Firm Characteristics, Industry and Time Effects, and the Cross-Section of Expected Stock Returns

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Abstract: We study the predictability of stock returns in a panel of US firms. Our formal models can deal with unbalanced panels, cross-sectional and time series correlation, and industry specific coefficients and time effects. We perform specification tests related to cross industry heterogeneity and poolability. We find that industry and time effects are significant. High expected returns are mostly related to size, cash flow-to-price ratio and liquidity and somewhat to earnings revisions and momentum. Combining firm characteristic boosts the prediction power. Our findings are robust to the data and the forecasting horizon. In-sample portfolio construction leads to significant abnormal returns and low risk exposure. Longer forecasting horizons drastically reduce portfolio turnover, do not deteriorate returns and change the portfolio risk exposure marginally.

Keywords: Stock returns, Forecasting, Panel data, Industry effects, Individual effects, Time effects

JEL codes: C23, G11

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1 Introduction

A huge body of empirical research has found that various firm characteristics help to predict future stock returns. Prominent predictors are size, valuation ratios, momentum and liquidity. In addition returns are related to industries (and countries).[1]

The vast majority of empirical studies have studied one or two predictors in isolation. The typical statistical procedure for documenting return predictability starts with the construction of portfolios. Stocks are sorted according to a particular firm 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. The best known two-dimensional sort are the 25 Fama and French (1995) portfolios, sorted with respect to five size and five book-to-market categories.[2] With only one or two characteristics this methodology is simple and statistically powerful.

Much less is known about the combined effect of multiple characteristics. When the number of explanatory variables grows, the portfolio formation methodology is bound to become problematic, since the number of portfolios grows 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 even further.

Although many effects are correlated and sometimes interact, all effects seem to contribute to the overall cross-sectional prediction of stock returns. According to Haugen (2002) it is the combination of various characteristics that leads to high expected returns:

> "Big, liquid, financially sound, low-risk, momentum in the market, profitable in every dimension, and becoming more profitable in every way. Yet they sell at dirt-cheap market prices."

Prominent examples of multivariate studies are Haugen and Baker (1996) and Brennan et al. (1998). Because they consider a large set of predictive variables, these studies also employ a different methodology. Instead of sorting stocks in portfolios

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

[2] The returns of these portfolios are used in many empirical studies. Some examples are Fama and French (1996), Hodrick and Zhang (2001), Campbell and Vuolteenaho (2004).

according to a particular firm characteristic, they work with cross sectional regressions on a panel of individual stock returns.

In this paper we extend these multivariate studies in several directions. As a first extension we consider the predictability over longer horizons. In the cross-sectional regressions of Haugen and Baker (1996) and Brennan et al. (1998) the dependent variable is always the one-month (excess) return. We consider the cumulative returns over one, three and six months as alternative dependent variables. Such longer holding periods are common in many studies using the portfolio sorting methodology, but do not seem to have been considered in panel regression models. If we can predict firm returns over longer periods, given a firm's current characteristics, portfolios sorted on expected returns will be much more stable in terms of turnover.

Our second extension deals with the interaction between industry effects and firm characteristics. Industries are often the first level of portfolio choice in managed portfolios. Apart from diversification arguments, the practice seems to be motivated by the considerable cross-sectional variation in expected returns across industries. Fama and French (1997) show that only a part of these cross-sectional differences can be attributed to risk factors.

Interaction between firm characteristics and industries arises in various forms. In international finance many studies have investigated the interaction between industries and countries.[3] Interaction between industries and the momentum effect has been studied by Moskowitz and Grinblatt (1999) and Lewellen (2004). Both studies report evidence that industry portfolios exhibit strong momentum. In a cross-sectional regression study this would suggest that momentum should become much weaker, or even disappear, once we include time-varying industry effects in a panel regression model. Another example are financial firms which are often omitted because their average high debt ratios are believed to distort the relation between returns and most valuation ratios.

In general, whenever a particular characteristic differs significantly across different industries, this correlation with industries creates a multicollinearity problem and could lead to omitted variables bias. In our panel regressions we introduce industry effects in three different ways. First, we simply add industry dummies to the list of explanatory variables. Second, we test whether firm characteristics have identical effects across industries. These two tests examine whether we can pool intercepts

[3] See, for example, Heston and Rouwenhorst (1994), Heston and Rouwenhorst (1995), Cavaglia et al. (2000), Cavaglia and Moroz (2002).

and/or slopes in the regression analysis. Third, we consider a much more extreme alternative, where the models for each industry are completely different. Firm characteristics are only valuable for within industry prediction and we will not be able to make any between industry predictions. At the level of portfolio sorts, it would mean that firms are first sorted into industries, using firm characteristics to find the best stocks within each industry.

Our third extension of Haugen and Baker (1996) and Brennan et al. (1998) is the inclusion of individual effects (μ_i). This introduces even more heterogeneity than the industry effects. With individual effects each stock has its own unconditional expected return, irrespective of its average characteristics. We consider individual effects for two reasons. First, the amount of unobserved cross-sectional heterogeneity in average stock returns ($\text{Var}(\mu_i)$) is a measure of the fit of the cross-section of expected returns. Important unobserved heterogeneity at the level of individual firms is an indication for missing predictive variables. Second, if the individual effects are correlated with one or more characteristics, they will affect estimates of the slope parameters in the panel. Conrad and Kaul (1998) and Jegadeesh and Titman (2002) provide examples of the interaction between individual effects and momentum. Both studies estimate how much of momentum profits can be explained by the cross-sectional variation of the unconditional expected returns ($\text{Var}(\mu_i)$). In this case there exists an obvious correlation between past returns and unconditional average returns. In our panel regressions we formally test whether firm characteristics have significantly different effects in models with and without individual effects.

Three further issues are worth discussing in this introduction: data snooping, risk adjustment and econometric tests. Our predictive variables (size, value, momentum and liquidity) have featured in many previous studies. These variables have been subjected to out-of-sample tests for different countries and sample periods. They also seem to create anomalies, as their effect cannot be fully captured by risk adjustment. As such it is not surprising that many of them show up "significantly" in our multivariate panel regressions. To mitigate the data snooping we use a data set that has been used less frequently. Our panel contains 1,243 US stocks over a period of 17 years that are followed by the Morgan Stanley Capital International (MSCI). This data set defines the investable universe for many institutional investors. Compared to other common data sets, the MSCI panel contains fewer small cap stocks.

Most challenging for statistical testing in panels of individual stocks are the contemporaneous covariances among the errors. Even after correcting for a limited number of risk factors, much cross correlation remains. Estimating a full cross-sectional covariance matrix will be infeasible given the large number of individual stocks and the short time series history of many stocks. To get around this problem many studies have used the Fama and MacBeth (1973) estimator, in which inference is based on a time series of cross-sectional regressions. This estimator will not be applicable, however, in our panel regressions when firm specific individual effects are introduced. These effects are specific for each stock and cannot be identified from a cross-sectional regression. We therefore use a single least squares regression in a two-way fixed effects panel data model. For the standard errors we rely on an estimator of the standard errors proposed by Driscoll and Kraay (1998), which is consistent in the presence of arbitrary cross-sectional correlation and heteroskedasticity.

From the panel models we obtain the expected returns for each stock in every time period. Sorting directly on the expected returns we can compare the typical characteristics of portfolios with high and low average returns. After sorting stocks on expected returns, we regress the portfolio returns on all well-known risk factors to examine how much of the variation in the expected returns can be attributed to differences in risk.

We find that firm characteristics have predictive power and interact with industry effects. Individual effects are insignificant while time effects are significant and should be pooled across industries. Industry effects are significant and can be captured by industry specific coefficients and intercepts. Multivariate prediction of expected stock returns is superior to univariate prediction. Panel models for financial industries do not seem to be much more different than for other industries. The results appear robust to the data and to alternative estimation procedures.

In-sample construction of long-short portfolios, based on our multivariate models, shows that long and short portfolios have very distinctive characteristics. Long and short portfolios are not in the extremes of one particular characteristic, but score well on many of them. Risk factor analysis shows that the portfolios earn substantial abnormal returns with significant exposure to size, low exposure to market risk and momentum and no exposure to value. The moderate risk exposure might imply that risk factors could be correlated with firm characteristics. Increasing the forecasting horizon sharply decreases the portfolio turnover, does not deteriorate returns, and changes only marginally the risk exposure. Moreover, the portfolios are very stable over time. Only about five percent of the top 30% highest expected return stocks differ from month to month.

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

Our interest is in predicting returns y_{it} of individual stocks using a vector of firm characteristics x_{it}. The basic model we consider is a two-way error component panel,

$$y_{it} = \mu_i + \lambda_t + x'_{it}\beta + e_{it}, \tag{1}$$

where μ_i is a stock specific effect, λ_t is a time effect, β is a K-vector of parameters, and e_{it} is an error term. The errors have a zero mean and are assumed to be uncorrelated with the regressors, i.e. $\mathsf{E}[x_{it}e_{it}] = 0$. In each period t complete data for returns and characteristics are observed for N_t firms. Return data are observed for T months. A total of N different firms are observed with T_i observations for firm i. The total number of data points is $n = \sum_t N_t = \sum_i T_i$.

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. We consider panel regressions for returns over holding periods from one to six months. For these regressions the dependent variable is the cumulative return over J months,

$$y^{(J)}_{i,t+J} = \prod_{j=1}^{J}(1 + R_{i,t+j}) - 1, \tag{2}$$

with R_{it} the single period returns. Though the explanatory variables x_{it} remain the same for all horizons, different values of J give rise to different dependent variables, different parameters and different errors. To keep notation simple we will keep the generic notation of Eq. (1) with y_{it} instead of the convoluted expression $y^{(J)}_{i,t+J}$. When returns are measured over a horizon longer than the sampling interval, e.g. three month returns, the panel regression uses overlapping data and we must take the resulting autocorrelation in the errors into account. Further details about estimation and inference are discussed the relevant sections below.

The characteristics in x_{it} consist of four types of variables: *size*, measured as the logarithm of market value; various *valuation ratios* like earnings-to-price and book-to-price; *momentum*, measured as various functions of past returns; and *liquidity*, measured as the logarithm of trading volume in previous months. All characteristics are observed prior to the return y_{it}.

Industry effects will be introduced through a set of L industry dummies $D_{i\ell}$ that take the value one if firm i is in sector ℓ ($\ell = 1, \ldots, L$). They lead to restrictions on μ_i, a generalization of λ_t, additional slope coefficients in β, or a combination of these modifications of the basic model. We will discuss the specification of industry effects in detail in a separate section below.

2.1 Time effects

The purpose of the model is to predict the cross-section of expected stock returns. We assume that the time effects λ_t are fully unrestricted fixed effects. One way to interpret these effects is that λ_t is an unobserved common factor against which all stocks have a beta equal to one. Since λ_t is an unrestricted parameter, we cannot predict this common factor with information at $t-1$. Absolute forecasts cannot be made with this model. The common factor cancels out, however, when making relative predictions of cross-sectional return differences $y_{it} - y_{jt}$.

Estimating the panel with time effects implies that all variables are taken in deviation from their cross-sectional mean. With a variable like earnings-to-price this implies that we only consider the cross-sectional effect whether a firm with a high *EP* ratio tends to generate higher returns than firms with a low *EP* ratio. The time effect λ_t accounts for a possible effect of a historically low *EP* ratio on all returns.

The time effects are a crude way to adjust for systematic risk. Since not all beta's are equal to one, and returns are generated by multiple factors, some cross-sectional covariance among the returns will remain. Still, time effects 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. We do not attempt to explicitly specify the full cross-sectional covariance structure of the errors e_{it} any further.

2.2 Individual Effects

The second element in the specification of Eq. (1) are the individual effects μ_i. They serve as a diagnostic, as one would hope that they can be omitted. With individual effects in the model the relative returns of stocks i and j depend on the difference $\mu_i - \mu_j$. Expected returns on stocks i and j differ for some unobserved reason. In searching for stocks with high expected returns, we would 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 usually 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 make a significant contribution to the cross-sectional variation of expected returns, there is much scope for improvement of the model. The larger the variance of μ_i, the more space for improvement.

If individual effects are correlated with the average characteristics of a firm, then omitting individual effects will affect the estimates of the slope parameters β. Such a correlation arises for example with the momentum effect. Since momentum is a function of lagged returns of stock i, it will be positively correlated with μ_i. The larger the dispersion in μ_i, the bigger the effect on the momentum coefficients in β, and the more likely to wrongly conclude that momentum is significant when instead individual effects should have been included. Conrad and Kaul (1998) and Jegadeesh and Titman (2002) both estimate how much of the momentum profits can be explained by the cross-sectional variation of the unconditional expected returns (the cross-sectional variance of μ_i). Contrary to Conrad and Kaul (1998), Jegadeesh and Titman (2002) conclude that $\text{Var}(\mu_i)$ is small and negligible relative to the potential gains of a momentum trading strategy. They also conclude, however, that it is difficult to estimate $\text{Var}(\mu_i)$ because many stocks have short time series histories, which precludes precise estimation of individual μ_i.

In our panel we pursue a different test of the interaction between individual effects and momentum. We will compare estimates of the slope coefficient of momentum in a panel with individual effects and in a panel with industry effects or with a pooled intercept ($\mu_i = \mu$). Section 2.4 contains the econometric details on the test statistic.

Individual effects can also interfere with firm characteristics. Some firms can have a high book-to-price ratio on average without generating especially high returns. The book-to-price effect might be much larger for a firm for which the book-to-price ratio has increased recently because something unusual has happened, like a sudden drop in its stock price. For these firms we might expect an increase in future returns, either because of an increase in the risk of that stock or due to an overreaction causing temporary undervaluation. If this hypothesis is true, we would expect a bigger coefficient of the book-to-price variable in a model with individual effects (compared to a model with a pooled intercept). If the book-to-price coefficient is significantly different in the two models, this has implications for portfolio trading strategies. In sorting stocks on their book-to-price ratio, it would be more effective to sort on the book-to-price in deviation of its historical mean.

Because of the possible interaction between the individual effects and the explanatory variables, we will treat the μ_i's 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.

2.3 Industry effects

Industry effects are introduced in three ways. First we introduce a vector of L industry specific time effects $\lambda_{\ell t}$ instead of the single time effect λ_t. Equation (1) is generalized to

$$y_{it} = \mu_i + \sum_{\ell=1}^{L} D_{i\ell}\lambda_{\ell t} + x_{it}'\beta + e_{it}. \tag{3}$$

As for the single time effect, we will assume that all industry specific $\lambda_{\ell t}$ are unrestricted parameters. They can be interpreted as industry risk factors. A direct consequence is that cross-sectional predictions can be made only within the same industry. For firms i and j that belong to separate industries k and ℓ the relative return $y_{it} - y_{jt}$ involves a term $D_{ik}\lambda_{kt} - D_{j\ell}\lambda_{\ell t}$, which is unknown at time $t-1$. Trading strategies based on a panel model with industry specific time effects imply picking the best stocks within each industry in every period.

Industry specific time effects can change the estimates of some of the slope parameters in β. A typical example is the Moskowitz and Grinblatt (1999) hypothesis that momentum is actually an industry effect. They find that momentum does not help predict the relative returns of individual firms, but rather the relative performance of entire industries. The predictive power of momentum should decrease once we correct for industry-wide effects. If the hypothesis of Moskowitz and Grinblatt (1999) is correct, and we estimate the panel with industry specific time effects, we should expect that the momentum parameters become smaller and less significant, otherwise we would be able to predict the relative returns within the same industry using individual firm momentum.

Second, industry effects could be useful as a restriction on the individual effects,

$$\mu_i = \sum_{\ell=1}^{L} D_{i\ell}\tau_\ell. \tag{4}$$

Industry specific intercepts are less restrictive than a single pooled intercept, and yet allow for considerable cross-sectional heterogeneity. In this sense Eq. (4) can be a good alternative to Eq. (1). We will test this restriction using a ranking based on the Schwartz information criterion and a version of the Hausman test. Whereas individual effects can be difficult to estimate, pooling the intercepts for all firms within the same industry will be more precise. The parameters τ_ℓ can explain the average differences in returns among industries. Due to lack of identification a model cannot contain industry specific time effects $\lambda_{\ell t}$ and industry specific intercepts τ_ℓ at the same time. The combination of a single time effect λ_t and industry intercepts τ_ℓ is fully identified.

The third way of accounting for industry effects is by allowing separate slope parameters β_ℓ for each industry. The most general specification of the panel model replaces Eq. (1) by

$$y_{it} = \mu_i + \sum_{\ell=1}^{L} D_{i\ell}\left(\lambda_{\ell t} + x_{it}'\beta_\ell\right) + e_{it}. \tag{5}$$

In this model industries are completely separated. Intermediate cases arise with either the time effects pooled, but separate slopes, or with individual effects restricted to industry intercepts. Without any pooling on either $\lambda_{\ell t}$ or β_ℓ we have L different panel data models.

2.4 Estimation and testing

Estimation and testing are affected by a number of issues that are typical for panels with stock returns at the individual firm level. 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 1,100 companies, while $T = 200$ months. Third, the errors e_{it} are likely to be strongly cross-sectionally correlated even after including time effects, whether pooled λ_t or industry specific $\lambda_{\ell t}$. Because of the large cross-sectional dimension, it will be infeasible, however, to estimate all $(N \times N)$ elements $\mathsf{E}[e_{it}e_{jt}]$ of the cross-sectional error covariance matrix. As a consequence we cannot derive an optimal efficient estimator. Instead of the infeasible optimal GMM estimator we estimate the parameters by OLS. For the standard errors of $\hat{\beta}$ we will use an estimator that is consistent in T, but not in N.

To discuss econometric issues we write the model in matrix notation. We ignore the unbalanced nature of the panel to keep the notation simple. The intricate computational details for an unbalanced panel with two-way effects can be found in Wansbeek and Kapteyn (1989) and Baltagi (2001, ch. 9), but are not essential for the issues we discuss below. The various specifications regarding the pooling of industries can all be subsumed within the following generic specification of the panel

$$y_t = \mu + D\lambda_t + Z_t\delta + e_t, \tag{6}$$

where we use the following vector notation:

- y_t : N-vector of returns in period t;
- D : $(N \times L)$ matrix of industry dummies indicating which industry each firm belongs to, $D\iota_L = \iota_N$;
- λ_t : L-vector of industry time effects $\lambda_{\ell t}$;
- Z_t : $(N \times M)$ matrix of explanatory variables which may include industry dummies, where the size of M depends on the industry pooling assumptions;
- δ : M-vector of coefficients depending on the industry pooling assumptions;
- e_t : N-vector of errors.

Some important special cases are tabulated below:

Pooled time effects	:	$\lambda_t = \iota_L\lambda_{0t}$, with λ_{0t} a scalar, so that $D\lambda_t = \iota_N\lambda_{0t}$
Pooled slopes	:	$M = K$, $Z_t = X_t$, the $(N \times K)$ matrix with rows equal to the predictor variables x'_{it} and $\delta = \beta$
Industry slopes	:	Z_t contains $M = KL$ explanatory variables with rows $z'_{it} = D_i \otimes x'_{it}$ and δ stacks all industry specific β_ℓ
Industry intercepts	:	$\mu = 0$, $Z_t = (X_t \quad D)$, and $\delta' = (\beta' \quad \tau')$, where τ is a L-vector of industry intercepts

Identification of the intercepts requires a normalization of either λ_t or μ_i in models where both are included. The normalization is arbitrary as we are mainly interested in the slope parameters δ.

Industry specific time effects are eliminated by premultiplying Eq. (6) by

$$Q = I - D(D'D)^{-1}D', \tag{7}$$

which takes all returns and regressors in deviation of their cross-sectional industry average. With a pooled time effect all variables are taken in deviation of the cross-sectional average for all firms. Both time and individual effects are eliminated by the standard transformation of a two-way fixed effects panel:

$$\tilde{y}_{it} = y_{it} - \bar{y}_{\ell,t} - \bar{y}_i + \bar{y}_\ell, \tag{8}$$

where $\bar{y}_{\ell,t}$ is the industry average of industry ℓ in period t, $\bar{y}_i$ is the time series average of firm i and $\bar{y}_\ell$ is the time series average of $\bar{y}_{\ell,t}$. All explanatory variables are transformed analogously.

After eliminating the fixed effects μ_i and/or λ_t, the OLS estimator of the slopes is

$$\hat{\delta} = \left(\frac{1}{T} \sum_{t=1}^{T} \tilde{Z}_t' \tilde{Z}_t \right)^{-1} \left(\frac{1}{T} \sum_{t=1}^{T} \tilde{Z}_t' \tilde{y}_t \right). \tag{9}$$

The number of elements in $\hat{\delta}$ is small relative to the sample sizes N and T. Due to the cross-sectional correlation, the cross-sectional sample size N is of little use for inference. We use a robust estimator of the covariance matrix of $\hat{\delta}$ proposed by Driscoll and Kraay (1998) that is consistent in T, independent of N. As in Driscoll and Kraay (1998) we use that

$$\mathrm{Var}(\sqrt{T}(\hat{\delta} - \delta)) = V_{ZZ}^{-1} S V_{ZZ}^{-1}, \tag{10}$$

where $V_{ZZ} = \operatorname{plim} \frac{1}{T} \sum_t \tilde{Z}_t' \tilde{Z}_t$ and

$$S = N \mathsf{E} \left[\sum_{s=-\infty}^{\infty} h_{t-s} h_t' \right], \tag{11}$$

with the time series of M-vectors h_t defined as

$$h_t = \frac{1}{\sqrt{N}} \tilde{Z}_t' \tilde{e}_t. \tag{12}$$

We estimate S using the Newey-West weights on the first m autocorrelations,

$$\hat{S} = \frac{N}{T} \sum_{s=-m}^{m} \left(1 - \frac{|s|}{m+1} \right) \sum_{t=1}^{T} \hat{h}_{t-s} \hat{h}_t', \tag{13}$$

where $\hat{h}_t$ uses the estimated residuals $\hat{e}_t$. The number of autocorrelations in the Newey-West estimator depends on the forecast horizon of the model and is at least as big as the number of months over which the cumulative returns y_{it} are computed. The matrix V_{ZZ} is replaced by its empirical finite sample counterpart. Both the estimator $\hat{\delta}$ and the covariance matrix estimator are straightforwardly modified if some elements in δ are pooled, or when individual effects are included. In the absence of autocorrelation in the errors the estimator reduces to the term with $s = 0$ in Eq. (13).

Other panel studies, for example Haugen and Baker (1996) and Brennan et al. (1998), use the Fama and MacBeth (1973) coefficient estimator. It is defined as the time series average of a series of T cross-sectional regressions, ignoring the individual effects,

$$\hat{\delta}_{FM} = \frac{1}{T} \sum_{t=1}^{T} \hat{\delta}_t, \tag{14}$$

$$\hat{\delta}_t = \left(Z_t' Q_t Z_t\right)^{-1} Z_t' Q_t y_t. \tag{15}$$

For comparison, the standard OLS estimator of the coefficient vector δ in a model without individual effects is a matrix weighted average of the Fama-MacBeth cross-sectional $\hat{\delta}_t$,

$$\hat{\delta}_{OLS} = \left(\sum_{t=1}^{T} Z_t' Q_t Z_t \right)^{-1} \sum_{t=1}^{T} Z_t' Q_t Z_t \hat{\delta}_t. \tag{16}$$

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 the firm characteristics will be more influential. Likewise, months with larger cross-sections will be more influential for estimating δ. Since the number of stocks in our panel grows over time, the more recent periods have a relatively large weight in the OLS 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.

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

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 rely on the Schwartz information criterion (SC),

$$SC = \ln s^2 + \frac{k}{n} \ln n, \tag{17}$$

where s^2 is the residual sum of squares of the estimated model, n is the total number of data points in the panel and k is the total number of parameters including all individual and time effects.[4] In the application we have more than 1100 firms and 200 months of data. After deletion of missing values more than 90,000 data points are available. With these values of N, T and n, and K fixed and small, the SC 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 Eq. (1) are very likely to be cross-sectionally correlated, even after allowing for time effects $\lambda_{\ell t}$. The Schwartz criterion will be more conservative than the F-test.

Incorrectly omitting the individual effects can have an effect on the slope parameters β, whenever μ_i and x_{it} are correlated. We use a version of the Hausman test to check if estimates of β differ significantly between a model with individual effects and a model with either a single intercept or industry specific intercepts. As an example, consider the model with a pooled time effect and pooled slope coefficients β,

$$y_t = \mu + \iota\lambda_t + X_t\beta + e_t \tag{18}$$

The fixed effects estimator of this model is denoted $\hat{\beta}_I$. Restricting the individual effects to $\mu = D\tau$ leads to the estimator $\hat{\beta}_P$. Under the null that μ_i is not correlated with x_{it} both estimators are consistent, with $\hat{\beta}_P$ likely to be more efficient, as it omits

[4] 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.

the unnecessary individual effects. Under the alternative, $\hat{\beta}_P$ will be inconsistent. Therefore the difference $\hat{\beta}_I - \hat{\beta}_P$ can tell us if individual effects have an effect on the slope coefficients β.

From the expression of the standard errors in Eq. (10) we know that we can write the difference between the two estimators as

$$\sqrt{T}(\hat{\beta}_I - \hat{\beta}_P) = V_{II}^{-1}\frac{1}{\sqrt{T}}\sum_t h_{It} - V_{PP}^{-1}\frac{1}{\sqrt{T}}\sum_t h_{Pt} = \frac{1}{\sqrt{T}}\sum_t g_t \tag{19}$$

where V_{II} and V_{PP} are the relevant matrices corresponding to the general V_{ZZ} in Eq. (10), and h_{It} and h_{Pt} the relevant time series related to h_t in Eq. (12). Having constructed g_t, the covariance matrix of $\sqrt{T}(\hat{\beta}_I - \hat{\beta}_P)$ follows as

$$D = \frac{1}{T}\sum_{s=-m}^{m}\left(1 - \frac{|s|}{m+1}\right)\sum_{t=1}^{T}\hat{g}_{t-s}\hat{g}_t', \tag{20}$$

We use this covariance matrix to compute the Hausman test statistic

$$W_H = T(\hat{\beta}_I - \hat{\beta}_P)'D^{-1}(\hat{\beta}_I - \hat{\beta}_P). \tag{21}$$

3 Data

Our data set is based on the Morgan Stanley Capital International (MSCI) US data universe. It covers the investable universe for most institutional investors as it contains relatively few small cap stocks. We include all US firms followed by the MSCI. Some of them are the constituents of the well-known published MSCI US index. Others are followed by the MSCI because of their size or relevance, and not because of high past returns, which minimizes the potential good-company bias. To minimize the potential back filling bias we include companies in the data set only when investors were able to obtain the information provided by the MSCI. The MSCI index covers about 70% of the US stock market capitalization. With the additionally followed firms the data set provides a fairly complete picture of the US market capitalization, for example the MSCU universe index matches the much broader Fama-French index. The sample period ranges from November 1984 until June 2002. The raw data set covers 1,243 large companies. Each company belongs to a specific industry.[5] The total number of industries is 22.

[5] We use the old MSCI industry classification that was used before April 1999. In April 1999 the MSCI introduced a new industry classification. Using the new industry classification in all periods would result in a look ahead bias, while using the new industry classification only after April 1999 would lead to unreliable results due to the short time series April 1999 - June 2002.

The number of firm characteristics (regressors) used to predict stock returns varies a lot in the literature. We have chosen eleven regressors that have been widely used over the last fifteen years, have proved to contribute to the prediction of stock returns and are likely to capture different facets of a company. The eleven explanatory variables are classified into four groups: size, valuation ratios, momentum and liquidity.

Size. Size (MV) is defined as the logarithm of the market capitalization of firm i in month t, measured in billions of dollars.

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). There are two sources of multicollinearity related to them. Firstly, their numerators contain accounting information and are updated quarterly. The monthly change in these ratios might be mostly due to price changes, and therefore might be correlated with short-term momentum. The strongest correlation between short-term momentum and a valuation ratio is -0.26. Secondly, the five valuation ratios are cross correlated, the strongest correlation is 0.53.

Momentum. We include two types of momentum variables. Short-term price momentum is defined as the cumulative return over the last six months (*R1-6*), and long-term price momentum is defined as the cumulative return over the six months prior to the last six months (*R7-12*) as in Brennan et al. (1998) and other studies. As common, the variable (*R1-6*) is lagged by an additional month to avoid any spurious relation between the current month return and the future month return caused by bid-ask spread effects and thin trading. The second type of momentum is earnings momentum (analyst earnings revisions), denoted as *CFY1*. It reflects the expectation revisions of financial analysts about the next year's earnings of the stock, and 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 this data is I/B/E/S.

Liquidity. We use two liquidity variables. The first one (VOL) is the log of monthly turnover volume, measured in dollars. The second variable (*52W*) is the log of average turnover volume for the last 52 weeks. Brennan et al. (1998) recommend defining separate liquidity variables for NYSE and NASDAQ stocks, since trading volume is measured differently between NYSE and NASDAQ. On the other hand the stocks traded at NASDAQ are concentrated in small number of industries. Since our general model in Eq. (5) includes industry specific coefficients and time effects, we do not split the liquidity variables.

Examples of each of the variables in the empirical literature are Rosenberg, Reid and Lanstein (1985), Fama and French (1992), Lakonishok et al. (1994), and Daniel and Titman (1997) for *MV*, *BP*, *EP* and *CP*. Momentum variables are used in Jegadeesh and Titman (1993) and Rouwenhorst (1998). Frankel and Lee (1998) focus on earnings momentum using I/B/E/S data. Chan et al. (1996) discuss both earnings momentum and price momentum. Cochrane (2001) discusses the use of valuation ratios like *SP* and *DP* for prediction of stock returns, while Vuolteenaho (2002) finds that cash flow news influences 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. Stoll (1978), among others, finds that volume is the most important determinant of the bid-ask spread, while Brennan and Subrahmanyam (1995) find that it is a basic determinant of liquidity. Brennan et al. (1998) and Koski and Michaely (2000) discuss the relation between liquidity and stock prices and returns. Fama and French (1992) study the interaction between firm characteristics.

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 the 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 strategies after controlling for firm characteristics. Baca et al. (2000) discuss the role of industry effects in the equity markets.

The numbers of companies per industry in the data set are reported in Table 1. Some industries[6] contain only a few firms, indicating that we should be careful in interpreting their industry specific parameters. Panel A of Table 2 reports descriptive statistics of the raw data set of 1,243 firms. Some firm characteristics like the valuation ratios have outliers. For the econometric analysis we delete all data points that contain either incomplete or missing data. This leads to a data set that contains 1,144 companies and 93,482 data points which amounts to 88.6% of the number of data points for which the monthly return (RET) is observed.[7] The outliers are less

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

[7] 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 11.4% of

extreme compared to the ones in panel A due to the deletion of incomplete data. After inspection of the worst outliers we concluded that they were real and not due to systematic deficiencies of the data. Since outliers in the valuation ratios have a strong influence on the regression results, we trimmed all valuation ratio outliers to the lower and upper 1% tail of the distribution. Descriptive statistics of the final data set data are reported in panel B of Table 2.

As a preliminary test for the predictive power of the firm characteristics we construct portfolios that are sorted on a single characteristic. At the beginning of each month t we construct a high and a low portfolio, based on sorting of the stocks by each characteristic x and buying the top 30% of the sorted stocks (the high portfolio), while selling the bottom 30% of the sorted stocks (the low portfolio). The portfolio is either equally weighted or weighted by the characteristic x. Next month $(t+1)$ we document the returns of the high and low portfolios. The resulting returns for each characteristic separately are reported in panel A of Table 3. Although the negative sign for size corroborates the small cap effect, it is not statistically significant. This might be due to the low number of small firms in the MSCI data. Surprising is the low predictive power of all valuation ratios. The strongest predictive variable is *CFY1* that captures the analyst earnings revisions. The effect of long-term price momentum (*R7-12*) is significant, while short-term price momentum (*R1-6*) has low predictive power in this investable universe. It is interesting that the liquidity variables *VOL* and *52W* have positive and significant effects. Most studies (like Brennan et al. (1998)) are based on data that include smaller and less liquid companies, and find a negative and significant liquidity effect. Our data includes a majority of big (i.e. more liquid) firms, and this simple univariate analysis shows that liquidity within the liquid companies might have a different effect.

We inspect whether the predictive power of firm characteristics is robust to industry effects, for example whether the low predictive power of valuation ratios and short-term price momentum is due to such effects. It is possible that some t-statistics in Table 3 are insignificant because of industry heterogeneity. Within each industry we construct equally weighted and characteristic weighted portfolios based on sorting on each characteristic as described in the previous paragraph. Next month, we calculate the return from an equally weighted composite portfolio that includes returns from all equally weighted industry portfolios. Further, we calculate monthly

the data points are incomplete we have not pursued the imputation estimator.

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 B of Table 3 reports the results from this industry neutral portfolio construction. The valuation ratios have higher t-statistics than those in panel A. In contrast to the strategy that does not correct for industry effects (panel A of Table 3), *CP* and *EP* have significant effects on the expected returns. This simple analysis underlines the importance of industry effects and motivates us to focus on the possibility of capturing these effects in a formal panel data model.[8] A related issue is whether industry effects should be broken up into individual firm effects.

4 Results

We estimate the general specification (5) and several restricted versions, and investigate whether individual effects, industry effects, time effects and firm characteristics can predict stock returns. We present the results in a series of graphs and tables.

4.1 Individual effects and time effects

In table 4 we rank various models on the Schwartz criterium (SC). The estimated models are the general specification Eq. (5) and a number of restricted versions. These models have industry specific coefficients β_ℓ and differ with respect to whether the time effects are missing ($\lambda_{\ell t} = 0$), pooled over industries ($\lambda_{\ell t} = \lambda_t$) or industry specific ($\lambda_{\ell t}$) and to whether the intercept is pooled (μ), industry specific (τ_ℓ) or firm specific (μ_i).

For monthly returns the Schwartz criterion always prefers a model without individual effects (i.e. a model with industry specific or pooled intercepts) to the same model with individual effects. The estimates of the individual effects contain huge positive and negative outliers. The 5% largest outliers (in absolute value) correspond

[8] We investigated the power 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. In case of three month horizon the earnings momentum *CFY1* has predicting power only in industry neutral portfolios, while *R7-12*, *VOL* and *52W* always are powerful predictors. In case of six month horizon the short-term momentum *R1-6* has predicting power only in industry neutral portfolios, while *VOL* and *52W* always are powerful predictors. Details on all results with longer forecasting horizon are available upon request.

to companies for which only few observations are available. We therefore repeated the model selection after excluding all firms with less than 60 observations. The bottom part of table 4 shows that although the number of firms is reduced by about 400, none of the results changes. The SC again selects the models without individual effects. From the model selection criterium we conclude that individual effects are not important. They do not improve the cross-sectional fit sufficiently to justify the inclusion of such a large number of parameters.

Repeating the model selection with three- and six-months cumulative returns as the dependent variable, we come to the same conclusion. The results in table 4 show that the lowest SC obtains for models without individual effects.[9] The only exception is the case of six-months returns, with all firms included, and on top of that also industry specific time effects, which is preferred to the same model without individual effects. The model is, however, still ranked worse than the model with a pooled time effect.

Turning to the specification of time effects, table 4 shows that the Schwartz criterion always prefers the model with pooled time effects λ_t to the same model with industry specific time effects $\lambda_{\ell t}$, or compared to the same model without any time effects ($\lambda_{\ell t} = 0$). This finding is robust to the forecasting horizon and to the exclusion of firms with less than 60 observations.[10]

4.2 Firm characteristics

Tables 5, 6 and 7 report the pooled estimates of β for different models using as dependent variable either one-, three- or six-month returns, respectively. The models differ again in the structure of the intercepts μ_i and λ_t. Based on the model selection exercise the preferred model has a pooled time effect and no individual effects. The other columns in tables 5, 6 and 7 are included to examine the robustness of the relation between returns and firm characteristics.

For the one-month returns table 5 shows that size (MV) and cash flow-to-price (CP) are always significant, independent of the specification of the intercepts. The significant negative size effect in this MSCI data set is in contrast to the univariate

[9] Excluding all firms with less than 60 observations for the six-months returns reduces the number of firms in the panel to 370. This is a peculiarity in the data, because 277 firms are observed in the last 66 months only.

[10] These findings are also confirmed by the SC-ranking of models with pooled coefficients ($\beta_\ell = \beta$) and with the same structure of intercepts and time effects as the models in Table 4 (not reported here).

analysis documented in Table 3. In models without individual effects dividend-to-price (*DP*) and volume (*VOL*) are also significant and have the same signs as in the univariate portfolio strategies. Even the standard errors of the effects are very similar. All valuation ratios have the correct sign and reasonably small standard errors, showing that multicollinearity does not seem to be a problem. The five valuation ratios are always jointly significant. As in the univariate analysis short-term-momentum (*R1-6*) is never significant.[11] Contrary to the univariate analysis in Table 3, earnings-momentum (*CFY1*) and medium-term-momentum (*R7-12*) are not always significant in a multivariate approach.

Although individual effects did not seem important, they do make a difference to the parameter estimates for some of the characteristics. The size effect is much more pronounced in models with unrestricted μ_i. The dividend-to-price effect completely disappears and even obtains the opposite sign. A similar sign change occurs for the long-term-volume, which becomes significantly negative as we would expect from the literature on liquidity. The Hausman test, reported in table 5, indicates that the two sets of parameters become indeed significantly different if individual effects μ_i are included. Not surprisingly, the t-statistics for the differences between individual elements of β are especially large for *MV*, *DP* and *52W*.

The model with individual effects itself is practically useless for forecasting purposes, since the individual effects are poorly estimated for most firms. But even though we cannot really estimate the individual effects themselves, the Hausman test indicates that there is substantial real cross-sectional variation in μ_i. We interpret the differences in β estimates as evidence that some important explanatory variables are still missing. Identifying these variables will not alleviate cross-sectional asset pricing puzzles. For example, the results show that the size effect will become more pronounced once we know what firm characteristics can explain the currently unobserved heterogeneity.

Continuing the comparison between the models with and without individual effects, it appears that the momentum variables are not affected by the inclusion of individual effects. This result is consistent with Jegadeesh and Titman (2002) who also find that cross-sectional differences in expected return cannot explain profits from momentum strategies.

[11] 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.

To summarize, individual effects capture some cross-sectional variation that is constant over time: some firms are bigger, pay systematically less dividends and always have higher liquidity. The regression slope picks up the real correlation between liquidity and returns, which is identified by different firms having high liquidity in different months. Once the individual effects amplify the size effect, the liquidity effect becomes negative, consistent with Brennan et al. (1998).

Tables 6 and 7 report the estimates of β for models with three- and six-months returns as the dependent variable. First, the estimates for both size and the valuation ratios are almost the same as for the monthly returns. Even standard errors are comparable. This implies that these characteristics are persistent over time. The relative size and value indicators of a firm do not change much from month to month.

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. Therefore valuation ratios might capture the dynamics of a three or six month variable better than the dynamics of a monthly variable. The coefficients of the long-term price momentum *R7-12* and earnings revisions *CFY1* are now insignificant, implying that analysts forecasts are short-sighted, consistent with the findings of Chan et al. (1996). While *R7-12* has significant univariate power to forecast three month returns (see Table 3), the multivariate approach documented in Table 6 shows that this effect is less significant, similarly to the monthly forecasting. The six month price momentum *R1-6* is significant in all models that forecast six month returns, consistent with Rouwenhorst (1998).

The last two columns of Tables 6 and 7 report regression results for models with individual effects and pooled β. The behavior of the *MV*, *DP*, *VOL* and *52W* coefficients is the same as in case of monthly forecasting. In case of three and six month forecasting the individual effects are related to *BP* and not any more to *CFY1*, confirming that valuation ratios are related to long-term variables, while analyst revisions are relatively short-sighted.

4.3 Industry effects

In Section 2 we distinguished three ways of introducing industry effects in the model. In Section 4.1 we already concluded that separate industry time effects $\lambda_{\ell t}$ do not improve the fit of model sufficiently given the large number of extra parameters required. A model with a pooled time effect λ_t was always preferred by the Schwartz criterion.

In this section we consider the pooling hypotheses $\tau_\ell = \tau$, and $\beta_\ell = \beta$, i.e. whether the firm characteristics have the same effect in all industries. For all models without individual effects from Table 5 we estimated a version with industry specific coefficients β_ℓ. We formally test whether coefficients 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 following version of the general model in Eq. (5)

$$y_{it} = \lambda_t + \sum_{\ell=1}^{L} D_{i\ell} \left(\tau_\ell + x_{it}'\beta_\ell\right) + e_{it}. \tag{22}$$

The robust Wald statistic for the 220 restrictions in the null hypothesis is 963.6, rejecting it at any reasonable significance level.

For a more detailed analysis of the cause for the rejection we test whether each characteristic has the same coefficients across industries. Table 8 reports the test statistics of the null hypothesis $\beta_{j\ell} = \beta_j$ for each characteristic j separately. For monthly returns the null hypotheses are rejected at the 5% significance level in all model specifications and for all characteristics with exception of *DP*, *CFY1*, *R7-12* and *52W* (the 5% critical value is 32.67). Rejections of the null hypothesis for other characteristics are not robust across alternative specifications of the time effects. In the case of industry specific time effects, the null hypotheses are rejected also for *R7-12* and *52W*.

In case of forecasting of three and six month returns the null hypothesis $\beta_{j\ell} = \beta_j$ is rejected for all models and characteristics, while in case of monthly forecasting the null is not rejected for five firm characteristics. The intuition is that in case of monthly forecasting horizon the heterogeneity across industries is not distinct (due to the short period), and therefore cannot be well captured by model coefficients, leading to model coefficients that do not vary much across industries. If the forecasting horizon increases, the heterogeneity across industries is more distinct,[12] and can be captured by the model coefficients, resulting in model coefficients that do vary across industries.

As illustration of the formal tests, Fig. 1 and 2 show the resulting industry specific coefficients[13] and t-statistics for the industry specific intercepts[14] and five character-

[12] Intuitively, since industries seem to be related to the business cycle (see e.g. Horvath (2000) and Hornstein (2000)) the differences among them become visible over a longer period that includes (a part of) the business cycle.

[13] In some 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] To be identified the model with industry specific time effects cannot contain industry specific

istics,[15] estimated with the models from Table 8. We performed Wald tests for the null hypotheses that the industry intercepts in each model are the same. The null is not rejected at the 10% (or 5%) confidence level for all models, indicating that there are no permanent differences in the expected industry returns. Expected return differences across industries seem to come mostly from the industry specific coefficients, implying that the intercepts should be industry specific as well, since the average values of the firm characteristics differ by industry.

It is interesting that coefficient estimates do not depend much on the specification of the time effects. Only industry specific time effects sometimes lead to higher or lower t-statistics for some of the characteristics, as shown by the third bars in Fig. 2. Both coefficients and t-statistics are very different across industries, distinct outliers are the 5^{th} industry (Commercial) and the 16^{th} industry (Semiconductors). The most extreme outlier is the 18^{th} industry (Data Processing), but this could be due to the low number of firms belonging to that industry. Coefficients and t-statistics also vary a lot across some industries with many companies.

In conclusion, we develop multivariate expected return models and find that firm characteristics have predictive ability. The predictive power of basic firm characteristics like size and momentum seems to be different in the univariate and multivariate analysis. Industry effects, industry specific coefficients and pooled time effects are important. Individual effects are related to size and liquidity. Varying the forecasting horizon changes the forecasting power of valuation ratios and momentum. These findings are robust to the estimation method. Now we focus on portfolios based on multivariate expected return models.

5 Portfolio management implications

The panel models are meant to predict the cross-sectional variation in returns. To investigate the portfolio management implications of the model specifications discussed so far, we consider the time series returns for a number of long-short portfolios that are based on in-sample simulations involving the models of interest. For each model

intercepts, as Section 2 explains. Therefore only two bars are related to each industry in the top graphs (that show industry intercepts) of fig. 1 and 2.

[15] The coefficients and the t-statistics of the other six firm characteristics vary across industries as well and are available upon request.

we construct the fitted values

$$\hat{y}_{it} = \sum_{\ell=1}^{L} D_{i\ell} \left(\tau_\ell + x'_{it}\hat{\beta}_\ell \right), \tag{23}$$

and consider restricted versions with β_ℓ equal across industries ($\beta_\ell = \beta$). We focus on three stock return predicting models: a model with pooled coefficients and time effects ($\beta, \tau_\ell, \lambda_t$), a model with industry specific coefficients ($\beta_\ell, \tau_\ell, \lambda_t$), and an industry neutral model ($\beta_\ell, \lambda_{\ell t}$).

Each period t the expected next month(s) returns $\hat{y}_{it}$ are sorted in a 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 value with the total portfolio market value adding up to 30% of the total market value observed in the respective month. The number of stocks in the value weighted portfolio 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 J months are constructed as follows. Each month t we predict the returns for the following J months and construct a long and a short portfolio using the procedure described in the previous paragraph. The portfolios are kept for the following J months and are liquidated at the end of month $t + J$. In month $t + 1$ we repeat this procedure and construct new long and short portfolios. These portfolios are liquidated at the end of month $t + J + 1$. Therefore after the start up period the aggregate portfolio consists of J overlapping long-short portfolios.

Individual effects and (industry specific) time effects are not part of the predictions. We consider models with pooled time effects λ_t and models with industry specific time effects $\lambda_{\ell t}$. Portfolio construction differs for both specifications. With pooled time effects λ_t we sort all stocks, and make only relative (i.e. cross-sectional) predictions and not absolute (i.e. time-series) ones, since λ_t drops out in comparing $\widehat{y}_{it}$ and $\widehat{y}_{jt}$. Any pattern in the long-short portfolio is therefore solely due to firm characteristics and industry effects. In case of industry specific time effects we sort stocks separately within each industry and construct long minus short industry portfolios. We do not predict the difference $\lambda_{\ell t} - \lambda_{kt}$ for firms belonging to industries ℓ and k. An aggregate portfolio is constructed by adding all industry specific long-short portfolios.

For an equally weighted portfolio industry returns are aggregated and weighted by the number of stocks in the industry; for the value weighted portfolio industry returns are weighted proportionally to the market weight for each industry. The aggregate portfolio is industry neutral. Stock picking is active only within industries.

Table 9 shows that the average returns of the long and short portfolios are significantly different at the 1% significance level for all models and forecasting horizons. All return differences are larger than those for the portfolios in Table 3 that are sorted on a single characteristic.[16] Combining different characteristics enhances the cross-sectional differences. For all forecasting horizons, long-short portfolios based on the models $(\beta, \tau_\ell, \lambda_t)$ generate lower returns and are more risky than portfolios based on the models with industry specific slopes $(\beta_\ell, \tau_\ell, \lambda_t)$. 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 9 reveals that the industry neutral portfolio (based on the model $\beta_\ell, \lambda_{\ell t}$) has a lower average return for the long portfolio and a higher average return for the short portfolio. The forced industry neutrality also leads to portfolios with much lower variances. The unrestricted portfolios (with pooled β) involve considerable industry bets. In some periods the highest (lowest) expected returns are concentrated in specific industries, consistent with Moskowitz and Grinblatt (1999), who show that momentum effects are often caused by industry momentum.

For a better understanding of the portfolio returns and their determinants we consider the portfolio profiles. Table 10 reports the average firm characteristics of the long and short portfolios. The most distinctive characteristic is *CP*, which is also identified by both univariate and multivariate analysis (see Tables 3, 5, 6 and 7) as one of the most powerful predictors, consistent with the findings of Lakonishok et al. (1994). The analyst earnings revisions have a significant effect, consistent with the results in Table 3. Other characteristics related to expected return differences are the market value *MV*, the momentum *R7-12* and the liquidity variables *VOL* and *52W*. The valuation ratios have discriminatory power which is higher than the one implied by Table 3. The profiles of the long and short portfolios are close to the ones analyzed by Haugen and Baker (1996), while our data set is an investable universe.

We also considered profiles of long and short portfolios based on three and six

[16] Some caution is necessary when comparing Tables 3 and 9. The reason is that Table 3 reports results from out-of-sample portfolio construction, while the model coefficients $\hat{\beta}_\ell$ that are used for calculation of the results in Table 9 are estimated in-sample.

month forecasting. Again the most distinctive characteristic is *CP*, while the effect of *SP* sharply increases. The effects of *CFY1* and *R1-6* remain significant but become weaker. The six month momentum *R1-6* is very strongly related to return differences for all six month portfolios, consistent Rouwenhorst (1998). The momentum profiles of the long and the short portfolios are consistent with Tables 3, 5, 6 and 7, and 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 medium term.

As next step we analyze the portfolio turnover that is related to the transaction costs. Expected returns are persistent. Most explanatory variables vary slowly through time or are time-invariant (industry dummies), leading to portfolios that remain fairly stable from month to month. The upper left panel of Table 11 reports the transition frequencies of stocks going from one portfolio to another in case of monthly forecasting. For the strategies that select stocks from the complete universe (based on the models $(\beta, \tau_\ell, \lambda_t)$ and $(\beta_\ell, \tau_\ell, \lambda_t)$), about 83% of the stocks that are in the long portfolio in month t remain there in month $t+1$, while about 81% of the stocks that are in the short portfolio in month t remain there in month $t+1$. In total 30% from the stocks from the neutral portfolio are equally re-distributed to the long and short portfolios. New stocks are equally distributed among the long, the neutral and the short portfolio.[17] On the other hand the industry neutral portfolios (based on the model $(\beta_\ell, \lambda_{\ell t})$) are less stable. The best stocks within an industry change more rapidly than the overall best stocks, partially due to the constant industry intercepts which give some industries a permanent expected advantage over other industries.

The lower panels of Table 11 report the transition frequencies of stocks going from one portfolio to another in case of three and six month forecasting. The only difference compared to monthly forecasting is the sharply reduced turnover – for example the persistence of the long (short) portfolio increases from 83% (81%) to 94% (94%) when the forecasting horizon grows from one to three months. Tables 9 and 11 show that longer forecasting horizons do not deteriorate returns and simultaneously drastically decrease portfolio turnover.

Finally we analyze the portfolio risk exposure and run performance attribution regressions of the long-short portfolio returns on the value weighted market portfolio,

[17] Stocks are only included in the portfolios if they have been in the data set for at least a year. This requirement is necessary for the computation of the momentum variable *R7-12*.

the Fama-French factors *SMB* and *HML*, and the momentum factor *UMD*.[18] The upper panel of Table 12 reports results for portfolios based on models that predict monthly returns. The coefficients and their significance are similar across models. The portfolios have moderate exposure to the market index and momentum and have virtually no exposure to *HML*, consistent with the insignificant coefficients of *BP* in Table 5. The exposure to *SMB* is high, consistent with the high predictive power of *MV* documented in Table 5. The performance regressions have a significant positive alpha intercept in all cases, regardless of the included risk factors.[19] The model with industry specific coefficients ($\beta_\ell, \tau_\ell, \lambda_t$) has higher alpha's than the other two models ($\beta, \tau_\ell, \lambda_t$ and $\beta_\ell, \lambda_{\ell t}$), while the risk exposure of all models is very similar. The value weighted portfolios generate lower abnormal returns than the equally weighted ones. 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 estimated the same regression for an industry specific portfolio based on sorting by *CFY1*, which is the most powerful predictor in Table 3. The resulting alpha is 0.44 and the portfolio has significant exposure to size, value and momentum, confirming that combining different characteristics enhances the cross-sectional heterogeneity.

Brennan et al. (1998) find that risk adjusted returns can be explained by market value, book-to-price ratio and price momentum. Intuitively, our returns, which are not adjusted for risk, should have significant exposures to *SMB*, *HML* and *UMD*, which is not the case.

The three panels of Table 12 show that portfolio risk exposure is robust to the forecasting horizon. The abnormal returns slightly decrease when the forecasting horizon increases, but remain significant and higher than one percentage point per month. The model with industry specific coefficients ($\beta_\ell, \tau_\ell, \lambda_t$) has higher abnormal returns than the other models, while in case of six month forecasting its risk exposure is lowest. In case of six month forecasting the model seems to be particularly interesting for (institutional) investors since it leads to a portfolio that is characterized by high and significant abnormal returns, very low turnover and very low risk exposure.

[18] Data for these factors are 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`

[19] The intercepts have high absolute values (they are measured in percentage points and all entries in Table 12 are on a monthly basis), but this result should be interpreted with some caution since it is based on in-sample forecasting without accounting for transaction costs.

6 Conclusion

We construct an investable unbalanced panel data set and perform specification tests on panel data models for stock return prediction. Individual stock effects seem to be related to size and liquidity, while time effects are significant and pooled over industries. The industry effects are important and can be captured by industry specific coefficients and intercepts that enable within industry predictions. Combining firm characteristics enhances the cross-sectional variation. Our findings are robust to the forecasting horizon and the data.

In-sample simulations of long-short portfolio strategies result in portfolios with low turnover and substantial abnormal returns with moderate exposure to market risk and momentum, but significant exposure to size. The risk exposure is robust to the forecasting horizon. Portfolios based on multivariate forecasting perform much better than their peers based on univariate forecasting. The specification of industry effects plays an important role. Longer forecasting horizons drastically reduce the portfolio turnover, do not deteriorate returns, and change only marginally the risk exposure. Some portfolios are characterized by high and significant abnormal returns, very low turnover and very low risk exposure. How well the portfolio strategies work in an out-of-sample framework and with transaction costs is an open question.

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Table 1: Summary Statistics by Industry

The summary statistics are based on 1144 US firms observed over 200 months from Dec. 1985 until June 2002. The first column reports the MSCI industry classification. The second column describes the industry. The column "All firms" refers to the number of companies per industry in the raw data set. 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 percentage points 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	74	70	7752	1.23	5.75	1.22	5.77
2	Automobiles	26	24	2402	1.38	6.94	1.31	6.77
3	Consumer	60	58	5578	1.29	5.73	1.29	5.71
4	Retail	97	89	7066	1.57	6.97	1.55	6.82
5	Commercial	35	33	1545	1.22	7.67	1.11	7.33
6	Food and Consumer	72	68	7300	1.75	4.79	1.70	4.74
7	Specialty	10	9	1347	1.20	5.90	1.20	5.89
8	Services	34	32	2449	1.58	5.89	1.57	5.73
9	Health Care	118	108	7794	1.70	6.22	1.69	5.84
10	Oil and Gas	58	53	4851	1.32	7.35	1.29	7.05
11	Banking and Insurance	114	103	6710	1.80	5.69	1.76	5.74
12	Diversified Financials	77	68	3833	1.48	5.68	1.54	5.75
13	Capital Goods	38	34	3592	1.35	5.89	1.34	5.75
14	Machinery-Diversified	56	50	5036	1.48	6.05	1.46	5.98
15	Technology Hardware	218	211	12806	1.48	9.48	1.43	9.24
16	Semiconductors	15	15	910	2.71	17.27	2.74	17.30
17	Computer Services	10	10	776	1.57	8.93	1.55	8.55
18	Data Processing	9	9	605	2.12	6.86	2.06	6.70
19	Telecom	30	19	1475	0.94	7.18	0.99	6.44
20	Utilities	60	51	6326	1.10	4.31	1.09	4.36
21	Power Producers	4	4	275	0.32	11.66	0.32	11.55
22	Transport	28	26	3054	1.39	6.28	1.34	6.21

Table 2: Summary Statistics of All Firm Characteristics

Panel A reports descriptive statistics of the raw data set. Panel B reports descriptive statistics for the subset of complete data points and after all valuation ratios were trimmed to the lower and upper 1% tail of the distribution. A data point is considered to be complete if all variables are available for that particular data point. Panel A is based on 1243 US firms observed over 200 months from Dec. 1985 until June 2002, while panel B is based on a subset of 1144 firms over the same period.
The first column reports the names of the variables: monthly return (*RET*), log of the market capitalization (*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*), short-term momentum (*R1-6*), long-term momentum (*R7-12*), log of the monthly volume (*VOL*) and log of the average volume over the last 52 weeks (*52W*). The other columns report descriptive statistics of the firm characteristics.

Variable	Average value	Standard deviation	Minimum value	1^{st} quantile	Median value	99^{th} quantile	Maximum value
A – All 1243 companies							
RET	1.28	14.38	-96.55	-37.04	1.08	43.02	640.74
MV	7.88	1.54	0.92	4.53	7.91	11.63	13.31
BP	0.52	0.96	-46.39	-0.22	0.43	2.31	112.08
CP	0.34	42.90	-31.10	-0.36	0.09	0.67	8337.01
DP	0.02	0.06	0.00	0.00	0.01	0.10	4.30
EP	0.00	0.83	-120.00	-0.93	0.05	0.20	2.88
SP	1.56	4.47	0.00	0.03	0.88	10.99	918.27
CFY1	-0.08	0.75	-1.00	-1.00	0.00	1.00	1.00
R1-6	7.61	35.83	-98.60	-66.67	5.81	118.92	1813.73
R7-12	8.12	37.64	-96.43	-63.34	5.65	126.14	1597.39
VOL	16.22	1.53	2.30	12.57	16.18	20.13	22.40
52W	13.15	1.52	0	9.71	13.10	17.00	18.46
B – 1144 companies with complete data							
RET	1.32	14.31	-96.55	-36.36	1.10	42.86	640.74
MV	7.93	1.53	1.49	4.65	7.96	11.67	13.31
BP	0.49	0.37	-0.15	-0.15	0.41	2.14	2.14
CP	0.11	0.12	-0.33	-0.33	0.09	0.63	0.63
DP	0.02	0.02	0.00	0.00	0.01	0.09	0.09
EP	0.03	0.11	-0.72	-0.72	0.05	0.19	0.19
SP	1.36	1.52	0.00	0.03	0.87	9.45	9.45
CFY1	-0.07	0.75	-1.00	-1.00	0.00	1.00	1.00
R1-6	7.95	34.95	-96.83	-64.74	5.95	119.85	985.96
R7-12	8.44	37.00	-96.43	-62.50	5.96	126.12	1597.39
VOL	16.27	1.51	2.30	12.79	16.22	20.25	22.40
52W	13.22	1.45	2.15	10.01	13.14	17.20	18.46

Table 3: Average Returns from Characteristic Sorted Portfolios

The table reports the average return of high and low portfolios based on sorting of all stocks by each characteristic x and buying the top 30% of the sorted stocks (the high portfolio), while selling the bottom 30% of the sorted stocks (the low portfolio). Next month we document the returns of the high and low portfolios, constructed in the previous month. This procedure is repeated each month. The first four columns report average returns for equally weighted high and low portfolios formed on x_{it}, the standard deviation ($s_{(H-L)}$) of the respective high minus low portfolio, and the t-statistics for testing the equality of the mean returns of the high and low portfolios. The same results for characteristic weighted portfolios are reported in the last four columns. The t-statistics are adjusted for autocorrelation. Panel A reports results for simple high minus low portfolios while panel B 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	Low	High	$s_{(H-L)}$	t-stat	Low	High	$s_{(H-L)}$	t-stat
A – Simple portfolios								
MV	1.63	1.33	3.99	-1.08	1.61	1.33	3.85	-1.05
BP	1.42	1.65	3.85	0.67	1.45	1.70	3.83	0.74
CP	1.15	1.66	4.85	1.49	1.30	1.76	5.33	1.22
DP	1.49	1.53	5.15	0.11	1.45	1.50	5.25	0.12
EP	1.38	1.64	4.78	0.76	1.59	1.68	7.39	0.17
SP	1.25	1.70	4.55	1.06	1.26	1.80	4.27	1.35
CFY1	1.19	1.77	2.39	3.43	1.19	1.76	2.59	3.08
R1-6	1.44	1.44	5.71	0.01	1.26	1.65	7.20	0.77
R7-12	1.12	1.88	3.87	2.79	1.18	2.10	5.14	2.53
VOL	1.08	1.74	2.98	2.54	1.09	1.76	3.02	2.51
52W	1.17	1.77	2.99	2.28	1.18	1.79	3.05	2.25
B – Industry neutral portfolios								
MV	1.46	1.33	3.17	-0.56	1.50	1.35	3.11	-0.69
BP	1.33	1.55	2.30	1.11	1.40	1.62	2.70	1.19
CP	1.19	1.69	2.25	2.63	1.34	1.84	3.14	2.22
DP	1.39	1.58	2.53	1.09	1.43	1.54	2.49	0.66
EP	1.27	1.66	2.35	2.39	1.52	1.69	4.07	0.71
SP	1.32	1.51	2.80	0.77	1.37	1.67	3.50	0.96
CFY1	1.20	1.72	1.63	4.49	1.23	1.77	1.70	4.52
R1-6	1.39	1.46	3.37	0.27	1.42	1.65	4.39	0.74
R7-12	1.17	1.69	2.32	3.16	1.22	1.94	3.13	3.23
VOL	1.13	1.62	2.27	2.59	1.15	1.73	2.39	2.92
52W	1.19	1.63	2.27	2.29	1.21	1.76	2.40	2.68

Table 4: Model Selection

The table reports OLS estimation results for various restricted versions of the panel data model

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

with returns y_{it} measured over different horizons. All models have industry specific coefficients β_ℓ. The results are based on 1144 US firms observed over 200 months from Dec. 1985 until June 2002. The first two columns indicate the restrictions on the intercepts μ_i and $\lambda_{\ell t}$. The intercepts μ_i are either not included ($\mu_i = 0$), pooled ($\mu_i = \mu$), industry specific ($\mu_i = \sum_{\ell=1}^{L} D_{i\ell}\tau_\ell$), or firm specific ($\mu_i$). The time effects $\lambda_{\ell t}$ are either not included ($\lambda_{\ell t} = 0$), pooled ($\lambda_{\ell t} = \lambda_t$), or industry specific ($\lambda_{\ell t}$). The total number of parameters is given as k; the R^2 is computed as one minus the ratio of the residual sum of squares to the total sum of squares of returns in deviation of the average return over all observations; SC denotes the Schwartz information criterion defined in Eq. (17). The upper panels are based on all complete data points. In the lower panels all firms with less than 60 observations are excluded. The first lines of each subpanel show the respective numbers of firms N and data points n.

		One month			Three months		Six months	
μ	λ	k	R^2	SC	R^2	SC	R^2	SC
		N=1,144			N=1,139		N=1,136	
		n=93,482			n=91,664		n=88,915	
μ_i	$\lambda_{\ell t}$	5522	0.318	5.597	0.372	6.715	0.410	7.381
0	$\lambda_{\ell t}$	4380	0.258	5.496	0.306	6.675	0.294	7.418
μ_i	0	1363	0.044	5.445	0.113	6.567	0.199	7.189
τ_ℓ	λ_t	418	0.152	5.212	0.164	6.394	0.156	7.123
μ	λ_t	397	0.151	5.211	0.161	6.394	0.150	7.127
τ_ℓ	0	220	0.016	5.337	0.040	6.507	0.071	7.194
		N=652			N=640		N=370	
		n=79,247			n=77,319		n=59,321	
μ_i	$\lambda_{\ell t}$	4842	0.331	5.271	0.373	6.387	0.407	6.891
0	$\lambda_{\ell t}$	4402	0.318	5.201	0.334	6.353	0.369	6.887
μ_i	0	872	0.033	5.087	0.091	6.200	0.126	6.577
τ_ℓ	λ_t	418	0.174	4.868	0.197	6.013	0.215	6.440
μ	λ_t	397	0.172	4.866	0.195	6.014	0.210	6.443
τ_ℓ	0	220	0.017	5.013	0.048	6.155	0.081	6.562

Table 5: Pooled Parameter Estimates - One Month Returns

The table reports estimation results for the pooled coefficient model

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

under different assumptions about the intercepts and time effects. The variable *MV* is the log of the market capitalization, measured in billions of dollars; *BP*, *CP*, *DP*, *EP* and *SP* are the valuation ratios book-to-price, cash flow-to-price, dividends-to-price, earnings-to-price, and sales-to-price, respectively; *CFY1* is the analysts earnings revisions; *R1-6* and *R7-12* are short-term and long-term price momentum, respectively; *VOL* and *52W* are logs of the previous month turnover and the average turnover from the preceding 52 weeks, respectively. Each column contains model coefficients and the respective standard errors in parentheses. To correct for scale, all entries for *R1-6* and *R7-12* are multiplied by six. The symbol * (**) means that the respective coefficient is significant at the 5% (1%) level. The column (β, τ_ℓ) refers to the model with industry intercepts ($\mu_i = \tau_\ell$, $\lambda_{\ell t} = 0$). The column $(\beta, \tau_\ell, \lambda_t)$ contains pooled time effects and industry effects τ_ℓ ($\mu_i = 0$, τ_ℓ, $\lambda_{\ell t} = \lambda_t$), while the column $(\beta, \lambda_{\ell t})$ relates to industry specific time effects ($\mu_i = 0$, $\tau_\ell = 0$, $\lambda_{\ell t}$). The column (β, μ_i) refers to a fully pooled model with individual intercepts (μ_i, $\lambda_{\ell t} = 0$). The column $(\beta, \mu_i, \lambda_t)$ 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 matrix in Eq. (10). The last line reports Hausman statistics that test whether the coefficients in the respective model are significantly different if the individual effects are replaced by industry effects. The last column reports t-statistics that test whether the coefficients of each characteristic of the models $(\beta, \tau_\ell, \lambda_t)$ and $(\beta, \mu_i, \lambda_t)$ are significantly different.

	Models					t-stat
variable	β, τ_ℓ	$\beta, \tau_\ell, \lambda_t$	$\beta, \lambda_{\ell t}$	β, μ_i	β, μ_i, λ_t	
MV	-0.88**	-0.80**	-0.74**	-2.32**	-3.36**	2.56**
	(0.16)	(0.13)	(0.14)	(0.60)	(0.31)	
BP	0.15	0.14	-0.01	1.48*	0.98	1.53
	(0.34)	(0.27)	(0.22)	(0.68)	(0.52)	
CP	2.18*	2.11**	2.08**	1.71**	1.68*	0.44
	(0.99)	(0.77)	(0.66)	(0.98)	(0.82)	
DP	26.64**	19.40**	15.55**	-16.26	-6.60	2.77**
	(12.48)	(5.18)	(4.56)	(14.41)	(9.64)	
EP	3.30**	2.13	1.73	-0.45	-0.69	-1.51
	(1.59)	(1.32)	(1.17)	(1.77)	(1.20)	
SP	0.12	0.12	0.12	0.44	0.14	1.25
	(0.09)	(0.08)	(0.07)	(0.29)	(0.17)	
CFY1	0.29	0.24**	0.28**	0.29	0.24**	0.33
	(0.15)	(0.12)	(0.08)	(0.15)	(0.12)	
R1-6	-0.03	0.05	0.03	-0.05	0.04	0.01
	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)	
R7-12	0.06	0.04	0.04**	0.07	0.08**	1.50
	(0.04)	(0.03)	(0.02)	(0.04)	(0.02)	
VOL	0.84**	0.52**	0.55**	0.82	0.38	-0.63
	(0.41)	(0.22)	(0.19)	(0.43)	(0.22)	
52W	-0.01	0.26	0.21	-1.04	-0.91**	-3.61**
	(0.42)	(0.23)	(0.19)	(0.56)	(0.27)	
Hausman				408.01	390.50	

Table 6: Pooled Parameter Estimates - Three Month Returns

The table reports estimation results for the pooled coefficient model

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

under different assumptions about the intercepts and time effects. The returns y_{it} are measured over three month periods. For further description see the note of Table 5.

variable	Models					t-stat
	β, τ_ℓ	$\beta, \tau_\ell, \lambda_t$	$\beta, \lambda_{\ell t}$	β, μ_i	β, μ_i, λ_t	
MV	-2.63**	-2.34**	-2.12**	-6.81**	-9.75**	-17.74**
	(0.39)	(0.33)	(0.33)	(1.57)	(0.64)	
BP	0.85	0.50	0.08	5.22**	3.08**	2.44**
	(0.90)	(0.76)	(0.63)	(1.91)	(1.22)	
CP	8.57**	7.44**	6.95**	5.79*	5.52**	-0.56
	(2.81)	(2.19)	(1.94)	(2.54)	(1.55)	
DP	73.02**	54.90**	41.08**	-46.60	-15.24	-3.53**
	(31.28)	(12.22)	(10.9)	(38.04)	(17.80)	
EP	6.74	3.92	3.07	-5.43	-5.61**	-5.43**
	(3.96)	(3.63)	(3.03)	(4.41)	(2.61)	
SP	0.23	0.26	0.26	0.98	0.21	0.15
	(0.24)	(0.22)	(0.21)	(0.61)	(0.27)	
CFY1	0.23	0.08	0.29	0.18	-0.04	-1.38
	(0.30)	(0.24)	(0.17)	(0.32)	(0.17)	
R1-6	0.12	0.25**	0.21**	0.02	0.19**	0.01
	(0.10)	(0.09)	(0.05)	(0.09)	(0.06)	
R7-12	0.02	0.02	0.03	0.07	0.10*	0.71
	(0.11)	(0.09)	(0.05)	(0.10)	(0.05)	
VOL	0.37	-0.09	0.02	0.16	-0.65**	-1.46
	(0.59)	(0.40)	(0.34)	(0.59)	(0.32)	
52W	2.25**	2.49**	2.28**	-0.89	-1.27**	-5.73**
	(0.67)	(0.47)	(0.43)	(1.20)	(0.48)	
Hausman				708.26	914.83	

Table 7: Pooled Parameter Estimates - Six Month Returns

The table reports estimation results for the pooled coefficient model

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

under different assumptions about the intercepts and time effects. The returns y_{it} are measured over six month periods. For further description see the note of Table 5.

variable	Models					t-stat
	β, τ_ℓ	$\beta, \tau_\ell, \lambda_t$	$\beta, \lambda_{\ell t}$	β, μ_i	β, μ_i, λ_t	
MV	-5.03**	-4.74**	-4.33**	-12.43**	-18.52**	-16.13**
	(0.75)	(0.67)	(0.64)	(3.05)	(1.05)	
BP	0.98	0.76	0.10	8.51**	5.39**	1.92
	(1.58)	(1.33)	(1.10)	(3.63)	(1.79)	
CP	16.72**	15.20**	13.78**	10.70*	10.92**	-0.56
	(5.31)	(4.05)	(3.41)	(4.71)	(2.27)	
DP	137.38**	109.82**	78.11**	-75.90	-14.47	1.12
	(54.61)	(21.64)	(20.57)	(56.05)	(19.13)	
EP	13.32**	9.30	8.05	-12.16	-11.04**	2.62**
	(6.23)	(6.06)	(5.13)	(7.26)	(3.17)	
SP	0.49	0.58	0.55	2.25*	0.86	0.41
	(0.43)	(0.41)	(0.42)	(1.13)	(0.47)	
CFY1	0.73	0.35	0.82**	0.61	0.10	1.57
	(0.51)	(0.36)	(0.28)	(0.53)	(0.19)	
R1-6	0.40**	0.52**	0.45**	0.21	0.38**	-0.01
	(0.16)	(0.13)	(0.09)	(0.16)	(0.06)	
R7-12	-0.18	-0.15	-0.13	-0.11	0.01	1.07
	(0.17)	(0.16)	(0.09)	(0.14)	(0.06)	
VOL	0.30	0.09	0.23	-0.28	-1.07**	1.59
	(0.84)	(0.66)	(0.59)	(0.88)	(0.37)	
52W	5.17**	5.17**	4.81**	-1.24	-2.76**	-8.41**
	(1.16)	(0.91)	(0.86)	(2.07)	(0.68)	
Hausman				724.39	597.69	

Table 8: Tests for Industry Specific Parameters

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

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

under different assumptions about the intercepts and time effects. The alternative is that β is different in all industries. The 5% critical value is 32.67. The forecasting horizon is one, three and six months. The variable *MV* is the log of the market capitalization, measured in billions of dollars; *BP*, *CP*, *DP*, *EP* and *SP* are the valuation ratios book-to-price, cash flow-to-price, dividends-to-price, earnings-to-price, and sales-to-price, respectively; *CFY1* is the analysts earnings revisions; *R1-6* and *R7-12* are short-term and long-term price momentum, respectively; *VOL* and *52W* are logs of the previous month turnover and the average turnover from the preceding 52 weeks, respectively. The columns (β_ℓ, τ_ℓ) refer to the fully pooled model ($\mu_i = \mu$, $\lambda_{\ell t} = 0$). The columns $(\beta_\ell, \tau_\ell, \lambda_t)$ contain pooled time effects and industry effects τ_ℓ ($\mu_i = \sum_{\ell=1}^{L} D_{i\ell}\tau_\ell$, $\lambda_{\ell t} = \lambda_t$), and the columns $(\beta_\ell, \lambda_{\ell t})$ relate to industry specific time effects ($\mu_i = 0$, $\lambda_{\ell t}$). The Wald-statistics have been computed using a robust estimator for the covariance matrices of $\hat{\beta}$ and $\hat{\beta}_\ell$.

	β_ℓ	β_ℓ	β_ℓ	β_ℓ	β_ℓ	β_ℓ	β_ℓ	β_ℓ	β_ℓ
variable	τ_ℓ	τ_ℓ, λ_t	$\lambda_{\ell t}$	τ_ℓ	τ_ℓ, λ_t	$\lambda_{\ell t}$	τ_ℓ	τ_ℓ, λ_t	$\lambda_{\ell t}$
MV	94.7	93.7	73.2	101.3	99.1	114.7	104.9	102.0	133.2
BP	39.4	41.3	40.4	63.0	66.1	92.0	121.4	124.6	184.3
CP	46.5	46.5	28.2	112.8	112.8	84.4	96.8	92.8	83.0
DP	15.1	18.2	25.3	34.2	38.2	43.6	98.2	112.3	88.3
EP	48.8	49.8	49.7	111.8	107.4	81.2	187.8	172.1	120.9
SP	33.2	34.1	37.9	64.0	66.3	63.6	70.5	75.3	137.9
CFY1	19.7	20.5	23.7	32.9	34.2	33.9	36.2	37.9	55.2
R1-6	46.5	47.0	33.3	98.6	100.8	81.1	68.2	67.6	94.8
R7-12	30.1	31.7	55.3	67.9	69.6	73.0	139.3	136.2	107.8
VOL	33.9	35.3	42.3	34.4	34.4	34.1	40.7	41.4	26.0
52W	25.4	26.1	35.7	40.1	43.0	69.1	82.5	90.2	115.6

Table 9: Expected Returns from Portfolio Strategies

The table contains four panels that show portfolio returns based on one, three and six month forecasting. The results are based on 1144 US firms observed over 200 months from Dec. 1985 until June 2002. All entries are on monthly basis; the entries for returns are in percentage points. For three different specifications of the panel model, each month the stocks are sorted with respect to the fitted values. The 30% stocks with the highest expected return are allocated to the long portfolio, while 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 with the 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 $(\beta_\ell, \lambda_{\ell t})$ 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.
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 as s_{L-S}. The t-statistic tests the null hypothesis that the long and short portfolios have equal expected returns.
The first line of each panel refers to a pooled model with a pooled time effect and pooled β $(\beta, \tau_\ell, \lambda_t)$, the second line relates to a model with pooled time effects and industry specific intercepts and coefficients $(\beta_\ell, \tau_\ell, \lambda_t)$, and the last line contains results for a model with industry specific time effects and coefficients $(\beta_\ell, \lambda_{\ell t})$.

One month forecast								
	Equally weighted				Value weighted			
Model	Short	Long	s_{L-S}	t-stat	Short	Long	s_{L-S}	t-stat
$\beta, \tau_\ell, \lambda_t$	0.60	2.38	3.01	8.34	0.60	2.33	2.95	8.26
$\beta_\ell, \tau_\ell, \lambda_t$	0.49	2.61	2.96	10.09	0.50	2.50	2.70	10.49
$\beta_\ell, \lambda_{\ell t}$	0.60	2.46	2.23	11.70	0.58	2.28	2.03	11.76
Three month forecast								
	Equally weighted				Value weighted			
Model	Short	Long	s_{L-S}	t-stat	Short	Long	s_{L-S}	t-stat
$\beta, \tau_\ell, \lambda_t$	0.77	2.41	3.03	7.58	0.75	2.36	3.01	7.48
$\beta_\ell, \tau_\ell, \lambda_t$	0.56	2.63	2.75	10.61	0.54	2.55	2.62	10.79
$\beta_\ell, \lambda_{\ell t}$	0.75	2.36	2.10	10.77	0.73	2.26	1.96	10.97
Six month forecast								
	Equally weighted				Value weighted			
Model	Short	Long	s_{L-S}	t-stat	Short	Long	s_{L-S}	t-stat
$\beta, \tau_\ell, \lambda_t$	0.80	2.41	2.81	7.97	0.77	2.36	2.76	7.98
$\beta_\ell, \tau_\ell, \lambda_t$	0.63	2.63	2.65	10.53	0.62	2.56	2.59	10.40
$\beta_\ell, \lambda_{\ell t}$	0.80	2.36	1.95	11.17	0.78	2.25	1.84	11.13

Table 10: Profiles of Long and Short Portfolios

The table reports the time series averages of the characteristics of the portfolios considered in Table 9. The results are based on monthly return forecasting. The columns "s_{L-S}" show the standard deviations of the time series formed by the differences in characteristics between the long and the short portfolio through time. The t-statistics are adjusted for autocorrelation and test the null hypothesis that the long and short portfolios have equal mean characteristics. The first panel refers to a model with a pooled time effect and pooled β $(\beta, \tau_\ell, \lambda_t)$, the second panel relates to a model with pooled time effects and industry specific coefficients $(\beta_\ell, \tau_\ell, \lambda_t)$ and the last panel contains results for a model with industry specific time effects and coefficients $(\beta_\ell, \lambda_{\ell t})$.

		Equally weighted				Value weighted			
Model	Variable	Short	Long	$s_{(L-S)}$	t-stat	Short	Long	$s_{(L-S)}$	t-stat
$\beta, \tau_\ell, \lambda_t$	*MV*	8.34	7.68	0.66	-6.39	8.59	7.88	0.74	-6.22
	BP	0.43	0.57	0.10	9.38	0.42	0.54	0.09	9.44
	CP	0.09	0.16	0.04	21.91	0.09	0.16	0.03	22.64
	DP	0.02	0.02	0.01	6.54	0.02	0.02	0.01	6.70
	EP	0.02	0.05	0.03	1.63	0.03	0.05	0.02	1.12
	SP	1.03	1.93	0.49	6.13	0.98	1.80	0.44	6.09
	CFY1	-0.28	0.08	0.13	12.30	-0.27	0.09	0.13	12.45
	R1-6	3.67	14.53	12.56	6.46	4.34	15.22	12.35	6.55
	R7-12	4.14	14.38	12.42	12.50	4.91	15.11	12.53	12.37
	VOL	15.79	16.82	0.78	8.59	15.97	16.95	0.82	7.69
	52W	12.79	13.72	0.80	7.56	12.97	13.86	0.83	6.86
$\beta_\ell, \tau_\ell, \lambda_t$	*MV*	8.20	7.76	0.58	-4.99	8.46	7.98	0.63	-4.87
	BP	0.43	0.57	0.10	10.19	0.41	0.55	0.10	9.93
	CP	0.09	0.15	0.03	11.71	0.09	0.15	0.03	12.07
	DP	0.02	0.02	0.00	5.18	0.02	0.02	0.00	5.66
	EP	0.02	0.04	0.02	6.19	0.03	0.05	0.02	6.42
	SP	1.19	1.82	0.46	7.05	1.12	1.71	0.42	7.15
	CFY1	-0.19	0.00	0.13	9.83	-0.19	0.02	0.14	9.75
	R1-6	12.00	5.91	7.41	-6.14	12.37	6.95	7.47	-5.37
	R7-12	4.70	12.88	8.98	12.55	5.48	13.68	9.06	12.23
	VOL	15.93	16.77	0.67	8.09	16.13	16.91	0.72	7.07
	52W	12.94	13.68	0.67	7.14	13.13	13.82	0.72	6.27
$\beta_\ell, \lambda_{\ell t}$	*MV*	8.40	8.02	0.52	-4.66	8.41	8.03	0.52	-4.68
	BP	0.44	0.54	0.07	10.92	0.44	0.54	0.07	10.93
	CP	0.09	0.15	0.02	15.73	0.09	0.15	0.02	15.94
	DP	0.02	0.02	0.00	8.01	0.02	0.02	0.00	8.23
	EP	0.03	0.05	0.01	7.44	0.03	0.05	0.01	7.46
	SP	1.16	1.67	0.31	11.36	1.15	1.65	0.30	11.53
	CFY1	-0.28	0.08	0.12	26.20	-0.28	0.08	0.12	25.98
	R1-6	7.07	10.93	6.81	4.26	7.21	11.14	6.80	4.34
	R7-12	5.03	13.88	8.18	8.14	5.33	13.90	7.71	8.48
	VOL	15.97	16.82	0.57	9.67	15.98	16.83	0.56	9.82
	52W	12.97	13.72	0.56	8.69	12.99	13.73	0.55	8.74

Table 11: 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 from different models. The *Long* portfolio contains 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. Transitions frequencies for portfolios P and Q are the average percentages of stocks that go from P to Q through time. The portfolio 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 three panels that show transition frequencies for portfolios based on forecasting for one, three and six months. The top subpanel of each panel refers to a model with a pooled time effect and pooled β ($\beta, \tau_\ell, \lambda_t$), the middle subpanel relates to a model with pooled time effects and industry specific β_ℓ ($\beta_\ell, \tau_\ell, \lambda_t$) and the last subpanel contains results for a model with industry specific time effects and coefficients.

		One month forecast				Three month forecast				Six month forecast			
		To				To				To			
Model	From	Long	Neutral	Short	Out	Long	Neutral	Short	Out	Long	Neutral	Short	Out
$\beta, \tau_\ell, \lambda_t$	Long	0.828	0.162	0.003	0.002	0.940	0.051	0.002	0.002	0.957	0.033	0.003	0.002
	Neutral	0.128	0.736	0.131	0.002	0.039	0.917	0.037	0.002	0.025	0.943	0.026	0.001
	Short	0.004	0.178	0.811	0.003	0.002	0.050	0.941	0.002	0.003	0.035	0.956	0.002
	New	0.377	0.318	0.295	–	0.368	0.332	0.294	–	0.360	0.311	0.323	–
$\beta_\ell, \tau_\ell, \lambda_t$	Long	0.790	0.186	0.016	0.003	0.915	0.067	0.011	0.002	0.951	0.035	0.007	0.002
	Neutral	0.145	0.687	0.161	0.002	0.052	0.882	0.059	0.001	0.027	0.936	0.031	0.001
	Short	0.020	0.215	0.757	0.003	0.012	0.080	0.901	0.002	0.007	0.043	0.943	0.002
	New	0.279	0.357	0.355	–	0.284	0.344	0.365	–	0.317	0.304	0.373	–
$\beta_\ell, \lambda_{\ell t}$	Long	0.734	0.243	0.016	0.003	0.908	0.078	0.007	0.002	0.947	0.041	0.005	0.002
	Neutral	0.149	0.692	0.152	0.002	0.049	0.895	0.050	0.001	0.026	0.941	0.027	0.001
	Short	0.018	0.243	0.730	0.003	0.007	0.079	0.907	0.002	0.005	0.043	0.945	0.002
	New	0.224	0.414	0.353	–	0.278	0.342	0.374	–	0.290	0.336	0.368	–

Table 12: 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 of 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 are on monthly basis and show parameter estimates with autocorrelation robust t-statistics in parentheses. The intercepts are measured in percentage points. The long-short portfolio returns are constructed using the six strategies shown in Table 9. The first two columns refer to a model with a pooled time effect and pooled β $(\beta, \tau_\ell, \lambda_t)$, the second two columns relate to a model with pooled time effects and industry specific β_ℓ $(\beta_\ell, \tau_\ell, \lambda_t)$ and the last two columns contain results for a model with industry specific time effects and coefficients $(\beta_\ell, \lambda_{\ell t})$. The upper panel reports results for portfolios based on one-month forecasting, the middle panel for three-month forecasting and the lower panel for six-month forecasting. EW stays for "equally weighted", and VW – for "value weighted".

	$\beta, \tau_\ell, \lambda_t$		$\beta_\ell, \tau_\ell, \lambda_t$		$\beta_\ell, \lambda_{\ell t}$	
Variable	EW	VW	EW	VW	EW	VW
One month forecast						
R^2	0.27	0.30	0.14	0.11	0.30	0.33
Intercept	1.53	1.48	2.14	1.97	1.81	1.64
	(5.69)	(5.90)	(7.61)	(7.94)	(7.57)	(7.90)
$R^M - R_f$	0.14	0.14	0.15	0.14	0.13	0.12
	(1.90)	(1.87)	(2.27)	(2.26)	(4.24)	(4.42)
SMB	0.37	0.37	0.21	0.17	0.32	0.29
	(4.01)	(4.38)	(2.05)	(1.85)	(5.14)	(5.31)
HML	0.11	0.08	0.19	0.20	0.09	0.05
	(1.00)	(0.69)	(1.67)	(1.82)	(1.24)	(0.67)
UMD	0.14	0.14	-0.17	-0.16	-0.06	-0.02
	(1.79)	(2.05)	(-2.32)	(-1.80)	(-1.00)	(-0.41)
Three month forecast						
R^2	0.35	0.37	0.16	0.15	0.33	0.33
Intercept	1.43	1.38	1.97	1.87	1.50	1.40
	(5.93)	(6.08)	(7.62)	(10.04)	(7.61)	(7.63)
$R^M - R_f$	0.11	0.11	0.15	0.14	0.12	0.10
	(1.62)	(1.58)	(2.40)	(3.01)	(4.62)	(3.83)
SMB	0.44	0.45	0.30	0.27	0.34	0.30
	(5.49)	(5.77)	(3.60)	(4.91)	(5.68)	(5.09)
HML	0.08	0.08	0.24	0.27	0.14	0.10
	(0.57)	(0.60)	(1.58)	(3.98)	(1.64)	(1.20)
UMD	0.13	0.15	-0.06	-0.03	-0.01	0.04
	(2.32)	(2.80)	(-1.00)	(-0.71)	(-0.04)	(1.26)
Six month forecast						
R^2	0.26	0.27	0.12	0.13	0.29	0.28
Intercept	1.40	1.37	1.78	1.70	1.40	1.33
	(6.26)	(6.35)	(7.48)	(7.52)	(8.01)	(7.87)
$R^M - R_f$	0.10	0.09	0.12	0.11	0.12	0.09
	(1.48)	(1.36)	(1.86)	(1.85)	(3.78)	(3.12)
SMB	0.34	0.34	0.24	0.21	0.24	0.26
	(4.07)	(4.09)	(2.83)	(2.63)	(4.92)	(4.60)
HML	0.11	0.11	0.28	0.31	0.17	0.14
	(0.68)	(0.73)	(1.59)	(1.73)	(1.73)	(1.48)
UMD	0.15	0.16	0.08	0.09	0.14	0.07
	(2.63)	(2.85)	(1.13)	(1.26)	(1.69)	(2.28)

Figure 1: Industry Specific Parameter Estimates

Each panel in the figure relates to the j^{th} firm characteristic and shows values of the j^{th} elements of the vectors β_ℓ for all industries. For each industry the figure shows estimates of β_ℓ^j for three different specifications of the model in Eq. (5). For each panel, the first bar refers to a model specification with industry intercepts and no time effects (β_ℓ, τ_ℓ). The second bar relates to a model with industry specific intercept and pooled time effects $(\beta_\ell, \tau_\ell, \lambda_t)$, and the third bar stays for a model with industry specific time effects $(\beta_\ell, \lambda_{\ell t})$. To be identified the third model $(\beta_\ell, \lambda_{\ell t})$ cannot contain industry specific intercepts, as Section 2 explains. Therefore only two bars are related to each industry in the first graph that shows industry intercepts. The numbers on the horizontal axes denote industries according to the MSCI classification in Table 1.

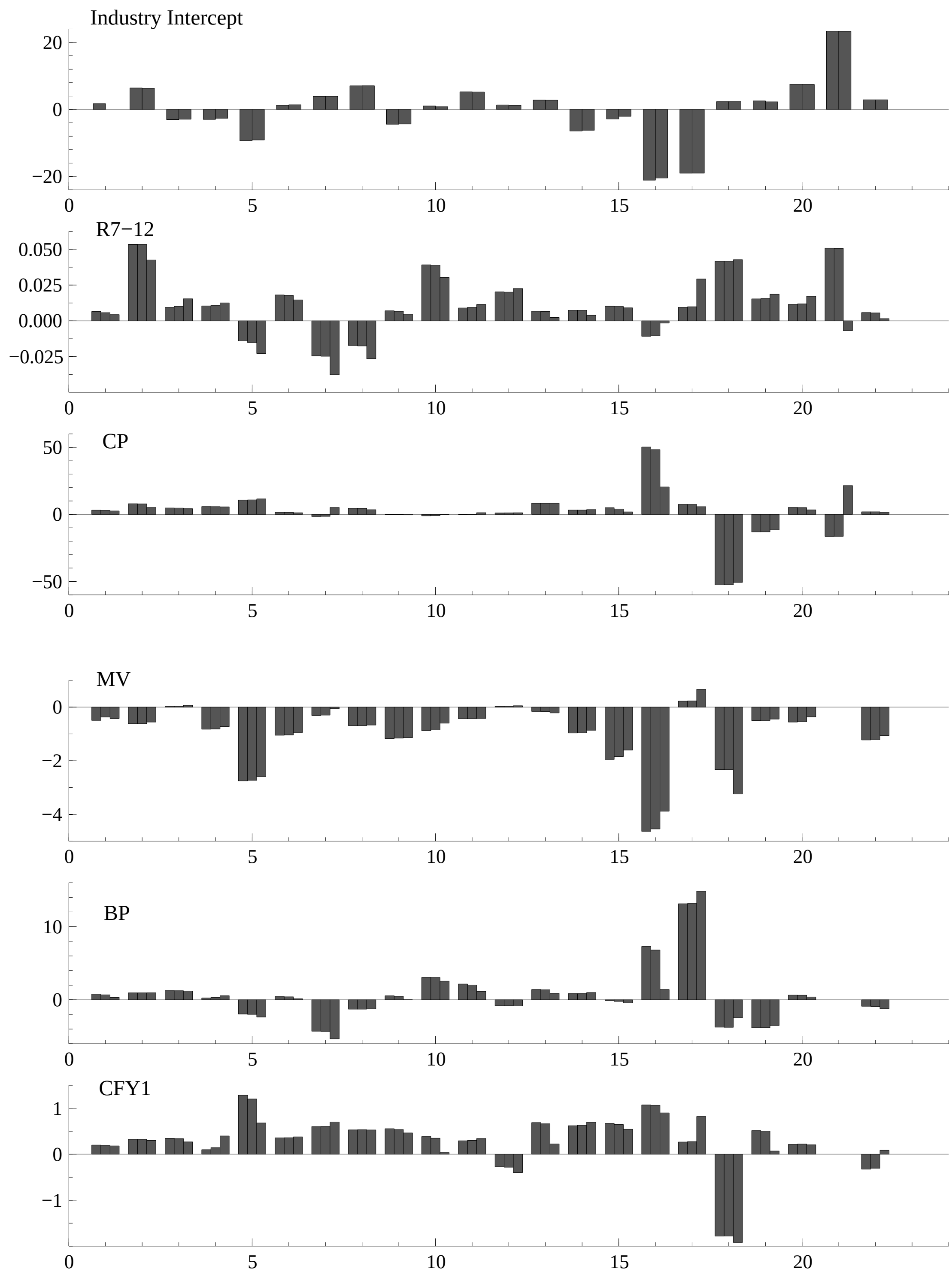

Figure 2: Industry Specific t-statistics of Model Coefficients

Each panel in the figure relates to the j^{th} firm characteristic and shows the values of the t-statistics of the j^{th} elements of the vectors β_ℓ for all industries. For each industry the figure shows the t-statistics of the estimated β_ℓ^j for three different specifications of the model in Eq. (5). For each panel, the first bar refers to a model specification with industry intercepts and no time effects (β_ℓ, τ_ℓ). The second bar relates to a model with industry specific intercept and pooled time effects $(\beta_\ell, \tau_\ell, \lambda_t)$, and the third bar stays for a model with industry specific time effects $(\beta_\ell, \lambda_{\ell t})$. To be identified the third model $(\beta_\ell, \lambda_{\ell t})$ cannot contain industry specific intercepts, as Section 2 explains. Therefore only two bars are related to each industry in the first graph that shows industry intercepts. The numbers on the horizontal axes denote industries according to the MSCI classification in Table 1.