta$ for all industries and all characteristics. The test is based on the general model:

$$y_{it} = \sum_{\ell=1}^{L} D_{i\ell} \left(x_{it}\beta_\ell + \lambda_{\ell t} \right) + e_{it}. \tag{18}$$

The robust Wald statistic for the 176 restrictions in this hypothesis is 973.6, rejecting the null hypothesis at any reasonable significance level.

For a more detailed analysis of the cause for the rejection we inspect each industry and each characteristic separately. Firstly, we test whether each characteristic has the same coefficients across industries. Tables 5, 6 and 7 report the pooled estimates of β for different models that predict one, three and six month returns, respectively. Table 8 reports the test statistics of the null hypothesis $\beta_{j\ell} = \beta_j$ for each characteristic separately. For monthly returns the null hypotheses are rejected at the 95%

confidence level in all model specifications for the price ratios *BP*, *CP*, *EP* and *SP*. Rejections of the null hypothesis for other characteristics are not robust across alternative specifications for the time effects. In the case of industry specific time effects, the null hypotheses are rejected also for *DP* and the momentum variables *RET6* and *RET12*. In the first three model specifications the null is never rejected for MV and *CFY1*.

For three and six month returns the null hypothesis $\beta_{j\ell} = \beta_j$ is rejected for almost all characteristics. The null hypothesis is not rejected for MV in the models without industry specific time effects and for *CFY1* in all models that predict three month returns. We conclude that the characteristic coefficients vary across industries. The differences across industries cannot be captured in characteristics over a very short horizon. If the horizon increases, these differences are better captured by the characteristics and thus the model coefficients vary more across industries. Since industries are related to the business cycle, the differences among them become visible over a longer period that captures (a part of) the business cycle.

Further we test the null hypothesis that all coefficients in the respective pooled model specifications are equal to zero. The alternative is that at least one coefficient is different from zero. The heteroskedasticity robust Wald-statistics for all forecast horizons are reported in the last line of table 8. They all exceed the 99% critical value of 21.67. Thus although the coefficients are not significant in the pooled model specification, the characteristics have predictive power in the industry specific model. In general when the forecast horizon grows, the respective χ^2-statistic increases.

It is remarkable that only a few characteristics seem to have significant predictive power in the models without individual effects that predict monthly returns (the first three specifications in table 5). The size effect (MV) is never significant. The CP ratio (*CP*), the twelve months momentum (*RET12*) and the analyst earnings revisions (*CFY1*) are significant and have the same sign as in the portfolio strategies reported in table 3. Even the standard errors of the effects are very similar.[12] The momentum variable *RET6* is never significant. This could be related to the correlation between momentum and earnings revisions. Mixon (2001) observes a similar phenomenon when sorting stocks both on momentum and earnings revisions. The two characteristics combined do not outperform a single sort on earnings revisions.

Tables 6 and 7 report the estimates of β for the three and six month returns,

[12] The coefficients of *RET12* have low absolute values because *RET12* is defined as cumulative returns for twelve months, while the dependent variable is monthly returns.

respectively. The valuation ratios are more important than for monthly returns. For example *CP* is always significant and *BP* is significant in six out of ten cases. The economic intuition can be that valuation ratios vary more over periods of three and six months because firm financial indicators (the nominators of the valuation ratios) are announced quarterly. The twelve month price momentum *RET12* is insignificant in models with longer forecast horizon. On the other hand the six month price momentum *RET6* is significant in all models that forecast six month returns. This result is consistent with Rouwenhorst (1998) who finds that holding stocks for six months yields the highest returns if the stocks are sorted on the *RET6*.

As a robustness check the last two columns of table 5 report results for models constructed by adding individual effects μ_i to the models from the first two columns. A comparison between the first and the fourth column and between the second and the fifth column reveals that the coefficients and the standard errors of the price momentum and the earnings momentum do not depend on the inclusion of individual effects μ_i. This finding is consistent with the results of Jegadeesh and Titman (2002) who claim that cross sectional differences in expected return do not explain profits from momentum strategies. Further, if individual effects are included, *MV*, *BP* and *SP* are always significant. Tables 6 and 7 report the same results for three and six month returns.

The industry specific coefficients and the t-statistics for the first three models in table 5 are shown in figures 4 and 5.[13] The figures show results for the industry intercept and five characteristics.[14] The first thing we observe is that coefficient estimates do not depend much on the specification of the time effects. Only industry specific time effects sometimes lead to higher t-statistics for some of the characteristics. Both the coefficients and the t-statistics are very different across industries. The biggest outlier is the 18^{th} industry (Data Processing), but this might be due to the low number of firms belonging to that industry. Still the coefficients and the t-statistics vary a lot across industries with high number of companies. It is interesting that the coefficients and the t-statistics of the two financial industries are not much different from those of the other industries. This is interesting provided that most finance studies exclude the financial industries from the empirical analysis.

[13] In the graphs industry 21 (Power Producers) is omitted. This industry contains only four firms and has extreme outliers for most of the parameter estimates that would greatly distort the scale of the graphs.

[14] The results for the other four characteristics are not much more different and are available upon request.

We conclude that industries matter. Using the industry specific intercepts and coefficients we can correct for industry heterogeneity and make within and between industry predictions.

4.3 Robustness to the Estimation Method

4.3.1 WLS Estimation

Panel C of table 4 reports the results from WLS estimation based on equation (12). The model ranking in terms of the *SC* is identical to the OLS results for all forecasting horizons. Our findings on individual, industry and time effects are robust to the choice of the estimation method.

In the first three columns of table 9 we report WLS estimation results of three models with pooled coefficients. For each characteristic we report the estimated coefficient, its standard error and the respective t-statistic. The OLS estimation results for the same model specifications are reported in table 5. A comparison between the two tables shows that the coefficients and their significance are similar, with exception of *MV*. Another difference is that the WLS coefficients of *CFY1* and *RET12* are significant at the 5% level in the fully pooled model. Without pooling WLS does not perform better than OLS, as shown by comparison of columns 2 and 3 of table 5 with columns 2 and 3 of table 9.

We estimated with WLS the same pooled coefficient models for longer forecast horizons. The results show that our findings are robust to the choice of estimation method.

Finally, we estimated residual variances specific for each month and industry. WLS estimations based on this assumption rank the models in the same way.

4.3.2 Fama-MacBeth Estimation

In this section we report results from the Fama-MacBeth estimation technique that as discussed in section 2. The last two columns of table 9 report Fama-MacBeth estimators for a fully pooled model and a model with pooled time effects. A comparison between the first two and the last two columns of table 9 reveals that the Fama-MacBeth standard errors are always lower than the Driscoll-Kraay standard errors.[15] The six month momentum *RET6* becomes significant and the other results

[15] On the other hand Jagannathan and Wang (1998) warn that the Fama-MacBeth procedure often underestimates the standard errors.

are very similar.

We performed the same analysis for models that predict three and six month returns. The resulting coefficients and statistics show that our conclusions are robust to the choice of estimation method.

In conclusion, we find that some firm characteristics have predicting ability. Industry effects are important. These findings are robust to the estimation method.

5 Portfolio Management Implications

The panel models are meant to explain the cross sectional variation in returns. To investigate the implications of the model we consider the time series returns for a number of long-short portfolios. For all models we construct the fitted values,

$$\hat{y}_{it} = \sum_{\ell=1}^{L} \left(D_{i\ell} x_{it}' \hat{\beta}_\ell \right), \tag{19}$$

and restricted versions with β_ℓ equal across industries. Individual effects and (industry specific) time effects are not part of the predictions. We do not make absolute forecasts, but only relative predictions. A pooled time effect λ_t drops out in comparing $\widehat{y}_{it}$ and $\widehat{y}_{jt}$. We consider both models with a pooled time effect λ_t and models with industry specific time effects $\lambda_{\ell t}$. Portfolio construction differs for both specifications. With a pooled time effect we sort all stocks, while with industry specific time effects we sort stocks separately within each industry.

Each period the fitted $\hat{y}_{it}$ are sorted in decreasing order. We construct both equally weighted and value weighted portfolios. For the equally weighted portfolios we allocate the top (bottom) 30% of the sorted stocks to a long (short) portfolio with equal weights. For the value weighted portfolios, the long (short) portfolio contains the best (worst) stocks in proportion to their market weight with the total weight adding up to 30%. The number of stocks in the value weighted portfolios can therefore differ from the number of stocks in the equally weighted portfolio. Long and short portfolios are constructed each month.

Portfolios based on models that predict cumulative returns for c months are constructed as follows. Each month we predict the returns for the following c months, sort the stocks on the predicted returns and assign them to long and short portfolios using the procedure described in the previous paragraph. The stocks remain in the respective portfolio for the following c months. The next month we repeat this procedure and assign new stocks to the existing long and short portfolios.

Since λ_t is the same for all stocks, the difference between the returns from the long and short portfolios does not depend on the time effect. Any pattern in the long-short portfolio is therefore solely due to the characteristics and the industry effects. For models with an industry specific time effect $\lambda_{\ell t}$ we compare firms within the same industry. We do not attempt to predict the difference $\lambda_{\ell t} - \lambda_{kt}$ for firms belonging to industries ℓ and k, respectively. An overall portfolio is constructed by adding all the industry specific long-short portfolios. For an equally weighted portfolio the industry returns are aggregated weighted by the number of stocks in the industry; for the value weighted portfolio the industry returns are weighted proportionally to the market weight for each industry. For the model with the industry specific time effects the aggregate portfolio is industry neutral. Stock picking is active only within industries.

Table 10 reports descriptive statistics of the long-short portfolio returns for various model specifications and forecasting horizons. The average returns of the long and short portfolios are significantly different for all model specifications. All long and short portfolios, for all forecasting horizons, generate average returns that are significant at the 1% significance level. For all forecasting horizons the differences are larger than those for the portfolios in table 3 that are sorted on a single characteristic. Combining different characteristics enhances the cross sectional differences. For the value weighted portfolio the average for the long-short portfolio is more than one percent per month, which is the same order of magnitude as the average excess return from the market portfolio. The return differences for the equally weighted portfolios are much bigger in all cases.

Table 10 shows a clear pattern across the specifications of the panel model that is valid for all forecasting horizons. For the fully pooled model with a single β for all industries, the average return from the long-short portfolio is less than the average return for the models with industry specific slopes β_ℓ. Also the ratio of average return to the standard deviation is lowest for the portfolios with a pooled β.

Comparing the second and the third lines of each panel of table 10 reveals that the industry neutral portfolio has a lower average for the long portfolio and a higher average for the short portfolio. The spread between the long and short portfolio is reduced by the restriction of industry neutrality. At the same time the industry neutral portfolios also have a much lower variance. Again this is a result of the forced industry neutrality in panels with industry specific time effects $\lambda_{\ell t}$. The unrestricted portfolios involve considerable industry bets. In some periods the highest (lowest) expected returns are concentrated in specific industries. This confirms the results of Moskowitz and Grinblatt (1999), who showed that momentum effects were often caused by industry momentum.

For a closer look at these returns we consider the profiles of the portfolios. Table 11 reports the average characteristics of the long and short portfolios. Consistent with the parameter estimation results in table 5 the most distinctive characteristic is the annual analyst earnings revision. Other characteristics associated with returns differences are the momentum variables *RET6* and *RET12*. Furthermore there is a small size effect. The price ratios have discriminatory power which is higher than the one implied by table 5.

We considered profiles of portfolios based on three and six month forecasting. In general the profiles are similar to the profiles of monthly based portfolios but there are some systematic differences. In contrast to monthly portfolios the fundamental characteristic *MV* is always associated with return differences for all three and six month portfolios and the respective t-statistics are significant at the 1% significance level. The earnings momentum *CFY1* is significant but the respective t-statistics are two times lower than the ones for the respective monthly portfolios. This shows that analyst forecasts influence strongly short run stock returns, but this influence is smaller for middle run stock returns. The economic intuition can be that in the short run investors (and stock prices) are influenced by the analyst forecast. On the other hand, analyst forecasts are often erratic, they randomly push the stock price up and down, and these fluctuations mutually compensate in the middle run. The six month momentum *RET6* is always associated with return differences for all six month portfolios and the respective t-statistics are significant at the 1% significance level. This evidence is consistent with the findings of Rouwenhorst (1998). Our findings for the three momentum characteristics are consistent with the results of Chan et al (1996) who document that earnings momentum influences stock returns mostly in the short run, while price momentum influences stock returns mostly in the middle run.

Expected returns are persistent. Many of the explanatory variables move only slowly over time or are constant (industry dummies). As a result the portfolio composition remains fairly stable from month to month. The upper left panel of table 12 reports the transition frequencies of stocks going from one portfolio to the other for portfolios based on monthly forecasting. For the strategies that can select stocks from the complete universe, about 80% of the stocks that are in the long portfolio at time t remain in the long portfolio at time $t+1$. Persistence for the stocks in the short portfolio is slightly lower - about 75% of the stocks that are in the long portfolio at time t remain in the long portfolio at time $t+1$. The stocks from the neutral portfolio are equally re-distributed to the long and short portfolios - about 15% of the stocks that are in the neutral portfolio at time t move to the long portfolio at time $t+1$, and the same percentage moves to the short portfolio. New stocks are equally distributed among the long, the neutral and the short portfolio.[16] In the other hand the industry neutral portfolios are less stable. The best stocks within an industry change more rapidly than the overall best stocks. Part of the explanation for this effect are the constant industry intercepts which give some industries a permanent expected advantage over other industries.

The lower panels of table 12 report the transition frequencies of stocks going from one portfolio to the other for portfolios based on three and six month forecasting. All qualitative findings on turnover that are reported in the previous paragraph (one month forecasting) apply also for turnover of portfolios based on two, three and six month forecasting. On the other hand the persistence of such portfolios is drastically increased - for example the persistence of the long (short) portfolio increased from 78% (77%) to 95% (94%) when the forecasting horizon grows from one month to three months. It is interesting that the turnover abruptly falls as soon as the forecast horizon increases from one month to two months.

The results reported by tables 10 and 12 show that when we increase the forecasting horizon we do not lose returns and simultaneously drastically decrease the portfolio turnover.

For our final results we run performance attribution regressions of the long-short portfolio returns on the value weighted market portfolio, the Fama-French factors *SMB* and *HML* and the momentum factor *UMD*.[17] The upper panel of table 13 reports results for portfolios based on models that predict monthly returns. The coefficients and their significance are similar across specifications. The portfolios do not have a significant exposure to the market index with a beta around 0.10. The exposure to *SMB* is low, consistent with the small explanatory power of size

[16] Stocks are only included in the regressions if they are in the data set for at least a year. This is the first time that the momentum variable *RET12* can be computed.

[17] Data for these factors are all obtained from the Fama-French database maintained by Professor Kenneth French at the Tuck School of Business at Dartmouth:
`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

in the panel regressions and with the low size effect documented in table 3. Only portfolios based on a pooled model with industry specific intercepts have substantial positive exposure to *UMD*. Surprisingly, given the panel regression results and the portfolio profiles, there is an exposure to *HML*, which is lower for the value weighted portfolios. The performance regressions have a significant alpha intercept in all cases and regardless of the included risk factors. This result shows that the portfolios have inherent positive return that is not based on factor bets. Abnormal returns for the value weighted portfolios are much lower than for the equally weighted portfolios.[18] On the other hand value weighted portfolios have less factor exposures than their equally weighted counterparts.

The middle and the lower panels of table 13 report results for portfolios based on models that predict tree month and six month returns, respectively. The intercepts are positive and significant at the 1% significance level. In contrast to portfolios based on monthly forecast horizon, all portfolios based on longer forecast horizon are significantly exposed to value and momentum and not to the market index. All equally weighted portfolios are exposed to the value factor, in contrast to most value weighted portfolios.

6 Conclusion

We perform specification tests in unbalanced panel data models for forecasting of stock returns. We find that the industry effects in the panel are significant and interact with firm characteristics. The industry specific intercepts and coefficients correct for the industry heterogeneity and enable within and between industry predictions. These findings are robust to the estimation method and the data set.

In-sample simulations of portfolio construction strategies based on models that predict monthly returns imply that the resulting long-short portfolios earn substantial abnormal returns with a limited exposure to market risk and size, but moderate exposure to value and momentum factors. Increasing the forecasting horizon drastically reduces the portfolio turnover without deteriorating performance. The resulting long-short portfolios earn significant abnormal returns and have significant exposure to size, value and momentum. How well the strategy works in an out-of-sample

[18] This could be related to the estimation of the model. All panels have been estimated with equal weights for all stocks in the sample. Weighted least squares could produce different results. We have not yet checked this.

environment and with transaction costs is an open question.

Appendix A Fixed Effects in an Unbalanced Panel

In this appendix we derive estimators of individual and time effects in unbalanced two-way error component models. Consider an unbalanced panel data specification with individual effects and pooled coefficients and time effects,

$$y_{it} = \mu_i + x'_{it}\beta + \lambda_t + e_{it}. \tag{A1}$$

The coefficient vector β is estimated following the methodology proposed by Wansbeek and Kapteyn (1989). Define $u_{it} = y_{it} - x_{it}\hat{\mathbf{b}}$. To obtain λ_t and μ_i we compute the cross sectional and time series averages of u_{it} over all available observations:

$$\bar{u}_{i.} = \frac{1}{T_i}\sum_{t\in\mathcal{P}_i} u_{it} = \mu_i + \frac{1}{T_i}\sum_{t\in P_i}\lambda_t, \tag{A2}$$

$$\bar{u}_{.t} = \frac{1}{N_t}\sum_{i\in\mathcal{C}_t} u_{it} = \lambda_t + \frac{1}{N_t}\sum_{i\in\mathcal{C}_t}\mu_i. \tag{A3}$$

where T_i is the number of months company i is observed, N_t is the number of companies observed in month t, and $\mathcal{P}_i$ is the set that contains the numbers of all months when company i is observed and $\mathcal{C}_t$ is the set that contains the numbers of all firms observed in month t. Equations A2 and A3 result in a linear system of $N+T$ equations and $N+T$ unknowns. Due to the underidentification of μ_i and λ_t we need to impose one restriction and delete one of the equations.

References

Baca, S.P., L.P. Garbe, and R.A. Weiss (2000), The Rise of Sector Effects in Major Equity Markets, *Financial Analysts Journal*, 34–40.

Bai, J. and S. Ng (2002), Determining the Number of Factors in Approximate Factor Models, *Econometrica*, **70**, 191–221.

Baltagi, B.H. (2001), *Econometric Analysis of Panel Data*, Wiley.

Bodie, Z., A. Kane, and A. Marcus (2002), *Investments*, Irwin/McGraw-Hill, 5^{th} ed..

Brennan, M.J., T. Chordia, and A Subrahmayam (1998), Alternative Factor Specifications, Security Characteristics and the Cross-Section of Expected Returns, *Journal of Financial Economics*, **49**, 345–373.

Campbell, J.Y., A.W. Lo, and A.C. MacKinlay (1997), *The Econometrics of Financial Markets*, Princeton University Press.

Campbell, J.Y. and T. Vuolteenaho (2002), Bad Beta, Good Beta, Harvard University working paper.

Cavaglia, S., C. Brightman, and M. Aked (2000), The Increasing Importance of Industry Factors, *Financial Analysts Journal*, 41–54.

Cavaglia, S. and V. Moroz (2002), Cross-Industry, Cross-Country Allocation, *Financial Analysts Journal*, 1–20.

Chan, L.K.C., N. Jegadeesh, and J. Lakonishok (1996), Momentum Strategies, *Journal of Finance*, **51**, 1681–1713.

Chang, M., I. Dallas, and J. Ng (2002), Analyst Forecast Revisions and Asset Allocation in Asia-Pacific Markets, *Journal of Multinational Financial Management*, **12**, 391–409.

Cochrane, J.H. (2001), *Asset Pricing*, Princeton University Press.

Cohen, R. and C. Polk (1998), An Investigation of the Impact of Industry Factors in Asset-Pricing Tests, Harvard working paper.

Daniel, K. and S. Titman (1997), Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, *Journal of Finance*, **52**, 1–33.

Davis, J.L., E.F. Fama, and K.R. French (2000), Characteristics, Covariances and Average Returns: 1929 to 1997, *Journal of Finance*, **55**, 389–406.

De Bondt, W.F.M. and R.J. Thaler (1985), Does the Stock Market Overreact?, *Journal of Finance*, **40**, 793–805.

Dempsey, S.J., G. Laber, and M.S. Rozeff (1993), Dividend Policies is Practice: Is there an Industry Effect?, *Quarterly Journal of Business and Economics*, **32**, 3–13.

Driscoll, J.C. and A.C. Kraay (1998), Consistent Matrix Estimation with Spatially Dependent Panel Data, *Review of Economics and Statistics*, **80**, 549–580.

Fama, E.F. and K.R. French (1992), The Cross-Section of Expected Stock Returns, *Journal of Finance*, **47**, 427–465.

Fama, E.F. and K.R. French (1996), Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance*, **51**, 55–84.

Fama, E.F. and K.R. French (1997), Industry Costs of Equity, *Journal of Financial Economics*, **43**, 153–193.

Fama, E.F. and J.D. MacBeth (1973), Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy*, **71**, 607–636.

Frankel, R. and C.M.C. Lee (1998), Accounting valuation, marjet expextation, and cross-sectional stock returns, *Journal of Accounting and Economics*, **25**, 283–319.

Grinold, R.C. and R.N. Kahn (1999), *Active Portfolio Management*, Irwin, 2^{nd} ed.

Haugen, R.A. (1999), *The New Finance: The Case against Efficient Markets*, Prentice Hall, 2^{nd} ed.

Haugen, R.A. (2001), *Modern Investment Theory*, Prentice Hall, 6^{th} ed.

Haugen, R.A. (2002), *The Inefficient Stock Market*, Prentice Hall, 2^{nd} ed.

Haugen, R.A. and N. Baker (1996), Commonality in the Determinants of Expected Stock Returns, *Journal of Financial Economics*, **41**, 401–439.

Heston, S.L. and K.G. Rouwenhorst (1994), Does Industrial Structure Explain the Benefits of International Diversification, *Journal of Financial Economics*, **36**, 3–27.

Hodrick, R.J. and Z. Zhang (2001), Evaluating the Specification Errors of Asset Pricing Models, *Journal of Financial Economics*, **62**, 327–376.

Jagannathan, R. and Z. Wang (1998), An Asymptotic Theory for Estimating Beta-Pricing Models Using Cross Sectional Regression, *Journal of Finance*, **53**, 1285–1309.

Jegadeesh, N. and S. Titman (1993), Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance*, **48**, 65–91.

Jegadeesh, N. and S. Titman (2001), Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance*, **56**, 699–720.

Jegadeesh, N. and S. Titman (2002), Cross-Sectional and Time Series Determinants of Momentum Returns, *Review of Financial Studies*, **15**, 143–157.

Kofman, P. and I. Sharpe (2003), Using multiple imputation in the analysis of incomplete observations in Finance, *Journal of Financial Econometrics*, **1**, 216–249.

Lewellen, J. (1999), The Time Series Relation among Expected Return, Risk, and Book-to-Market, *Journal of Financial Economics*, **54**, 5–43.

Lewellen, J. (2002), Predicting Returns with Financial Ratios, MIT working paper.

Mixon, S. (2001), Earnings Revisions and Portfolio Returns, *Journal of Investing*, **10**, 33–41.

Moskowitz, T.J. and M. Grinblatt (1999), Do Industries Explain Momentum?, *Journal of Finance*, **54**, 1249–1290.

Nijman, T., L. Swinkels, and M. Verbeek (2002), Do Countries or Industries Explain Momentum in Europe?, forthcoming in *Journal of Empirical Finance*.

Peterson, D. and P. Peterson (1995), Abnormal Returns and Analysts' Earnings Forecast Revisions Associated with the Publication of "Stock Highlights" by Value Investment Survey, *Journal of Financial Research*, **18**, 465–477.

Rouwenhorst, K.G. (1998), International Momentum Strategies, *Journal of Finance*, **53**, 267–284.

Rouwenhorst, K.G. and S. Heston (1995), Industry and Country Effects in International Stock Returns, *Journal of Portfolio Management*, **21**, 53–58.

Wansbeek, T.J. and A. Kapteyn (1989), Estimation of the Error Components Model with Incomplete Panels, *Journal of Econometrics*, **41**, 341–361.

Table 1: Summary Statistics by Industry

The first column reports the MSCI industry classification. The second column describes the industry. The column "All firms" refers to the number of companies available per industry. The column "Included firms" reports the number of companies remaining after deletion of missing or incomplete data points. The fifth column reports the number of data points per industry. The last four columns report the average returns ($\bar{R}$) and the standard deviations ($\sigma(R)$) of equally weighted (EW) and value weighted (VW) industry portfolios. Average returns and standard deviations are measured in percents per month.

		All	Included	Data	EW port.		VW port.	
Code	Industry description	firms	firms	points	$\bar{R}$	$\sigma(R)$	$\bar{R}$	$\sigma(R)$
1	Basic Materials	73	71	7798	1.27	5.76	1.57	6.13
2	Automobiles	26	26	2651	1.39	6.92	1.59	7.12
3	Consumer	59	59	5609	1.30	5.72	1.73	5.83
4	Retail	96	91	7317	1.57	7.05	2.09	6.74
5	Commercial	35	34	1614	1.31	7.47	1.68	7.90
6	Food and Consumer	72	69	7445	1.79	4.83	1.97	5.08
7	Specialty	10	9	1347	1.26	5.89	1.66	6.12
8	Services	33	32	2449	1.59	5.90	1.82	5.51
9	Health Care	113	108	7795	1.76	6.20	1.98	5.27
10	Oil and Gas	56	55	4939	1.30	7.35	1.44	4.89
11	Banking and Insurance	111	104	6800	1.80	5.71	1.91	6.03
12	Diversified Financials	75	68	3833	1.53	5.71	2.06	6.41
13	Capital Goods	37	35	3768	1.33	5.87	1.71	5.80
14	Machinery-Diversified	55	51	5056	1.49	6.10	1.73	5.84
15	Technology Hardware	218	214	12859	1.50	9.54	2.06	8.03
16	Semiconductors	15	15	910	2.62	17.00	3.20	16.90
17	Computer Services	10	10	776	1.46	8.72	1.79	8.21
18	Data Processing	9	9	605	2.11	6.91	2.00	6.30
19	Telecom	26	22	1566	0.78	7.44	1.38	5.68
20	Utilities	58	52	6496	1.12	4.29	1.28	4.58
21	Power Producers	4	4	275	0.45	11.48	0.66	11.34
22	Transport	27	27	3228	1.35	6.46	1.53	6.01

Table 2: Summary Statistics of All Characteristics

Panel A reports descriptive statistics of the raw data set. Panel B reports descriptive statistics for the subset of complete data points. An observation is complete if all variables are available for that observation.
The first column reports the names of the variables and namely return (*RET*), size (*MV*), book-to-price (*BP*), cash flow-to-price (*CP*), dividend-to-price (*DP*), earnings-to-price (*EP*), sales-to-price (*SP*), analyst earnings revisions (*CFY1*), 6-month momentum (*RET6*) and 12-month momentum (*RET12*).

Variable	Average value	Standard deviation	Minimum value	1^{st} quantile	Median value	99^{th} quantile	Maximum value
A – All 1216 companies							
RET	1.28	14.38	-96.55	-37.04	1.08	43.02	640.74
MV	0.0020	0.0040	2.1×10^{-7}	8.93×10^{-6}	0.0008	0.0220	0.1000
BP	0.52	0.96	-46.39	-0.22	0.43	2.30	112.08
CP	0.34	42.9	-31.10	-0.35	0.09	0.67	8337
DP	0.02	0.06	0	0	0.01	0.10	4.30
EP	-0.004	0.830	-120	-0.900	0.050	0.200	2.880
SP	1.56	4.47	0	0.03	0.88	10.95	918.30
CFY1	-0.08	0.75	-1	-1	0	1	1
RET6	7.51	35.85	-99.04	-67.33	5.79	118.80	1813.70
RET12	16.36	60.26	-99.65	-80.21	10.86	222.43	2619.40
B – 1165 companies with complete data							
RET	1.29	14.39	-96.55	-36.81	1.09	43.05	640.74
MV	0.002	0.004	3.45×10^{-7}	9.9×10^{-6}	0.001	0.022	0.100
BP	0.50	0.72	-21.58	-0.19	0.42	2.17	88.21
CP	0.11	0.25	-7.07	-0.33	0.10	0.65	23.20
DP	0.02	0.06	0	0	0.01	0.09	4.3
EP	0.01	0.46	-44	-0.79	0.05	0.20	2.88
SP	1.49	2.97	0	0.03	0.88	10.20	226.97
CFY1	-0.07	0.75	-1	-1	0	1	1
RET6	7.73	35.30	-96.83	-65.97	5.85	119.40	1463.10
RET12	17.05	60.74	-99.15	-78.87	13.04	225	2619.40

Table 3: Average Returns on Characteristic Sorted Portfolios

The table reports the average return of long and short portfolios based on sorting by deviation from a specific threshold $\bar{x}_t$ for each characteristic x. The long portfolio includes all stocks for which $x_{it} - \bar{x}_t \geq 0$. The short portfolio includes stocks for which $x_{it} - \bar{x}_t < 0$. The first four columns report average returns for equally weighted portfolios of the stocks in the short and long portfolio formed on x_{it}, the standard deviation ($\sigma(L-S)$) of the respective long minus short portfolio, and the t-statistic for testing the equality of the mean returns of the long and short portfolios. The characteristic weighted portfolio averages are computed by weighting stocks proportionally to $x_{it} - \bar{x}_t$, so that the weights for each pair of long and short portfolio sum up to one. The results for characteristic weighted portfolios are reported in the last four columns. The t-statistics are adjusted for autocorrelation. In panel A and C the threshold $\bar{x}_t$ is equal to the cross-sectional average at time t for the respective characteristic, while in panel B it is equal to the cross-sectional median value. Panel C reports results for industry neutral portfolios. Portfolios are first constructed within each industry as described above and then aggregated with weights proportional either to the number of firms in the industry or to the market weight of the industry.

	Equally weighted				Characteristic weighted			
Variable	Short	Long	$s_{(L-S)}$	t-stat	Short	Long	$s_{(L-S)}$	t-stat
A – Breakpoints from average								
MV	1.47	1.30	2.55	-0.76	1.51	1.26	3.48	-0.82
BP	1.36	1.56	2.69	0.83	1.40	1.70	4.04	0.85
CP	1.30	1.64	3.07	1.29	1.24	1.81	4.56	1.76
DP	1.39	1.53	3.97	0.51	1.44	1.50	4.90	0.18
EP	1.42	1.47	4.53	0.14	1.54	1.57	7.68	0.06
SP	1.35	1.64	2.98	1.03	1.35	1.80	4.88	1.07
CFY1	1.24	1.67	1.82	3.33	1.19	1.72	2.33	3.22
RET6	1.41	1.49	4.56	0.24	1.30	1.65	7.26	0.69
RET12	1.25	1.70	4.40	1.43	1.15	2.13	7.47	1.85
B – Median breakpoints								
MV	1.53	1.35	2.86	-0.86	1.59	1.27	4.01	-1.10
BP	1.37	1.51	2.71	0.61	1.41	1.67	3.90	0.76
CP	1.26	1.62	3.34	1.53	1.26	1.78	4.87	1.51
DP	1.38	1.49	4.34	0.35	1.44	1.49	5.13	0.12
EP	1.33	1.55	3.29	0.97	1.50	1.68	6.69	0.39
SP	1.34	1.53	3.23	0.65	1.30	1.74	4.99	0.95
CFY1	1.27	1.58	1.97	2.16	1.18	1.67	2.45	2.80
RET6	1.41	1.47	4.01	0.20	1.28	1.64	6.91	0.73
RET12	1.22	1.66	3.99	1.57	1.12	2.07	7.14	1.89
C – Breakpoints from average, industry neutral								
MV	1.41	1.32	2.11	-0.58	1.48	1.33	3.18	-0.66
BP	1.34	1.49	1.95	1.06	1.42	1.53	3.27	0.48
CP	1.21	1.61	1.74	3.25	1.30	1.79	3.44	2.01
DP	1.29	1.50	2.22	1.37	1.40	1.59	3.31	0.81
EP	1.20	1.51	2.45	1.78	1.49	1.61	4.81	0.44
SP	1.34	1.48	2.38	0.82	1.38	1.66	3.99	0.86
CFY1	1.22	1.58	1.20	4.24	1.20	1.74	1.78	4.24
RET6	1.38	1.40	2.67	-0.12	1.45	1.72	4.79	0.81
RET12	1.30	1.51	2.59	1.15	1.23	2.02	4.80	2.31

Table 4: Model Selection

The table reports OLS estimation results for the panel data model

$$y_{it} = \mu_i + \sum_{\ell=1}^{L} D_{i\ell}\,(x'_{it}\beta_\ell + \lambda_{\ell t}) + e_{it},$$

and various restricted versions for different forecasting horizons. The first two columns indicate the restrictions on μ_i (CONST) and $\lambda_{\ell t}$ (TIME). The intercepts (CONST) are either pooled ($\mu_i = \mu$), industry specific ($\mu_i = \sum_{\ell=1}^{L} D_{i\ell}\tau_\ell$), where τ_ℓ is the effect of industry ℓ, or firm specific (μ_i). The time effects are either pooled ($\lambda_{\ell t} = \lambda_t$), industry specific ($\lambda_{\ell t}$) or not included (none). The total number of parameters is given as k; RSS denotes the Residual Sum of Squares; the R^2 is computed as one minus the ratio of RSS to the total sum of squares of returns in deviation of the average return; SC denotes the Schwartz information criterion. The numbers in the column "RRS" are factors of 10^7. Explanatory variables in x_{it} are MV, BP, CP, DP, EP, SP, CFY1, RET6 and RET12. Panels A are based on all complete data points. In panels B all firms with less than 60 observations have been omitted. Panels C report WLS estimates based on the entire data set. The first lines of each subpanel show the respective numbers of firms and data points.

		One Month				Three Month		Six Month	
CONST	TIME	k	RSS	R^2	SC	R^2	SC	R^2	SC
		A-1165, 95136				**A-1160, 93299**		**A-1157, 90511**	
individual	industry	5544	1.356	0.311	5.652	0.354	6.786	0.382	7.464
pooled	industry	4380	1.400	0.289	5.522	0.296	6.709	0.275	7.456
individual	none	1363	1.897	0.037	5.460	0.096	6.591	0.174	7.217
industry	pooled	418	1.675	0.149	5.222	0.150	6.414	0.132	7.148
pooled	pooled	397	1.677	0.149	5.220	0.148	6.373	0.129	7.148
industry	none	220	1.950	0.010	5.350	0.024	6.528	0.044	7.220
		B-674, 81504				**B-662, 79536**		**B-379, 60696**	
individual	industry	4864	0.815	0336	5.309	0.370	6.440	0.378	6.971
pooled	industry	4402	0.829	0.327	5.232	0.339	6.396	0.346	6.924
individual	none	872	1.199	0.026	5.112	0.078	6.234	0.113	6.588
industry	pooled	418	1.019	0.172	4.887	0.184	6.009	0.188	6.470
pooled	pooled	397	1.020	0.172	4.885	0.182	6.009	0.181	6.475
industry	none	220	1.218	0.011	5.037	0.034	6.189	0.051	6.591
		C-WLS-1165, 95136				**C-1160, 93299**		**C-1157, 90511**	
individual	industry	5544	1.360	0.309	5.655	0.350	6.794	0.375	7.477
pooled	industry	4380	1.403	0.288	5.524	0.293	6.714	0.270	7.463
individual	none	1363	1.903	0.034	5.463	0.090	6.598	0.166	7.223
industry	pooled	418	1.680	0.147	5.224	0.144	6.421	0.122	7.159
pooled	pooled	397	1.681	0.147	5.222	0.143	6.420	0.121	7.158
industry	none	220	1.956	0.007	5.352	0.016	6.536	0.032	7.232

Table 5: Pooled Parameter Estimates - One Month Forecasting

The table reports estimation results for the model

$$y_{it} = \mu_i + x_{it}\beta + \sum_{\ell=1}^{L} D_{i\ell}\lambda_{\ell t} + e_{it}$$

under different assumptions about the intercepts and time effects. Each column contains model coefficients and the respective standard errors in parentheses. The symbol ** means that the respective coefficient is significant at the 99% level. The first column refers to the fully pooled model ($\mu_i = \mu$, τ_ℓ, $\lambda_{\ell t} = 0$). The second column contains pooled time effects and industry effects τ_ℓ ($\mu_i = 0$, τ_ℓ, $\lambda_{\ell t} = \lambda_t$) and the third column shows industry specific time effects ($\mu_i = 0$, $\tau_\ell = 0$, $\lambda_{\ell t}$). The column "individual pooled" refers to a fully pooled model with individual intercepts (μ_i, $\lambda_{\ell t} = 0$). The column "individual pooled time" refers to a model with individual intercepts and pooled time effects (μ_i, $\lambda_{\ell t} = \lambda_t$). The standard errors have been computed using a robust estimator for the covariance matrices of $\hat{\beta}$ and $\hat{\beta}_\ell$.

variable	fully pooled	pooled time effect	industry specific	individual pooled	individual pooled time
MV	1.88	-13.78	-14.48	-114.12**	-140.07**
	(28.09)	(15.93)	(14.83)	(56.40)	(34.83)
BP	0.50	0.44	0.20	2.91**	2.66**
	(0.32)	(0.27)	(0.24)	(0.69)	(0.53)
CP	1.74	1.93**	1.80**	2.47**	2.23**
	(0.98)	(0.77)	(0.68)	(1.04)	(0.80)
DP	3.61	8.35	4.73	10.58	-2.37
	(9.80)	(5.58)	(5.05)	(15.67)	(9.30)
EP	2.45	1.48	1.21	-1.08	-2.75**
	(1.77)	(1.35)	(1.22)	(1.75)	(1.19)
SP	0.18	0.15	0.14	0.66**	0.65**
	(0.10)	(0.08)	(0.08)	(0.22)	(0.17)
CFY1	0.23	0.24	0.29**	0.27	0.24
	(0.16)	(0.13)	(0.09)	(0.16)	(0.12)
RET6	-0.0120	-0.0022	-0.0050	-0.0168	-0.0085
	(0.009)	(0.008)	(0.006)	(0.009)	(0.008)
RET12	0.0078	0.0070**	0.0060**	0.0081	0.0067**
	(0.004)	(0.003)	(0.002)	(0.005)	(0.003)

Table 6: Pooled Parameter Estimates - Three Month Forecasting

The table reports estimation results for the model

$$y_{it} = \mu_i + x_{it}\beta + \sum_{\ell=1}^{L} D_{i\ell}\lambda_{\ell t} + e_{it}$$

under different assumptions about the intercepts and time effects. The forecasting horizon is three months. Each column contains model coefficients and the respective standard errors in parentheses. The symbol ** means that the respective coefficient is significant at the 99% level. The table contains two panels that report results for three month and six month forecasting. The first column of each panel refers to the fully pooled model ($\mu_i = \mu$, $\lambda_{\ell t} = 0$). The second column contains pooled time effects and industry effects τ_ℓ ($\mu_i = 0$, τ_ℓ, $\lambda_{\ell t} = \lambda_t$) and the third column shows industry specific time effects ($\mu_i = 0$, $\tau_\ell = 0$, $\lambda_{\ell t}$). The column "μ_i pooled" refers to a fully pooled model with individual intercepts (μ_i, $\lambda_{\ell t} = 0$). The column "individual pooled time" refers to a model with individual intercepts and pooled time effects (μ_i, $\lambda_{\ell t} = \lambda_t$). The standard errors have been computed using a robust estimator for the covariance matrices of $\hat{\beta}$ and $\hat{\beta}_\ell$.

variable	fully pooled	pooled time effect	industry specific	individual pooled	individual pooled time
MV	-5.68	-46.85	-46.54	-395.90**	-457.53**
	(66.01)	(42.56)	(38.88)	(131.42)	(70.06)
BP	1.88	1.71**	0.99	9.65**	8.77**
	(0.85)	(0.79)	(0.70)	(1.85)	(1.17)
CP	6.84**	7.29**	6.50**	9.32**	7.97**
	(2.35)	(2.07)	(1.83)	(2.44)	(1.52)
DP	1.32	21.15	8.52	26.70	-7.13
	(22.48)	(12.63)	(11.65)	(38.31)	(16.67)
EP	4.10	1.96	1.42	-7.60	-11.34**
	(4.24)	(3.42)	(2.91)	(4.23)	(2.54)
SP	0.31	0.31	0.26	1.51**	1.64
	(0.27)	(0.21)	(0.19)	(0.46)	(6.27)
CFY1	0.23**	0.06	0.29	0.35	0.05
	(0.34)	(0.30)	(0.20)	(0.31)	(0.21)
RET6	-0.02	0.014	0.008	-0.032	-0.005
	(0.02)	(0.020)	(0.011)	(0.019)	(0.014)
RET12	0.02	0.013	0.012**	0.014	0.012
	(0.01)	(0.010)	(0.006)	(0.012)	(0.007)

Table 7: Pooled Parameter Estimates - Six Month Forecasting

The table reports estimation results for the model

$$y_{it} = \mu_i + x_{it}\beta + \sum_{\ell=1}^{L} D_{i\ell}\lambda_{\ell t} + e_{it}$$

under different assumptions about the intercepts and time effects. The forecasting horizon is six months. Each column contains model coefficients and the respective standard errors in parentheses. The symbol ** means that the respective coefficient is significant at the 99% level. The table contains two panels that report results for three month and six month forecasting. The first column of each panel refers to the fully pooled model ($\mu_i = \mu$, $\lambda_{\ell t} = 0$). The second column contains pooled time effects and industry effects τ_ℓ ($\mu_i = 0$, τ_ℓ, $\lambda_{\ell t} = \lambda_t$) and the third column shows industry specific time effects ($\mu_i = 0$, $\tau_\ell = 0$, $\lambda_{\ell t}$). The column "μ_i pooled" refers to a fully pooled model with individual intercepts (μ_i, $\lambda_{\ell t} = 0$). The column "individual pooled time" refers to a model with individual intercepts and pooled time effects (μ_i, $\lambda_{\ell t} = \lambda_t$). The standard errors have been computed using a robust estimator for the covariance matrices of $\hat{\beta}$ and $\hat{\beta}_\ell$.

variable	fully pooled	pooled time effect	industry specific	individual pooled	individual pooled time
MV	3.53	-60.26	-62.70	-862.21**	-904.14**
	(127.65)	(87.03)	(80.64)	(278.31)	(115.02)
BP	3.15	3.03**	1.78	17.05**	16.11**
	(1.28)	(1.29)	(1.18)	(3.33)	(1.42)
CP	14.75**	12.53**	17.10**	15.19**	15.19**
	(4.24)	(4.00)	(3.45)	(4.67)	(2.25)
DP	4.46	40.44	12.31	54.50	1.03
	(37.16)	(21.76)	(19.84)	(60.65)	(18.67)
EP	7.61	4.67	3.73	-15.74**	-24.41**
	(7.03)	(5.4)	(4.67)	(6.89)	(3.18)
SP	0.58	0.70	0.58	3.31**	3.72**
	(0.51)	(0.37)	(0.37)	(0.92)	(0.47)
CFY1	0.66**	0.23	0.72**	0.85	0.21
	(0.59)	(0.41)	(0.31)	(0.49)	(0.22)
RET6	0.06	0.08**	0.07**	0.03	0.047**
	(0.03)	(0.03)	(0.02)	(0.03)	(0.014)
RET12	-0.01	-0.01	-0.01	-0.02	-0.016
	(0.02)	(0.02)	(0.01)	(0.02)	(-0.010)

Table 8: Tests for Industry Specific Parameters

The table shows Wald-statistics for the null hypothesis $\beta_\ell = \beta$ ($\ell = 1...L$) in the model

$$y_{it} = \mu_i + \sum_{\ell=1}^{L} x_{it}\beta_\ell + \sum_{\ell=1}^{L} D_{i\ell}\lambda_{\ell t} + e_{it}$$

under different assumptions about the intercepts and time effects. The forecasting horizon is one, three and six months. The alternative is that β is different in all industries. The columns "fully pooled" refer to the fully pooled model ($\mu_i = \mu$, $\lambda_{\ell t} = 0$). The columns "pooled time" contain pooled time effects and industry effects τ_ℓ ($\mu_i = 0$, τ_ℓ, $\lambda_{\ell t} = \lambda_t$), and the columns "industry specific" show industry specific time effects ($\mu_i = 0$, $\tau_\ell = 0$, $\lambda_{\ell t}$). The Wald-statistics have been computed using a robust estimator for the covariance matrices of $\hat{\beta}$ and $\hat{\beta}_\ell$. The last line reports Wald-statistics for the null hypothesis that all coefficients in the corresponding models with pooled coefficients are zeros.

	One Month			Three Month			Six Month		
variable	fully pooled	pooled time	industry specific	fully pooled	pooled time	industry specific	fully pooled	pooled time	industry specific
MV	14.3	13.9	18.6	21.1	20.0	29.8	33.2	31.5	54.1
BP	34.0	34.6	41.8	57.5	58.6	77.1	60.7	60.8	145.7
CP	40.4	39.2	30.1	96.9	95.5	60.4	107.6	97.2	59.9
DP	27.0	27.9	32.4	43.2	42.7	35.1	58.6	54.7	53.2
EP	44.2	44.6	45.8	105.3	99.1	64.4	185.9	179.4	141.8
SP	44.3	43.3	34.0	100.2	98.4	88.1	166.2	174.7	185.5
CFY1	17.3	17.5	24.3	25.2	22.7	30.0	36.4	35.5	48.4
RET6	16.7	17.9	32.4	70.8	75.6	33.7	168.9	171.4	87.4
RET12	20.2	21.3	38.6	73.6	76.9	82.5	129.9	133.2	91.7
χ^2-stat	28.1	42.6	55.4	36.3	40.7	48.9	48.3	75.3	92.7

Table 9: Pooled Parameter Estimates - WLS and Fama-MacBeth Estimators

The table reports estimation results for the model

$$y_{it} = x_{it}\beta + \sum_{\ell=1}^{L} D_{i\ell}\lambda_{\ell t} + e_{it}$$

under different assumptions about the intercepts and the time effects. The first three columns report results from WLS estimation, and the last two columns - from Fama-MacBeth estimation. The first column refers to the fully pooled model ($\mu_i = \mu,\ \lambda_{\ell t} = 0$). The second column contains pooled time effects and industry effects τ_ℓ ($\mu_i = 0,\ \tau_\ell,\ \lambda_{\ell t} = \lambda_t$), and the third column shows individual effects and industry specific time effects ($\mu_i,\ \lambda_{\ell t}$). The first row for each variable reports parameter estimates of β. The second row has standard error in parenthesis. The third row contains the t-values. The standard errors and the t-statistics have been computed using a robust estimator of the covariance matrices of $\hat{\beta}$ and $\hat{\beta}_\ell$.

		WLS			Fama-MacBeth	
variable		fully pooled	pooled time effect	industry specific	fully pooled	pooled time effect
MV	coefficient	13.00	-3.45	-1.46	-11.45	-11.61
	St. Error	(28.08)	(15.10)	(14.82)	(13.70)	(25.27)
	t-stat	[0.46]	[-0.22]	[-0.10]	[-0.84]	[-0.46]
BP	coefficient	0.28	0.43	0.27	0.38	0.15
	St. Error	(0.32)	(0.27)	(0.24)	(0.19)	(0.27)
	t-stat	[0.86]	[1.59]	[1.15]	[1.94]	[0.57]
CP	coefficient	1.52	1.46	1.46	0.87	2.02
	St. Error	(0.98)	(0.77)	(0.68)	(0.55)	(0.72)
	t-stat	[1.56]	[1.90]	[2.15]	[1.58]	[2.80]
DP	coefficient	7.23	8.56	5.09	-0.68	4.94
	St. Error	(9.82)	(5.60)	(5.07)	(5.84)	(6.57)
	t-stat	[0.74]	[1.53]	[1.01]	[-0.12]	[0.75]
EP	coefficient	3.25	1.82	1.52	-0.42	-0.66
	St. Error	(1.76)	(1.35)	(1.22)	(1.03)	(1.30)
	t-stat	[1.85]	[1.35]	[1.24]	[-0.41]	[-0.51]
SP	coefficient	0.16	0.09	0.06	0.05	0.11
	St. Error	(0.10)	(0.08)	(0.08)	(0.06)	(0.07)
	t-stat	[1.62]	[1.11]	[0.81]	[0.86]	[1.48]
CFY1	coefficient	0.31	0.27	0.29	0.24	0.05
	St. Error	(0.16)	(0.13)	(0.09)	(0.07)	(0.09)
	t-stat	[1.94]	[2.04]	[3.17]	[3.32]	[0.57]
RET6	coefficient	-0.013	-0.006	-0.005	-0.016	-0.005
	St. Error	(0.010)	(0.008)	(0.006)	(0.005)	(0.006)
	t-stat	[-1.45]	[-0.68]	[-0.94]	[-2.97]	[-0.95]
RET12	coefficient	0.010	0.011	0.008	0.014	0.010
	St. Error	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
	t-stat	[2.28]	[3.38]	[3.96]	[4.36]	[2.94]

Table 10: Returns from Expected Return Portfolio Strategies

The table contains four panels that show portfolio returns based on one, two, three and six month forecasting.
For three different specifications of the panel model, each month stocks are sorted with respect to the fitted values. The 30% stocks with the highest expected return are allocated to the *long* portfolio, the 30% stocks with the lowest expected returns to the *short* portfolio. For the equally weighted portfolio long and short portfolios contain the same number of stocks. For the value weighted portfolios the long portfolio contains the stocks highest expected returns making up 30% of the total market value, and the *short* portfolio includes 30% market value with the lowest expected returns. For the model with industry specific time effects portfolios are first constructed industry by industry and aggregated with weights proportional either to the number of firms in the industry or to the market weight of the industry.
Entries in the columns *Long* and *Short* contain the average returns of the portfolios over the entire sample period. The standard deviation of the long-short portfolio is denoted s_{L-S}. The t-statistic tests the null hypothesis that the *long* and *short* portfolios have equal mean returns.
The first line of each panel refers to a pooled model with a pooled time effect and pooled β, the second line shows a model with pooled time effects and industry specific intercepts and coefficients, and the last line contains results for a model with industry specific time effects and coefficients.

One Month Forecast

	Equally Weighted				Value Weighted			
Model	Short	Long	s_{L-S}	t-stat	Short	Long	s_{L-S}	t-stat
pooled	0.83	2.10	3.30	5.39	0.80	1.76	3.09	4.37
industry specific β_ℓ	0.62	2.22	2.95	7.64	0.49	1.85	2.96	6.49
industry specific β_ℓ and $\lambda_{\ell t}$	0.87	2.19	2.28	8.15	0.85	1.66	1.86	6.13

Two Month Forecast

	Equally Weighted				Value Weighted			
Model	Short	Long	s_{L-S}	t-stat	Short	Long	s_{L-S}	t-stat
pooled	0.96	2.07	3.15	4.96	0.75	1.78	3.25	4.46
industry specific β_ℓ	0.70	2.19	2.59	8.12	0.65	1.77	2.76	5.71
industry specific β_ℓ and $\lambda_{\ell t}$	0.77	1.97	1.87	8.98	0.87	1.62	2.05	5.16

Three Month Forecast

	Equally Weighted				Value Weighted			
Model	Short	Long	s_{L-S}	t-stat	Short	Long	s_{L-S}	t-stat
pooled	1.02	2.09	3.27	4.56	0.73	1.82	3.40	4.50
industry specific β_ℓ	0.76	2.20	2.46	8.24	0.72	1.87	3.01	5.34
industry specific β_ℓ and $\lambda_{\ell t}$	0.89	1.98	1.99	7.68	0.96	1.72	2.41	4.44

Six Month Forecast

	Equally Weighted				Value Weighted			
Model	Short	Long	s_{L-S}	t-stat	Short	Long	s_{L-S}	t-stat
pooled	1.10	1.95	3.08	3.85	0.99	1.79	3.41	3.27
industry specific β_ℓ	0.86	2.16	2.76	6.55	0.83	2.03	3.06	5.45
industry specific β_ℓ and $\lambda_{\ell t}$	0.98	1.93	2.03	6.49	1.08	1.59	1.80	3.98

Table 11: Profiles of Expected Return Long - Short Portfolios

For the six portfolio strategies considered in table 10 this table reports the time series averages of the characteristics of these portfolios. The results are based on monthly return forecasting. The columns "s_{L-S}" show the time series standard deviations of the differences in characteristics between the long and the short portfolio. The t-statistics test the null hypothesis that the *long* and *short* portfolios have equal mean characteristics and are adjusted for autocorrelation. The first panel refers to a pooled model with a pooled time effect and pooled β, the second panel has a model with industry specific coefficients and the last panel contains results for a model with industry specific time effects and coefficients.

		Equally weighted				Value weighted			
Model	Variable	Short	Long	$s_{(L-S)}$	t-stat	Short	Long	$s_{(L-S)}$	t-stat
pooled	*MV*	0.003	0.002	0.001	-9.35	0.020	0.007	0.006	-11.20
	BP	0.42	0.60	0.11	11.10	0.34	0.41	0.07	7.43
	CP	0.08	0.18	0.04	15.40	0.10	0.14	0.03	8.21
	DP	0.020	0.023	0.004	4.99	0.023	0.024	0.004	0.87
	EP	0.012	0.050	0.04	7.11	0.045	0.054	0.01	5.45
	SP	0.98	2.15	0.52	15.10	0.76	1.29	0.31	11.60
	CFY1	-0.43	0.17	0.15	31.00	-0.32	0.29	0.18	30.60
	RET6	3.24	13.00	10.50	6.61	6.67	16.70	11.70	6.26
	RET12	3.65	32.00	26.50	7.18	3.65	32.00	26.50	7.18
industry	*MV*	0.003	0.002	0.001	-1.56	0.012	0.010	0.006	-2.32
specific	*BP*	0.42	0.64	0.11	13.70	0.35	0.42	0.09	5.33
coefficients	*CP*	0.08	0.17	0.03	17.60	0.10	0.14	0.04	8.18
	DP	0.018	0.025	0.005	9.50	0.021	0.027	0.005	7.78
	EP	0.02	0.05	0.03	7.44	0.04	0.06	0.01	9.54
	SP	1.17	2.04	0.50	12.10	0.84	1.23	0.36	7.58
	CFY1	-0.24	0.05	0.14	16.90	-0.25	0.24	0.21	20.30
	RET6	11.50	5.25	9.55	-4.86	10.90	12.10	8.06	1.24
	RET12	13.70	20.30	14.90	3.20	17.30	34.60	22.50	5.31
industry	*MV*	0.003	0.002	0.001	-5.67	0.010	0.008	0.003	-1.21
specific	*BP*	0.43	0.59	0.10	12.00	0.36	0.41	0.08	4.08
coefficients	*CP*	0.03	0.05	0.02	6.01	0.09	0.13	0.02	13.10
and time	*DP*	0.019	0.024	0.004	11.6	0.021	0.025	0.003	9.94
effects	*EP*	0.010	0.020	0.02	2.82	0.038	0.053	0.01	9.26
	SP	1.39	2.25	0.62	13.80	0.87	1.15	0.20	9.75
	CFY1	-0.35	0.14	0.19	19.70	-0.36	0.26	0.18	27.90
	RET6	9.46	7.15	6.60	-2.68	7.60	14.20	9.06	10.30
	RET12	14.20	19.00	10.20	6.04	14.50	35.70	26.30	5.39

Table 12: Persistence in Expected Returns

The table reports transition frequencies among the *Long*, *Neutral* and *Short* portfolios that are constructed using the cross sectional expected returns. The *Long* portfolio holds the 30% stocks with the highest expected returns, the *Short* portfolio the 30% with the lowest expected returns, and the *Neutral* portfolio the remaining 40%. All stocks are equally weighted. Expected returns are generated with three different specifications of the panel. Transitions frequencies are the average fractions of stocks that are in portfolio P at time t and in portfolio Q at time $t+1$. The additional categories *New* and *Out* refer to stocks that were not in the panel at time t, and left the panel at time $t+1$, respectively. The table consists of four panels that show transition frequencies for portfolios based on forecasting for one, two, three and six months. The first subpanel of each panel refers to a pooled model with a pooled time effect and pooled β, the second subpanel has a model with industry specific β_ℓ and the last subpanel contains results for a model with industry specific time effects and coefficients.

		One Month Forecast				Two Month Forecast			
		To				To			
Model	From	Long	Neutral	Short	Out	Long	Neutral	Short	Out
pooled	Long	0.785	0.184	0.024	0.002	0.930	0.062	0.002	0.002
	Neutral	0.186	0.633	0.175	0.002	0.064	0.880	0.050	0.001
	Short	0.026	0.200	0.765	0.003	0.003	0.088	0.901	0.003
	New	0.335	0.300	0.357	–	0.413	0.352	0.229	–
industry specific coefficients	Long	0.844	0.146	0.003	0.002	0.879	0.098	0.016	0.002
	Neutral	0.207	0.660	0.127	0.002	0.102	0.799	0.092	0.001
	Short	0.005	0.206	0.781	0.004	0.020	0.111	0.861	0.003
	New	0.406	0.329	0.257	–	0.353	0.266	0.374	–
industry specific coefficients and time	Long	0.712	0.251	0.029	0.003	0.854	0.125	0.013	0.003
	Neutral	0.157	0.675	0.161	0.002	0.078	0.831	0.084	0.001
	Short	0.026	0.263	0.703	0.003	0.013	0.135	0.844	0.002
	New	0.302	0.352	0.338	–	0.327	0.315	0.351	–

		Three Month Forecast				Six Month Forecast			
		To				To			
Model	From	Long	Neutral	Short	Out	Long	Neutral	Short	Out
pooled	Long	0.954	0.038	0.002	0.002	0.955	0.033	0.005	0.001
	Neutral	0.041	0.925	0.028	0.001	0.038	0.927	0.028	0.001
	Short	0.003	0.053	0.935	0.003	0.009	0.042	0.941	0.003
	New	0.403	0.353	0.238	–	0.397	0.293	0.304	–
industry specific coefficients	Long	0.913	0.065	0.014	0.002	0.941	0.038	0.014	0.001
	Neutral	0.072	0.861	0.061	0.001	0.038	0.918	0.038	0.001
	Short	0.018	0.075	0.898	0.003	0.015	0.044	0.933	0.003
	New	0.340	0.271	0.382	–	0.293	0.250	0.452	–
industry specific coefficients and time	Long	0.902	0.081	0.010	0.002	0.935	0.047	0.012	0.002
	Neutral	0.051	0.890	0.053	0.001	0.030	0.933	0.032	0.001
	Short	0.009	0.086	0.900	0.002	0.011	0.052	0.930	0.002
	New	0.320	0.287	0.386	–	0.278	0.305	0.412	–

Table 13: Performance Evaluation

The table reports time series regression results of the model

$$R_t^{LS} = a + b(R_t^M - R_{ft}) + sSMB_t + hHML_t + uUMD_t + \epsilon_t,$$

where R_t^{LS} is the monthly return of the expected return sorted long-short portfolio, $R^M - R_f$ is the excess return on the value weighted market index, *SMB* is the Fama-French "Small minus Big" size factor, *HML* is the Fama-French "High minus Low" book-to-market factor and *UMD* is the "Up minus Down" momentum factor. The entries show parameter estimates with autocorrelation robust t-statistics in parenthesis. The long-short portfolio returns are constructed using the six strategies shown in table 10. Intercepts are in percents per month. The first two columns refer to a pooled model with a pooled time effect and pooled β, the second two columns have a model with industry specific β_ℓ and the last two columns contain results for a model with industry specific time effects and coefficients. The upper panel reports results for portfolios based on one-month forecasting, the middle panel - on three-month forecasting and the lower panel - on six-month forecasting.

	pooled		industry specific β_ℓ		β_ℓ and $\lambda_{\ell t}$	
Variable	EW	VW	EW	VW	EW	VW
			One Month Forecast			
R^2	0.38	0.35	0.20	0.25	0.09	0.27
Intercept	0.70	0.42	1.40	0.97	1.20	0.56
	(2.94)	(2.21)	(6.07)	(4.94)	(7.17)	(4.64)
$R^M - R_f$	0.03	0.09	0.06	0.08	0.08	0.03
	(0.42)	(1.86)	(0.90)	(1.59)	(2.06)	(1.09)
SMB	0.11	0.09	0.03	-0.16	0.16	0.01
	(1.25)	(1.54)	(0.26)	(-2.82)	(3.31)	(0.32)
HML	0.38	0.22	0.43	0.27	0.24	0.22
	(-1.82)	(3.15)	(4.26)	(3.80)	(3.86)	(0.42)
UMD	0.40	0.40	0.01	0.24	-0.05	0.22
	(4.60)	(9.84)	(0.09)	(5.76)	(-0.14)	(8.26)
			Three Month Forecast			
R^2	0.46	0.38	0.22	0.25	0.298	0.394
Intercept	0.53	0.60	1.16	0.79	0.82	0.39
	(2.87)	(2.84)	(6.99)	(3.96)	(6.38)	(2.70)
$R^M - R_f$	0.01	-0.02	0.01	0.02	0.05	0.03
	(0.28)	(-0.33)	(1.93)	(0.45)	(1.63)	(0.86)
SMB	0.25	0.20	0.17	0.04	0.21	0.20
	(4.70)	(2.58)	(3.57)	(0.62)	(5.66)	(4.80)
HML	0.29	0.27	0.42	0.42	0.39	0.22
	(4.35)	(2.04)	(6.83)	(5.70)	(6.21)	(4.14)
UMD	0.45	0.43	0.10	0.21	0.15	0.30
	(11.45)	(6.01)	(2.86)	(4.90)	(5.63)	(9.68)
			Six Month Forecast			
R^2	0.24	0.19	0.20	0.23	0.20	0.14
Intercept	0.44	0.41	1.01	0.88	0.73	0.32
	(2.04)	(1.88)	(5.19)	(4.62)	(4.28)	(2.89)
$R^M - R_f$	0.004	-0.026	0.009	0.002	-0.004	0.01
	(0.01)	(-0.46)	(0.18)	(0.04)	(-0.09)	(0.34)
SMB	0.21	0.15	0.18	0.09	0.24	0.08
	(2.18)	(1.40)	(2.16)	(1.10)	(3.10)	(1.27)
HML	0.34	0.37	0.39	0.46	0.29	0.19
	(2.18)	(2.14)	(2.29)	(2.19)	(2.33)	(3.72)
UMD	0.28	0.26	0.15	0.16	0.14	0.11
	(2.53)	(2.11)	(2.15)	(2.10)	(1.57)	(2.19)

Figure 1: Equally Weighted and Value Weighted Index

The upper panel shows the average monthly returns from equally weighted portfolios constructed from all MSCI universe stocks. The returns have an average value of 1.44% per month and a standard deviation of 5.12%. The lower panel shows two value weighted average monthly return series. The series with the solid line is computed from our MSCI data set. The average return from this portfolio is 1.28% per month and has a standard deviation of 4.63%. The other series with the dashed line is the Fama and French value weighted benchmark return series. The average return of this series is 1.20% with a standard deviation of 4.50%.

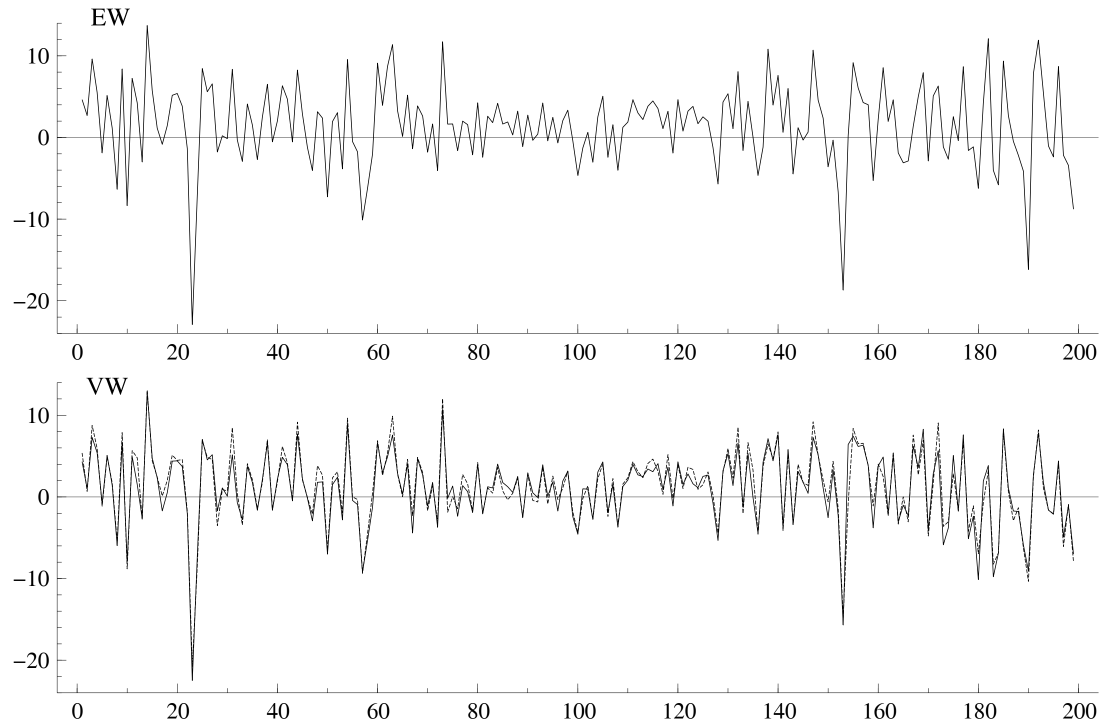

Figure 2: Individual Effects

The figure shows histograms of the estimated individual effects μ_i in the general model (1). Estimates are ordered by industry according to the MSCI classification shown in table 1. The units on the horizontal axes are percentage points, while the units on the vertical axes are percents.

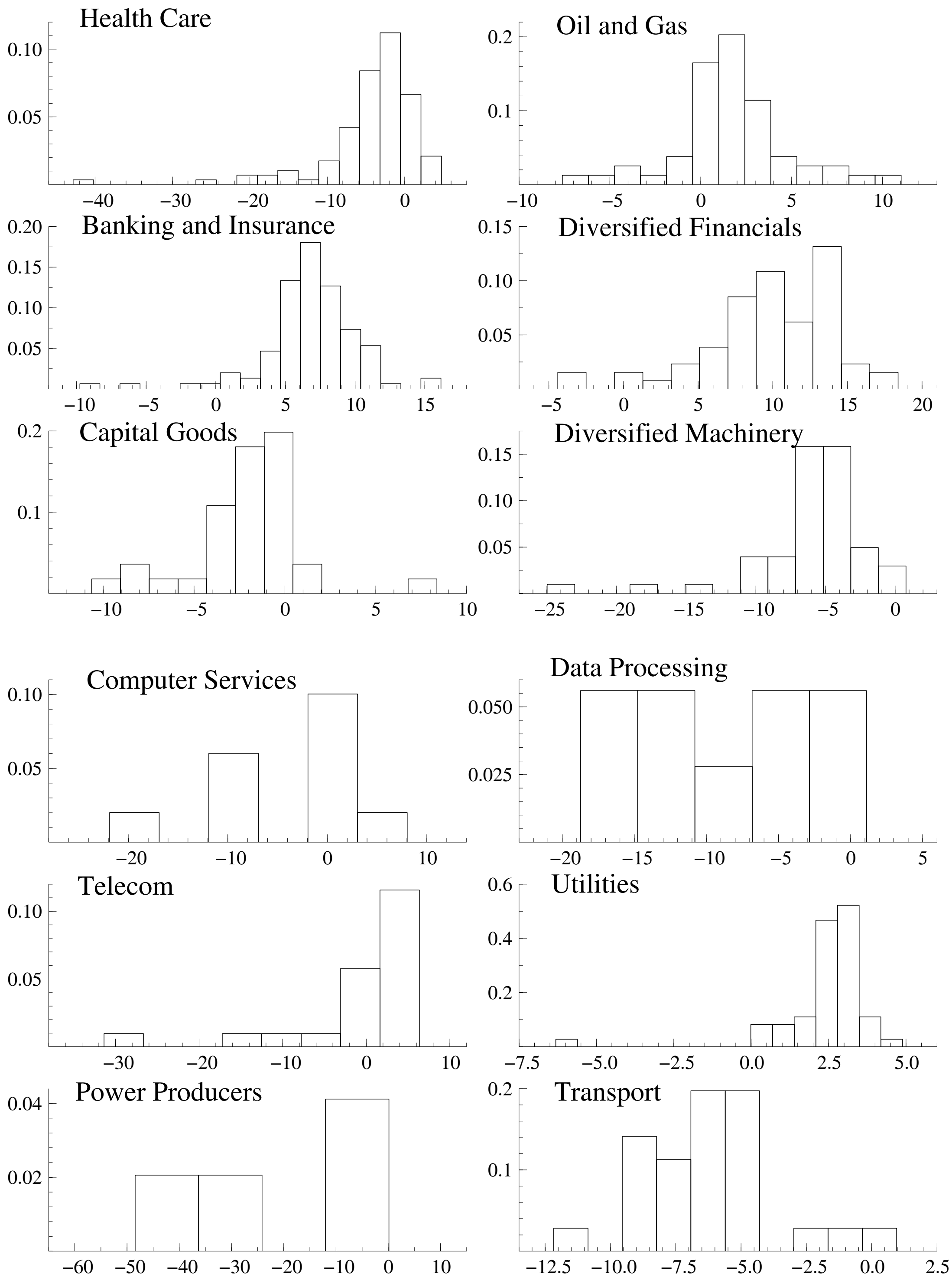

Figure 3: Histograms of the Data Set and the Outliers

The upper panel shows the histogram of the number of observations per industry outlier. The lower panel shows the histogram of the number of observation per company from the whole data set. The horizontal axes show the number of observations per firm. The vertical axes show absolute frequencies, i.e. the number of firms within each observation group.

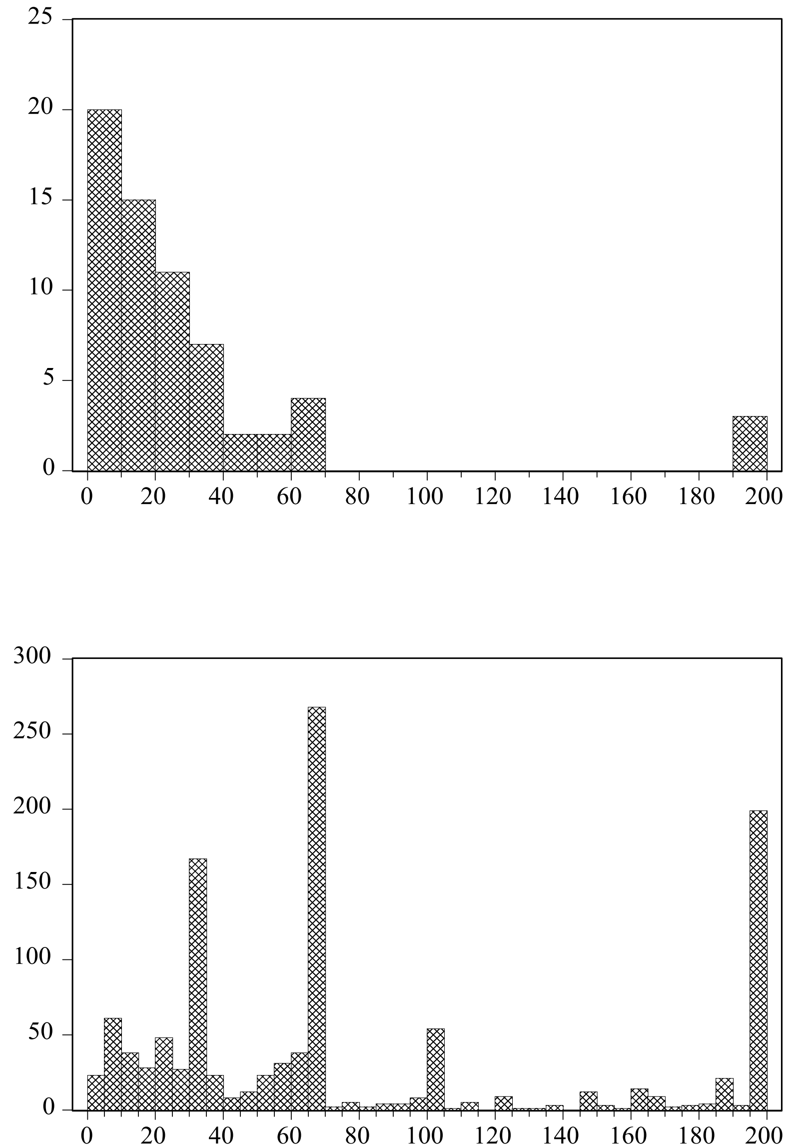

Figure 4: Industry Specific Parameter Estimates

Each panel shows values of an element of β_ℓ for all industries. For each industry the figure shows estimates of $\beta_{j\ell}$ for three different specifications of the panel. For each industry, the first bar refers to a model specification with industry intercepts and no time effects ($\lambda_{\ell t} = 0$). The second bar stays for the specification with industry specific intercept and pooled time effects ($\lambda_{\ell t} = \lambda_t$), and the third bar stays for the model with industry specific time effects ($\mu_i = 0$, $\lambda_{\ell t}$). The numbers on the horizontal axes denote industries according to the MSCI classification shown in table 1.

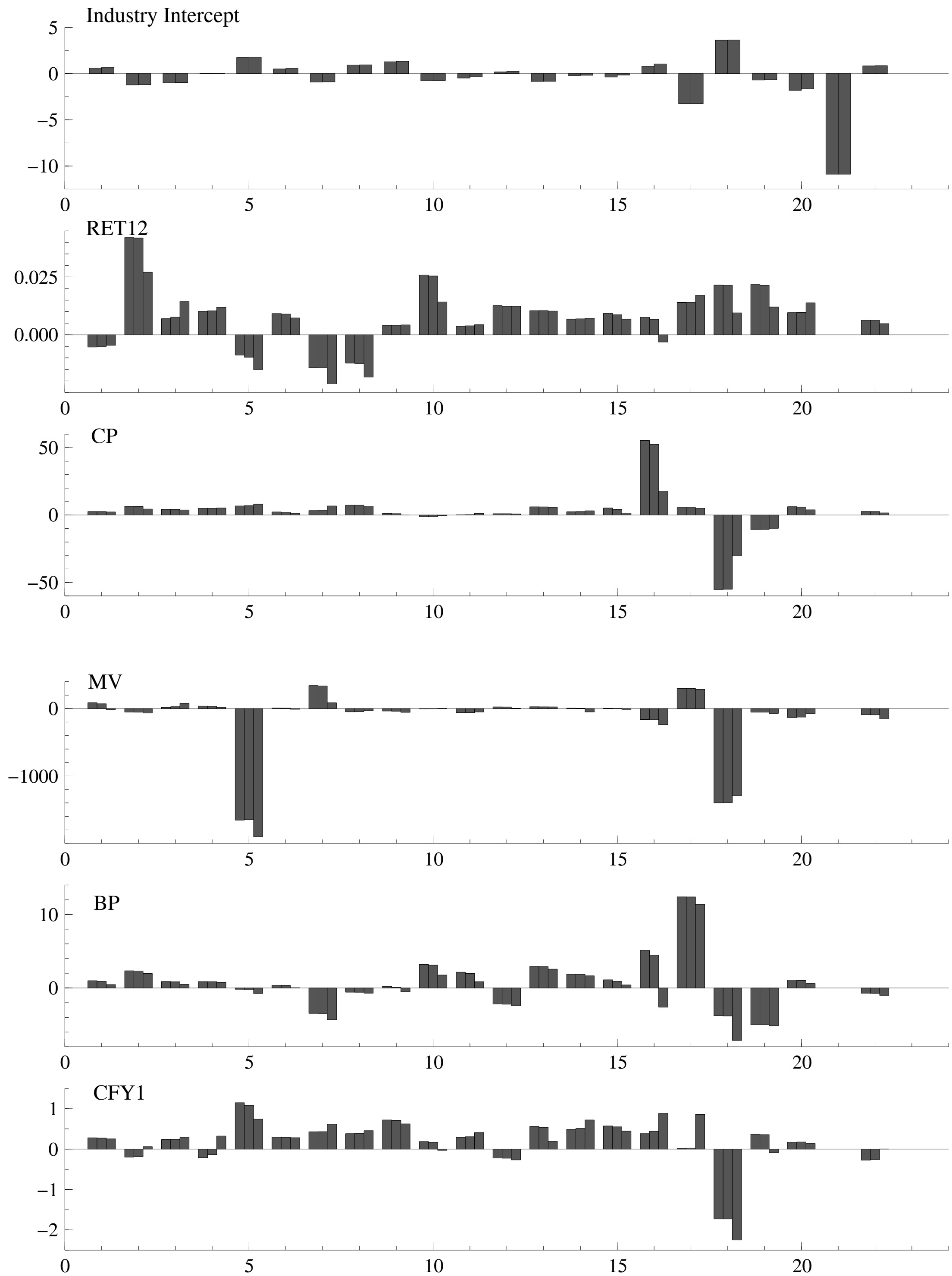

Figure 5: Industry Specific t-statistics of Model Coefficients

Each panel shows values of the t-statistics of an element of β_ℓ for all industries. For each industry the figure shows estimates of $\beta_{j\ell}$ for three different specifications of the panel. For each industry, the first bar refers to a model specification with industry intercepts and no time effects ($\lambda_{\ell t} = 0$). The second bar stays for the specification with industry specific intercept and pooled time effects ($\lambda_{\ell t} = \lambda_t$), and the third bar stays for the model with industry specific time effects ($\mu_i = 0$, $\lambda_{\ell t}$). The numbers on the horizontal axes denote industries according to the MSCI classification shown in table 1.