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Stock selection, style rotation, and risk

André Lucas [a,b,*], Ronald van Dijk [c], Teun Kloek [b,d]

[a] *Department of Finance and Financial Sector Management, Vrije Universiteit, De Boelelaan 1105, NL-1081HV Amsterdam, The Netherlands*
[b] *Tinbergen Institute Amsterdam, Keizersgracht 482, NL-1017EG Amsterdam, The Netherlands*
[c] *ING Investment Management, Department of Quantitative Research, The Netherlands*
[d] *Department of. Econometrics and Econometric Institute, Erasmus University Rotterdam, P.O. Box 1738, NL-3000DR Rotterdam, The Netherlands*

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Abstract

Using US data from June 1984 to July 1999, we show that the impact of firm-specific characteristics like size and book-to-price on future excess stock returns varies considerably over time. The impact can be either positive or negative at different times. This time variation is partially predictable. We investigate whether the partial predictability signals security mispricing or risk compensation by formulating alternative modeling strategies. The strategies are compared empirically. In particular, we allow for a state-dependent choice of investment styles rather than a once-and-for-all choice for a particular style, for example based on high book-to-price ratios or small market cap values. Using alternative ways to correct for risk, we find significant and robust excess returns to style rotating investment strategies. Business cycle oriented approaches exhibit the best overall performance. Purely statistical models for style rotation or fixed investment styles reveal less robust behavior. © 2002 Elsevier Science B.V. All rights reserved.

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* Corresponding author.
E-mail addresses: alucas@econ.vu.nl (A. Lucas), ronald.van.iim.dijk@ingim.com (R. van Dijk), kloek@few.eur.nl (T. Kloek).

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1. Introduction

In examining the forecasting power of firm characteristics for excess returns, the academic literature conventionally focuses on long-term averages of monthly and annual returns. The systematic patterns found provide evidence that some equity classes generate above-average returns in the long run. In particular, value stocks outperformed growth stocks historically, and small capitalization stocks had higher annual returns than large capitalization stocks. See for example the papers of Fama and French (1992), La Porta (1996), Daniel and Titman (1997), Barber and Lyon (1997) and Lewellen (1999). In the investment management industry nowadays, value and size strategies are used for discriminating relative future performance. This implementation is known as style investing.

At least, three alternative theories have been put forward to explain the long-term outperformance of value and small capitalization stocks. First, the firm variables might proxy for a risk factor. Fama and French (1993), Jensen et al. (1997) and Lewellen (1999) argue that the higher returns are a compensation for higher risk. Firms with similar firm characteristics are sensitive to the same macroeconomic factors like economic growth surprises and interest rate risk. A second and alternative view is that the firm variables provide information about security mispricing. Lakonishok et al. (1994) suggest that the higher returns on value strategies are due to an incorrect extrapolation of past stock performance. La Porta (1996) finds evidence that value strategies work because expectations about future growth in earnings are too optimistic. As a third possible reason for reported outperformance, it can be argued that unexpected technological innovations are historically more related to particular equity classes. As a result, the uncovered return patterns can be due to data snooping, see, e.g., Lo and MacKinlay (1990), Black (1993) and MacKinlay (1995).

The performance of value or size related investment styles is not stable over time. Some periods depart from the long-term patterns documented in the literature. Chan et al. (2000), for example, show that the regular size and value effects are inverse over the period 1990 through 1998. This can be a major worry for professional investment managers with value or size-based investment styles. Returns over a multi-year period are frequently not a sufficient factor to consider a particular fixed investment style a success. Professional money managers are often assessed on their intra-year returns relative to a prespecified benchmark. Both annual outperformance and intra-year variability of the outperformance are important (Roll, 1992). Managers are therefore looking for systematic patterns in the time-varying impact of value and size on returns in order to enhance their performance. As argued above, such patterns may be caused by macroeconomic conditions.

Some authors use the time-variation in the relation between firm characteristics and returns to investigate whether the mispricing or risk compensation view provides a more plausible explanation for realized excess returns. Fama and

French (1993), Daniel and Titman (1997) and Lewellen (1999), for example, examine the returns on value and size based investment styles using a factor model with three factors: (i) the returns on a value-weighted market portfolio, (ii) the excess returns on a small-capitalization over a large-capitalization portfolio, and (iii) the excess return on a high book-to-market portfolio over a low book-to-market portfolio. By relating returns on value or size-based investment styles to current realizations of the risk factors, the authors argue that excess returns are more in line with the risk compensation rather than with the mispricing view.

Our paper adds to the current literature on asset pricing by further examining whether Size and book-to-price generate excess returns. Previous papers focused on models that imply fixed investment styles, mainly small Size and/or high book-to-price. By contrast, our model allows the investment style to vary over time. We investigate whether style effectiveness shows any persistence over time. In particular, we test whether the impact of Size and book-to-price varies with macroeconomic conditions. For this, we formulate both statistical time-series models for style rotation and macroeconomic regression models. We correct any excess returns of such style rotation schemes for risk using either a standard market (one-factor) model or the Fama–French three-factor model, mentioned above. If the excess returns are explained by these factor models, risk corrected excess returns will be insignificant. As a result, the risk compensation rather than the mispricing view will then appear to be more plausible.

As a first result, we find that for no rotation and for pure statistical rotation schemes the risk compensation view provides an adequate explanation of realized excess returns. More striking results are obtained, however, if we consider a variant of our model in which we relate style effectiveness explicitly to macroeconomic conditions. This model produces a bilinear forecasting framework. Bilinear models to examine the value and size styles can also be found in He et al.(1996). Our approach and goals, however, differ markedly. They use 25 portfolios sorted by book to market and size and they assume that expectations of investors are unbiased. Their aim is to find a disrete time equilibrium multifactor model that is consistent with the returns of the 25 portfolios. He et al. (1996) conclude that their models are inconsistent with the portfolio return data. By contrast, we aim at predicting future individual stock returns. No assumptions about rational expectations are made.

We use two macroeconomic variables in our style rotation model. The first variable is the term-spread of interest rates, which is defined as the long-term interest rate minus the short-term rate. At least two reasons can be given for the potential influence of this variable on expected stock returns. First, the term spread can be considered as an indicator of economic activity. In an expanding economy, it decreases because short rates generally rise more than long rates. Similarly, during a contraction, it generally increases. Hence, the term spread may affect expected stock market returns because of the effect on expected company earnings (see, also, Schwert, 1990; Chen, 1991; Jensen et al., 1996). This suggests that in periods of a small term spread some equity classes, likely to be small and rapidly growing firms, show higher returns as a result from higher and better quality earnings expectations. Second, the term spread affects the sensitivity of stock prices to changes in interest rates. An increase in the term spread causes short-term earnings to play a relatively more important role in a dividend or free-cash flow discount model, while the long-run earnings are relatively less significant. How shifts of the term structure of interest rates influence a stock price depends on the term spread and distribution of earnings. Consequently, equity premia, which are among other factors determined by interest rate risks, may differ over equity classes. The second macroeconomic variable is a composite of leading indicators of the business cycle. Different equity classes may profit in different ways from changes in the business cycle. We hypothesize that especially small and growing firms are likely to be flexible to react on and profit from improving economic conditions. Large and mature firms are in general more diversified, which makes them less sensitive to deteriorating economic circumstances.

The results reveal that style rotation based on macroeconomic predictive variables generates historical excess returns. In order to prevent data snooping biases, we check the robustness of our results to a range of alternative specifications. In particular, we show that the excess returns remain significant after various ways of risk-correction. In addition to the earlier literature, we also investigate the robustness of the results with respect to the portfolio rebalancing period. We use monthly, quarterly, semi-annual, and annual horizons. It turns out that risk-corrected returns reveal a remarkable stability for the business cycle based model, especially for the stocks with the strongest ex-ante predicted outperformance. By contrast, excess returns on traditional, fixed investment styles (size or book-to-price) or on purely statistical style rotation schemes are not robust with respect to the rebalancing horizon. Moreover, the business cycle model returns are also robust to the way portfolios are constructed and the way potential outliers are dealt with. In short, the results point out that the rotating investment styles based on firm characteristics and macroeconomic predictors provide consistent and robust (risk-corrected) excess returns. Risk correction is performed using a one-factor market model or the three-factor Fama–French model. Therefore, the excess returns on style rotation schemes appear incompatible with the standard risk compensation view using the three Fama–French risk factors. This provides a further dimension to the current debate by allowing more flexibility in the choice of investment strategies.

The paper is organized as follows. In Section 2, we give a description of the data. In Section 3, we describe the time-varying impact of firm characteristics on excess returns. We focus on value and size-based investment styles and test whether there is any evidence of systematic patterns in the time-variation. In Section 4, we provide alternative modeling approaches to transform predictability into style rotation schemes. In Section 5, we implement the models and discuss the results. Section 6 concludes the paper.

2. The data

The firm-specific data come from two sources. Monthly stock price and dividend data in the period from June 1984 to July 1999 come from Interactive Data Corporation (IDC). IDC is a leading provider of securities pricing data. Our prices and dividends are adjusted for stock splits. Monthly total returns are calculated using these price and dividend data. The monthly returns are used to compute quarterly, semi-annual and annual returns. For the annual frequency, we consider the July–July end of month returns. For the quarterly and semi-annual frequencies, the annual return period is divided into an appropriate number of subperiods. Hence, non-overlapping samples are used. The COMPUSTAT database provides book values, which are used to compute the book-to-price (B/P) ratio. Size is measured as the logarithm of market capitalization. The book-to-price and Size variable are cross-sectionally demeaned to remove any trends. The book-to-price ratio is calculated at the end of every month (or quarter, half-year, year) using the most recent reported book value and end-of-month market capitalization. The market capitalization is equal to the number of outstanding stocks times the stock price. Size is also measured at the end of the month. When making a forecast at the moment of rebalancing, we use the most recent information on Size and book-to-price available to investors. For example, for the end July–end August return in 1985 we use the accounting data available end of July 1985, and similarly if we consider the end July 1985–end July 1986 return.

The stock universe is the Russell 3000, meaning that we observe 7860 stocks in total over the sample period. Most of these, however, are observed for only part of the complete sample period (including dead stocks). The Russell 3000 universe comprises the 3000 largest US companies based on total market capitalization. They represent approximately 98% of the investable US equity market.

We use two sources for our macroeconomic variables. First, we use a seasonally adjusted composite index of leading indicators made public by the Business Cycle Indicators section of The Conference Board. The index is constructed by taking a (weighted) average of 10 individual series that are supposed to have turning points that occur before those in aggregated economic activity. Among these indices are (i) average working hours by production workers, (ii) initial claims for unemployment insurance, (iii) new orders for consumer goods, (iv) new orders for capital goods, (v) vendor performance, (vi) residential building permits, (vii) S&P 500 price movements, (viii) money supply M2, (ix) interest rate spread, and (x) index of consumer expectations. The leading indicator is transformed into annual growth rates. Second, the Federal Reserve provides information on spreads in the term structure of interest rates. This type of variable is also a component of the Business Cycle indicator, in which it is the difference between the 10-year Treasury bond rate and an overnight interbank borrowing rate. Our definition of the term-spread variable depends on the data frequency in the modeling and backtesting frameworks. For the monthly return frequency, we consider the difference between the yield on 10-year treasury notes (constant maturity) and 1-month certificates of deposit (CDs). For the quarterly, semi-annual and annual return frequencies, we replace the yield on the 1 month CDs by the yield on 3-month, 6-month and 1-year treasury bills, respectively.

3. Time variation

In this section, we illustrate how the effect of Size and B/P varies over time. As a reference point, we use the standard factor model representation of returns,

$$R_{it} = \boldsymbol{\beta}_{it}' \boldsymbol{f}_t + \varepsilon_{it}, \tag{1}$$

where R_{it} is the (excess) return on asset i over period t, $\boldsymbol{\beta}_{it}$ is a k-dimensional vector of factor loadings, $\boldsymbol{f}_t$ is a vector of common risk factors, and ε_{it} is an idiosyncratic risk component independent of $\boldsymbol{f}_t$. Of course, Eq. (1) is too general to be useful. One way to go about is to drop the time index from $\boldsymbol{\beta}_{it}$ and use observables for $\boldsymbol{f}_t$, see for example Fama and French (1993). Another way is to proxy the $\boldsymbol{\beta}_{it}$ by observable firm characteristics, like size or book-to-price, see Lewellen (1999). Taking a linear specification $\boldsymbol{\beta}_{it} = \boldsymbol{\Gamma}' \boldsymbol{x}_{i,t-1} + \upsilon_{it}$, we obtain

$$R_{it} = \boldsymbol{x}_{i,t-1}' \boldsymbol{\Gamma} \boldsymbol{f}_t + \tilde{\varepsilon}_{it}, \tag{2}$$

with $\boldsymbol{x}_{i,t-1}$ an m-dimensional vector of firm characteristics containing for example size and book-to-price of firm i at time $t-1$, $\boldsymbol{\Gamma}$ an $(m \times k)$ parameter matrix, and $\tilde{\varepsilon}_{it} = \varepsilon_{it} + \upsilon_{it} \boldsymbol{f}_t$. Note that $\boldsymbol{x}_{i,t-1}$ is lagged with respect to the return R_{it}, such that it is known at the time of forecasting next period's return, see also Section 2. By defining $\gamma_t = \boldsymbol{\Gamma} \boldsymbol{f}_t$, we have a regression model with time-varying coefficients,

$$R_{it} = \boldsymbol{x}_{i,t-1}' \gamma_t + \tilde{\varepsilon}_{it}, \tag{3}$$

where the γ_t's can be estimated using the cross-sectional dimension of the sample. Eq. (3) clearly shows that $\boldsymbol{x}_{i,t-1}$ has a time-varying impact on the return R_{it} and that this time variation is caused by the time-variation in the common risk factors $\boldsymbol{f}_t$. As both $\boldsymbol{x}_{i,t-1}$ and $\boldsymbol{f}_t$ may contain a constant term, Eq. (2) specializes to the model of Lewellen (1999) if $\boldsymbol{x}_{i,t-1}$ is the (portfolio) book-to-price ratio and $\boldsymbol{f}_t$ contains the three factors of Fama–French: market return, return differential between a large and small cap portfolio, and return differential between a high and low book-to-price portfolio. Lewellen uses this model to support his claim that the book-to-price ratio is mainly an indicator for risk and not as much of (anomalous) excess return.

In the present paper, we take a different perspective. Given Eq. (3), we investigate whether there is any persistence in the sign and/or magnitude of γ_t over time. If this is the case, it would allow for a timely switch from for example a large cap to a small cap strategy, or from a value to a growth strategy. Persistence in γ_t can be caused by for example persistence in the underlying common factors $\boldsymbol{f}_t$. Alternatively, there might be an omitted variables bias resulting in some persistence in the parameter estimate of γ_t, $\hat{\gamma}_t$. This can be tested in two ways. First, one can postulate observables for $\boldsymbol{f}_t$ and test whether these are serially uncorrelated. This, however, would render one prone to misspecification of the risk factors. Therefore, we follow a second route and estimate Eq. (3) per cross-section. In this way, we obtain a time series of coefficients for the constant term, the size variable, and the book-to-price ratio. These time series are plotted in Figs. 1 and 2 for the period June 1984 up to July 1999.

Figs. 1 and 2 show that for both Size and B/P there is a large number of times the effect on returns is positive, while for a similar number of times the effect is negative. This result does not change if we only take the significant coefficients into account (not shown). The results imply that there are periods during which Size has a significantly positive effect on returns. During other periods, however, the effect might be either opposite or statistically insignificant. Such time variation has important implications for practical asset management. At different points in time either a large or small cap investment style may be preferable. Styles that are very effective now can easily become obsolete or even counterproductive after a relatively short period. Also when we look at the scatter-diagrams of the coefficients in Fig. 2, we see that there were many periods during which either a large or small cap strategy combined with either a value or growth strategy proved most profitable. So also the optimal combination of different styles varies over time. All these results are qualitatively similar and stable over the different sampling frequencies. Hence, the factor pay-offs look like pure noise without any obvious pattern of predictability.

Given the time variation in the regression coefficients, we perform a preliminary data analysis on the coefficients to see whether there are any signs of serial correlation. If present, the amount of serial correlation signals to what extent we can expect to capture part of the time-variation in a predictive framework. The results are given in Table 1 for the four different investment horizons discussed earlier.

At the monthly frequency, the Size coefficient shows significant (at the 10% level) positive autocorrelation using the first partial autocorrelation (see column AR1). The Cowles–Jones (CJ) test is not significant, but exceeds unity. The mean coefficient is insignificantly positive, while the median is significantly positive at the 1% level. This suggests that large cap stocks have outperformed small ones on a monthly basis over the past 15 years, see also Chan et al. (2000). The coefficient of B/P is insignificant on average (as well as in the median sense) at the monthly frequency and shows no serial autocorrelation. At the quarterly frequency, the positive autocorrelation in Size has reversed to an insignificant negative correlation. The CJ-test points in the same direction. For the B/P ratio, an insignificant positive correlation is found. At semi-annual and annual frequencies, no significant correlations are found for both variables. This might be due to the limited

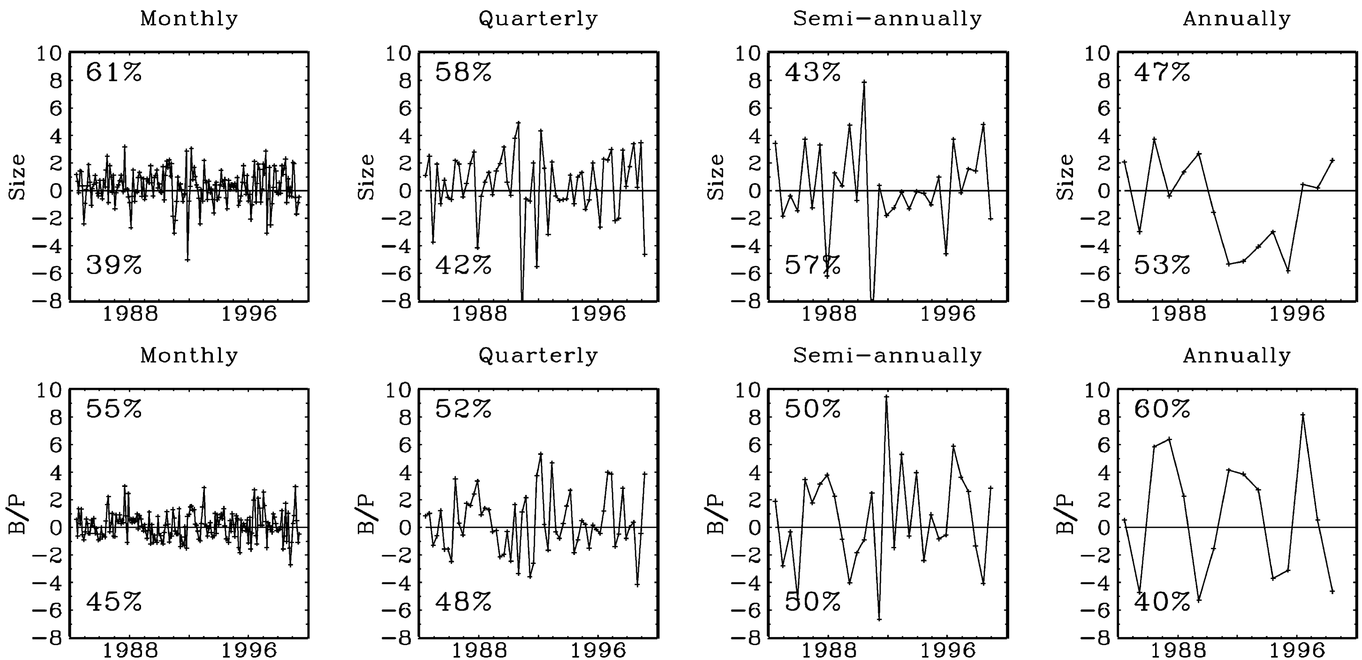

Fig. 1. Cross-sectionally estimated coefficients over time. The figures contain the estimated coefficients per cross-section of a regression of excess returns (in excess of an equally weighted portfolio) on lagged Size and book-to-price (B/P). The top and bottom row of figures give the results for Size and B/P, respectively. The results for monthly, quarterly, semi-annual, and annual returns are in the first, second, third, and fourth column of graphs, respectively. The top (bottom) percentages presented in each graph give the percentage of positive (non-positive) coefficients.

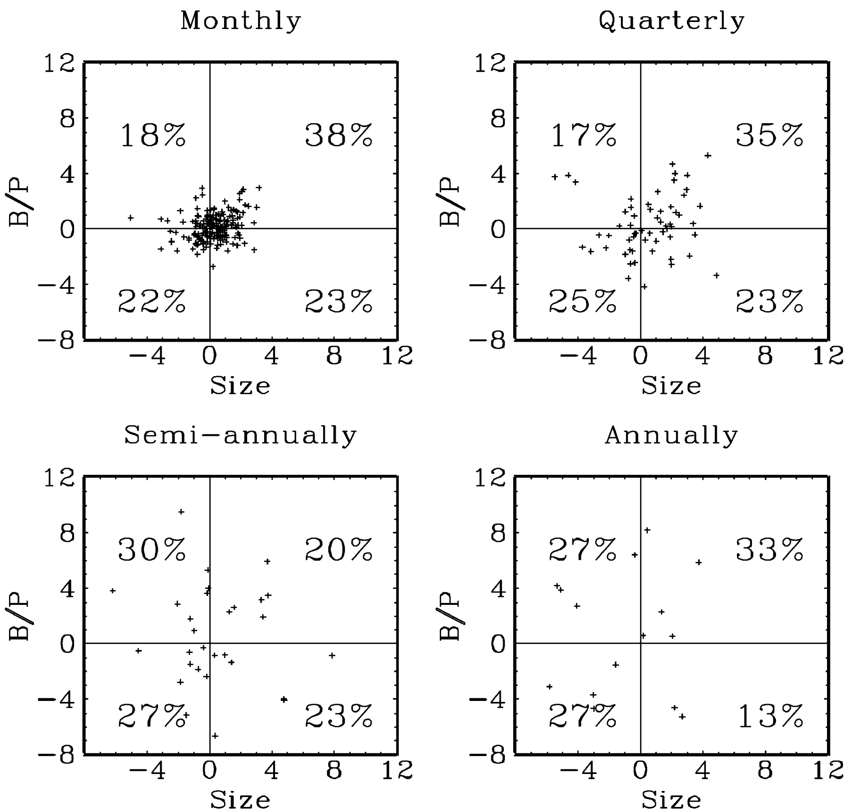

Fig. 2. Scatter diagrams of cross-sectionally estimated coefficients. The figures contains scatter diagrams of the estimated coefficients per cross-section of a regression of future excess returns in excess of an equally weighted portfolio on Size and book-to-price (B/P). The percentages give the fraction of coefficient couples (Size, B/P) present in the quadrant.

number of observations at that frequency. The partial autocorrelation and the CJ test generally point in the same direction, except for the B/P ratio at the semi-annual frequency. Also the mean and median of B/P at the two longest frequencies reveal conflicting results. Looking at the graphs in Fig. 1, it is not surprising to see a difference between the outlier non-robust (Mean, AR1) and outlier robust (Median, CJ) statistics in the table. The medians are significantly negative, while the means are insignificantly positive. This is due to the large value of the coefficient during 1992. In later sections, we also check the robustness of our results with respect to outliers.

The results in Table 1 point out that there is only weak preliminary evidence on the predictability of Size and B/P impact. Monthly frequencies appear most

Table 1
Summary statistics for cross-sectional coefficients

	% > 0	Mean	Std	Median	AR1	CJ
Monthly horizon, n = 181						
Size	57.5	0.16	1.32	0.20[a]	0.13[c]	1.17
B/P	53.0	0.10	0.84	0.05	−0.00	0.98
Quarterly horizon, n = 60						
Size	56.7	0.16	2.74	0.58[a]	−0.25	0.90
B/P	51.7	0.42	2.14	0.08	0.10	1.11
Semi-annual horizon, n = 30						
Size	43.3	−0.29	3.99	−0.51[a]	−0.45	0.71
B/P	50.0	1.59	7.94	−0.15[a]	−0.10	1.42
Annual horizon, n = 15						
Size	33.3	−1.69[c]	3.52	−0.67[a]	0.41	1.33
B/P	46.7	1.17	6.90	−0.40[a]	0.18	1.00

This table contains summary statistics of cross-sectional regressions of returns on Size and B/P, see Eq. (1). The results are presented for four data frequencies, with n denoting the number of cross-sections for each frequency. The second column gives the percentage of positive coefficients (% > 0). The columns labeled Mean, Std and Median give the time-series average, the standard deviation and median of the estimated coefficients, respectively. The column labeled AR1 gives the first order autocorrelation. The column labeled CJ is the Cowles and Jones (1937) test statistic based on the signs of the coefficients. Under the null of no sign predictability, the statistic should be equal to 1. Significance of the statistics in this table at the 1%, 5%, and 10% level is indicated by [a], [b], and [c], respectively. Significance of CJ is determined using Eq. (2.2.8) in Campbell et al. (1997). For significance of the median, we use Phillips (1991), where we estimate the coefficient's density using a Gaussian kernel with bandwidth $h = \sigma n^{-1/5}$, where σ is the time-series standard deviation of the coefficient, see also Silverman (1986).

promising. Given the strong variation in predictability for varying data frequencies, it is important to check the robustness of subsequent results with respect to the rebalancing period in order to prevent data snooping biases. This is done in Section 5.

4. Modeling frameworks

Given the evidence from the previous section on potential serial correlations in the impact of Size and B/P on returns, we now discuss alternative modeling frameworks for capturing the time-variation in γ_t in Eq. (3). We distinguish between two approaches. First, we consider simple statistical approaches like pooling, averaging cross-sectional coefficients, and building time-series models for the coefficients. Second, we consider a framework where time variation in the coefficients is related to economic business cycle variables.

4.1. Pooling

As a first approach to tackling the time variation, one can pool all available firms and time periods $1,\ldots,t$ and do a panel data analysis of Eq. (3). This produces an estimate $\hat{\gamma}_t$, which together with the firm characteristics $\boldsymbol{x}_{it}$ can be used to forecast future returns. The estimate $\hat{\gamma}_t$ is indexed by time, because it depends on the sample used (cross section 1 up to t). As more data become available, two approaches may be followed: the new observations may be added to the sample with or without deleting the oldest observations. If old observations are not deleted, the sample is extended. If old observations are deleted, one uses a rolling window to estimate γ_t.

The pooling approach is a valid procedure if the common risk factors $\boldsymbol{f}_t$ are serially uncorrelated with constant conditional mean $f = E_{t-1}(\boldsymbol{f}_t)$. In that case, we can rewrite Eq. (3) as

$$R_{it} = \boldsymbol{x}'_{i,t-1}\gamma + \tilde{e}_{it}, \tag{4}$$

with $\gamma = \boldsymbol{\Gamma} f$, and $\tilde{e}_{it} = \tilde{\varepsilon}_{it} + \boldsymbol{x}'_{\mathrm{i},t-1}\boldsymbol{\Gamma}(\boldsymbol{f}_t - f)$. The error term in Eq. (4) is now heteroskedastic and cross-sectionally correlated. Consequently, the OLS estimator for γ is still valid, though not efficient. If $E(\boldsymbol{f}_t)$ is non-constant and slowly evolves over time, Eq. (4) can still be a useful approximative model for forecasting.

An additional methodological issue concerns the elimination of redundant variables. Starting from a regression model including both Size and B/P, we sequentially eliminate the variables that have absolute t-values below 1. In this way, we hope to enhance the forecasting power of the model, as argued by Pesaran and Timmermann (1995)[1].

4.2. Averaging

A similar approach to pooling is that of time-series averaging of cross-sectional coefficients. As in Section 3, we can estimate Eq. (3) per cross-section. Using the estimated values $\hat{\gamma}_t$ for each cross-section $1,\ldots,t$, the average effect at time t can be computed as

$$\bar{\gamma}_t = \sum_{s=1}^{t} \hat{\gamma}_s / t. \tag{5}$$

The value of $\bar{\gamma}_t$ can then be used to forecast R_{it}. This approach is very similar to the pooling approach and, therefore, shares the same advantages and disadvantages. The main difference between the two approaches is that the pooling approach produces biased standard errors using standard OLS results.

[1] We also performed the same analysis without eliminating variables to check for data snooping biases, but results turned out to be very similar. See also the discussion in Section 5.

4.3. Random walk model

The main disadvantage of both the averaging and the pooling approach is that the coefficients are relatively rigid over time. In case of swiftly switching coefficients t, these approaches are less suited. In a rapidly changing environment it might be much more useful to base the current estimate of γ_t to be used for forecasting on recent data only. As an extreme, we consider a random walk forecast, where γ_t is estimated by γ_{t-1}. We then use the information in the most recent cross-section only. This is a sensible approach if the true factor model underlying asset returns is a standard random coefficients model,

$$R_{it} = \boldsymbol{x}'_{i,t-1}\gamma_t + \tilde{\varepsilon}_{it} = \boldsymbol{x}'_{i,t-1}\gamma_{t-1} + \left(\tilde{\varepsilon}_{it} + \boldsymbol{x}'_{i,t-1}\eta_t\right) \tag{6}$$

where η_t is an innovation to the random walk $\gamma_t = \gamma_{t-1} + \eta_t$. As demonstrated below in Section 4.4, using the cross-sectional estimate $\hat{\gamma}_t$ for γ_{t+1} results in a consistent predictor. As the random walk model constitutes a good benchmark model in various fields of economics, we also incorporate it in our analysis.

4.4. Autoregressive modeling

Both the random walk and the averaging approach can be interpreted as using a weighted sum of past cross-sectional estimates to predict the future regression coefficients γ_t. Whereas the averaging approach distributes the weight evenly over all past cross-sections, the random walk methodology puts all weight on the most recent cross-section only. Alternatively, both methods can be viewed as special cases of the following scheme,

$$\gamma_t = \mu + \Phi\gamma_{t-1} + \eta_t, \tag{7}$$

with $\Phi = 0$ for the averaging method, and $\Phi = I$ and $\mu = 0$ for the random walk approach. More generally, however, one can try to estimate μ and Φ unrestrictedly from the data. The principal difficulty with this is that we do not directly observe γ_t, but only the cross-sectional estimates $\hat{\gamma}_t$. Instead of directly incorporating Eq. (7) into Eq. (3) and doing full maximum likelihood estimation, we consider a simpler approach. First, we estimate the parameters in Eq. (7) by OLS using $\hat{\gamma}_t$ rather than γ_t. This gives us a biased estimate of μ and Φ. Next, we introduce a bias correction in order to alleviate the potential bias in the estimate of Φ. The bias correction is given in Appendix A. The parameters μ and Φ are estimated using cross-sections 1 up to t in order to forecast γ_{t+1}.

4.5. Business cycle indicators

The approaches in the previous subsections are purely statistical. They do not try to relate the effectiveness of investment styles and the time-variation in t to economic conditions. Various studies have linked macroeconomic indicators to asset returns, e.g., Chen et al. (1986), Chen (1991) and Pesaran and Timmermann (1994,1995). The main idea underlying these models is that differing growth prospects and expectations on discount factors can make stock investments more or less attractive at different points in time. Analogously, alternative investment styles can be preferred at different points in time. If, for example, one expects an increase in the level and slope of the term structure of interest rates, a switch from long duration to short duration stocks can be warranted. In terms of investment styles, this implies a switch from a growth strategy to a value strategy. Also, macroeconomic growth prospects and the associated uncertainty might affect different firms in different ways.

In order to capture these effects, we augment the set of regressors from $\boldsymbol{x}_{it}$ to $X_{it} = \boldsymbol{x}_{it} \otimes M_t$, where $\otimes$ is the Kronecker product. For M_t, we use a set of business cycle predictors. In particular, M_t contains a constant term, the term spread of interest rates (Term_t) and the annual growth rate in the composite index of leading business cycle indicators (Lead_t).

An alternative interpretation of the business cycle approach is that we predict the risk factors $\boldsymbol{f}_t$ by a linear combination of M_{t-1} (and possibly an error term). If we let $\boldsymbol{\Gamma}_2$ be a parameter matrix, we have

$$R_{it} = \boldsymbol{x}'_{i,t-1} \boldsymbol{\Gamma}_2 M_{t-1} + \tilde{\varepsilon}_{it} \tag{8}$$

$$R_{it} = (M_{t-1} \otimes \boldsymbol{x}_{i,t-1})' \delta + \tilde{\varepsilon}_{it}, \tag{9}$$

where $\delta = \text{vec}(\boldsymbol{\Gamma}_2)$ contains the stacked columns of $\boldsymbol{\Gamma}_2$. As with the pooling approach in Section 4.1, δ can be estimated using the cross-sections 1 up to t to forecast cross-section $t+1$. Subsequently, we sequentially eliminate all regressors with absolute t-values below 1 to enhance the forecasting powerof the model. In this way, we obtain an estimate $\hat{\delta}_t$ that together with M_t and $\boldsymbol{x}_{it}$ can be used in Eq. (9) to forecast $R_{i,t+1}$.[2]

5. Results

In this section, we present the results of our empirical analysis. We first discuss the results of a monthly rebalancing period in depth. Next, we go over the results for longer holding periods. Finally, we discuss the robustness of the results.

5.1. Monthly returns

Each month's end, from June 1989 onwards, we obtain forecasts of stock returns using seven different approaches. All approaches use size and book to market as the factors for $\boldsymbol{x}_{it}$ in Eq. (3). The approaches differ in the way estimates

[2] As with the pooling approach, we checked whether the results are robust with respect to the model selection procedure. This is indeed the case.

of γ_t are obtained, as discussed in Section 4. The use of different methods implies that different parts of the data set are used to estimate the parameters. The pooling, averaging, autoregressive, and business cycle methods employ data from June 1984 up to June 1989 to estimate the first set of parameters γ_t. After the end of June 1989, the panel extends through time and each month a new estimate for γ_t is obtained. The random walk method uses previous month's data to estimate γ_t each month.

We construct portfolio returns from the forecasts for individual stock returns as follows. First, we generate forecasts for the expected performance of each stock and select the stocks with a positive forecasted return. We thus concentrate on investment strategies where only long positions are allowed and absolute returns matter. Next, we sort the forecasted returns from high to low and construct five portfolios. Portfolio 1 contains the 20% highest predicted (positive) returns and Portfolio 5 contains the 20% smallest (positive) returns. The stocks are equally weighted in each portfolio. During the holding period of 1 month, the portfolios are not rebalanced. For a fixed Size style, we use present market capitalizations instead of predicted returns. Portfolio 1 contains the large caps, and Portfolio 5 contains the small caps. Similarly, for a fixed B/P style, we use the observed B/P ratio, sorted from high to low. Panels B through H in Table 2 contain the investment results for the seven (possibly rotating) investment styles. Panel A provides a benchmark for panels B through H. Note that all models so far construct five investment portfolios based on a linear predictor of future returns. Each linear predictor is based on Size and book-to-price as explanatory variables. A natural benchmark, therefore, is given by the returns on portfolios based on the *best* linear predictor of returns that uses these two firm characteristics. We compute this benchmark using the standard regression model

$$R_{it} = \lambda_{0t} + \lambda_{1t}\mathrm{Size}_{i,t-1} + \lambda_{2t}(\mathrm{B/P})_{i,t-1} + \varepsilon_{it}, \tag{10}$$

where λ_{0t}, λ_{1t} and λ_{2t} are parameters. We estimate the parameters in Eq. (10) using cross-section t only. As before, we form five portfolios based on the predicted positive returns, i.e., on the positive values of $\hat{\lambda}_{0t} + \hat{\lambda}_{1t}\mathrm{Size}_{i,t-1} +$

Notes to Table 2:

This table contains return and risk statistics for several investment strategies. Each month, we construct five equally weighted portfolios given the return forecasts that we obtain from factor models. The portfolios contain only stocks for which the return forecasts are positive. We use Size and book-to-market ratios as factors. The factor loadings differ across the models. Each month, we estimate the factor models using extending samples from June 1984 onwards. We make the first forecasts in June 1989. Panel A gives the results if we have perfect foresight on the optimal (in a linear context) factor payoffs of Size and book-to-market. Panels B and C show the findings relating to a value and a large cap investment style, respectively. Panels D through G show results obtained from time-dependent models for the factor loadings, and Panel H makes use of macroeconomic variables to model the dynamics in the factor loadings. The average and the standard deviation of the equally weighted market index (benchmark) are 1.14 and 4.71, respectively.

$\hat{\lambda}_{2t}(\mathrm{B/P})_{i,t-1}$ instead of the true returns R_{it}. The returns on these five portfolios provide insight into the maximum performance that can be attained given the chosen set of predictors and the linear prediction framework.

Table 2
Investment results from monthly return factor models

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	3.27	2.52	2.14	1.72	1.34	1.27	1.20	0.97	1.03	1.21
Standard deviation	5.26	4.80	4.78	4.90	4.84	5.08	4.13	4.40	4.88	5.93
Tracking error volatility	2.08	1.17	1.04	0.93	1.07	1.79	1.14	0.81	0.88	2.09
Turnover indicator	32.4	27.2	25.3	24.5	28.8	83.7	75.3	74.4	78.8	86.6
0th order LPM	0.11	0.10	0.19	0.26	0.46	0.50	0.51	0.53	0.59	0.47
1st order LPM	0.06	0.05	0.09	0.13	0.31	0.59	0.41	0.37	0.39	0.78
2nd order LPM	0.06	0.05	0.08	0.11	0.41	1.13	0.57	0.53	0.50	2.11
	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	1.33	1.20	1.11	1.05	0.97	1.38	1.30	1.27	1.21	1.13
Standard deviation	3.97	4.59	5.00	5.19	5.84	3.83	4.10	4.34	4.56	4.70
Tracking error volatility	2.06	1.03	0.85	0.99	2.23	2.44	1.87	1.46	1.04	1.07
Turnover indicator	93.3	87.0	81.4	78.3	81.8	89.9	81.1	74.2	68.6	64.4
0th order LPM	0.45	0.46	0.53	0.58	0.54	0.45	0.43	0.45	0.45	0.47
1st order LPM	0.69	0.35	0.34	0.43	0.90	0.84	0.64	0.51	0.36	0.41
2nd order LPM	2.10	0.51	0.39	0.51	2.16	2.75	1.69	0.97	0.49	0.62
	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	1.39	1.33	1.21	1.25	1.14	1.47	1.35	1.32	1.20	1.11
Standard deviation	3.82	4.15	4.33	4.54	4.71	4.09	4.20	4.34	4.67	4.79
Tracking error volatility	2.43	1.85	1.46	1.05	1.07	2.38	1.69	1.37	1.08	1.01
Turnover indicator	89.7	80.8	74.1	68.4	64.3	56.8	46.2	41.5	37.7	36.8
0th order LPM	0.44	0.43	0.48	0.45	0.46	0.38	0.43	0.43	0.48	0.51
1st order LPM	0.83	0.62	0.54	0.34	0.41	0.76	0.56	0.43	0.39	0.40
2nd order LPM	2.68	1.62	1.06	0.47	0.60	2.77	1.34	0.87	0.60	0.52
	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	1.42	1.37	1.32	1.16	1.15	1.70	1.48	1.32	1.21	1.16
Standard deviation	4.67	4.45	4.61	4.70	4.91	4.41	4.39	4.55	4.71	4.82
Tracking error volatility	2.67	1.78	1.35	1.18	0.97	2.51	1.85	1.32	1.14	0.99
Turnover indicator	33.3	27.6	25.7	24.5	29.9	73.9	62.6	58.0	55.2	53.0
0th order LPM	0.46	0.43	0.40	0.48	0.50	0.40	0.44	0.45	0.46	0.47
1st order LPM	0.84	0.58	0.43	0.43	0.36	0.75	0.58	0.42	0.40	0.38
2nd order LPM	3.29	1.46	0.91	0.65	0.43	2.28	1.37	0.74	0.61	0.48

In this paper, we focus on the economic properties of portfolios to assess which model or forecasting method performs best. Two criteria are used. First, we consider whether a forecasting method leads to portfolios that outperform a reference portfolio. We use an equally weighted benchmark portfolio for this purpose. Rebalancing of the benchmark portfolio takes place at the same moment as used to construct the new portfolios based on the forecasting models. A market-capitalization-weighted benchmark might be influenced by a persistent size bias. We check the robustness of our results with respect to the choice of benchmark later on. Second, we examine whether a monotonic relation exists

Table 3
Monthly risk analysis: market risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	1.77[a]	1.03[a]	0.67[a]	0.19	−0.14	−0.12	−0.14	−0.45	−0.51	−0.52
Market $\boldsymbol{\beta}$	1.08	1.06	1.04	1.10[c]	1.07	0.96	0.91[c]	1.00	1.12[b]	1.31[a]
R^2	0.62	0.73	0.71	0.75	0.72	0.53	0.72	0.76	0.78	0.73
	Panel C: Fixed Size method					**Panel D: Pooling method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	−0.10	−0.30	−0.40	−0.45	−0.49	−0.02	−0.13	−0.19	−0.26	−0.32
Market $\boldsymbol{\beta}$	1.01	1.07	1.09	1.08	1.04	0.98	1.01	1.04	1.05	1.03
R^2	0.97	0.81	0.71	0.64	0.47	0.96	0.91	0.85	0.79	0.71
	Panel E: Averaging method					**Panel F: Autoregressive method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	−0.01	−0.12	−0.24	−0.23	−0.32	0.07	−0.07	−0.11	−0.30	−0.37
Market $\boldsymbol{\beta}$	0.97	1.03	1.03	1.05	1.03	0.98	1.00	1.01	1.07	1.05
R^2	0.96	0.91	0.84	0.79	0.71	0.85	0.85	0.81	0.79	0.72
	Panel G: Random walk method					**Panel H: Business cycle method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	0.04	−0.02	−0.12	−0.32	−0.37	0.30[c]	0.05	−0.16	−0.28	−0.32
Market $\boldsymbol{\beta}$	0.96	0.97	1.01	1.05	1.10	0.97	1.01	1.05	1.07	1.06
R^2	0.63	0.71	0.72	0.74	0.74	0.72	0.79	0.79	0.76	0.71

This table shows the results from the regression of monthly portfolio returns on a constant and returns on a market-capitalization-weighted market index. Estimates for the constant and slope parameters are denoted by Jensen's α and Market $\boldsymbol{\beta}$, respectively. The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. For Panels A and D through H, the portfolios q, $q=1,\ldots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels, where we use a one-sided test for $\alpha > 0$ and a two-sided test for $\boldsymbol{\beta} \neq 1$. The symbol R^2 denotes the coefficient of determination.

Table 4
Monthly risk analysis: the FF risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	2.09[a]	1.33[a]	1.00[a]	0.52[a]	0.19[c]	0.19[b]	0.06	−0.18	−0.15	0.04
FF_{Rm}	1.06	1.04	1.02	1.08[a]	1.05	0.94[b]	0.90[a]	0.98	1.10[a]	1.28[a]
FF_{HML}	0.26[a]	0.21[a]	0.19[a]	0.15[a]	0.11[b]	0.66[a]	0.40[a]	0.20[a]	−0.05	−0.47[a]
FF_{SMB}	0.76[a]	0.68[a]	0.73[a]	0.71[a]	0.72[a]	0.95[a]	0.59[a]	0.63[a]	0.68[a]	0.85[a]
R^2	0.84	0.93	0.94	0.95	0.94	0.97	0.97	0.97	0.97	0.97
	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	−0.09	−0.07	0.01	0.03	0.08	−0.07	−0.11	−0.08	−0.03	−0.01
FF_{Rm}	1.01	1.06[b]	1.07[a]	1.05[a]	1.00	0.98	1.01	1.03	1.04	1.01
FF_{HML}	0.15[a]	0.15[a]	0.04	0.09[a]	0.31[a]	0.18[a]	0.27[a]	0.29[a]	0.22[a]	0.17[a]
FF_{SMB}	0.09[a]	0.53[a]	0.82[a]	0.99[a]	1.26[a]	−0.01	0.19[a]	0.36[a]	0.56[a]	0.69[a]
R^2	0.98	0.95	0.97	0.99	0.93	0.98	0.96	0.94	0.95	0.93
	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	−0.06	−0.09	−0.13	0.00	−0.01	0.09	0.04	0.08	−0.06	−0.03
FF_{Rm}	0.98[c]	1.02	1.03	1.04	1.01	0.98	1.00	1.00	1.06[b]	1.03
FF_{HML}	0.18[a]	0.27[a]	0.30[a]	0.21[a]	0.19[a]	0.23[a]	0.22[a]	0.17[a]	0.21[a]	0.13[a]
FF_{SMB}	−0.00	0.20[a]	0.37[a]	0.56[a]	0.70[a]	0.15[a]	0.33[a]	0.46[a]	0.58[a]	0.72[a]
R^2	0.98	0.95	0.94	0.95	0.93	0.89	0.93	0.93	0.95	0.94
	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	0.24	0.21[c]	0.16	−0.02	−0.04	0.41[b]	0.19	0.06	0.00	0.02
FF_{Rm}	0.95	0.96	1.00	1.03	1.08[a]	0.97	1.00	1.04	1.05[c]	1.04
FF_{HML}	0.11	0.16[a]	0.17[a]	0.12[b]	0.15[a]	0.18[b]	0.19[a]	0.16[a]	0.14[a]	0.12[a]
FF_{SMB}	0.45[a]	0.55[a]	0.64[a]	0.65[a]	0.71[a]	0.31[a]	0.39[a]	0.52[a]	0.62[a]	0.73[a]
R^2	0.73	0.86	0.91	0.93	0.95	0.78	0.87	0.92	0.93	0.94

This table shows the results from the regression of monthly portfolio returns on a constant (FF_{α}) and the Fama and French risk factors. These factors are a market return factor (FF_{Rm}), a return differential of high B/P minus low B/P firms (FF_{HML}), and a return differential of small minus big firms (FF_{SMB}). The latter two are orthogonalized with respect to (FF_{Rm}). The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. The Portfolios q, $q=1,\dots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels, where we use a one-sided test for $FF_{\alpha} > 0$, a two-sided test for $FF_{Rm} \neq 1$, and two-sided tests for $FF_{HML} \neq 0$ and $FF_{SMB} \neq 0$. The symbol R^2 denotes the coefficient of determination.

between the returns of the Portfolios 1 through 5. Both criteria are examined before and after correcting for risk.

Panel A of Table 2 shows that the average monthly return of Portfolio 1 equals 3.27, which is substantially higher than the return on the market portfolio. The latter equals 1.14. The results show that it can be economically useful to attempt to forecast the time-variation in the relation between returns, Size and B/P: We now turn to the risk characteristics, which are given in the remaining rows of Panel A. The high return of Portfolio 1 is counterbalanced by a high standard deviation and tracking error volatility, where the tracking error volatility is defined as the time-series standard deviation of the difference between the portfolio's return and the equally weighted benchmark. The standard deviations and tracking error volatilities for Portfolios 2 through 5 are almost equal, implying that these portfolios can be mainly distinguished on the basis of excess returns. Standard deviations and tracking error volatilities are symmetric risk measures. As investors are also interested in asymmetric risk, we consider three alternative downside risk measures. The kth order lower partial moments presented in the table are defined as the average of $|R_t^M - R_{it}|^k \cdot 1\{R_t^M < R_{it}\}$ gover the forecast period. Here, $1\{R_{it} < R_t^M\}$ takes the value 1 if the portfolio return R_{it} falls below the equally weighted benchmark return R_t^M. Otherwise, it equals zero. For $k = 0$, we obtain an estimate of the probability of shortfall with respect to the benchmark return. This risk measure is closely related to value-at-risk, see Jorion (1996). For $k = 1$, we obtain expected shortfall with respect to the benchmark, and for k = 2 we obtain a semi-tracking error volatility. Using these downside-risk measures, we see that the higher average returns on the perfect foresight portfolios are not offset by higher risk values. All risk measures appear roughly increasing if we shift into stocks with smaller predicted positive returns. The turnover indicator for Portfolio 1 equals 32.4, which reveals that on average about 67.6% of the stocks are sold at portfolio construction. The use of optimal linear predictors of future returns (perfect foresight) thus results in an active trading strategy.

Notes to Table 5:

This table contains return and risk statistics for several investment strategies. Every 3 months, we construct five equally weighted portfolios given the return forecasts that we obtain from factor models. The portfolios contain only stocks for which the return forecasts are positive. We use Size and book-to-market ratios as factors. The factor loadings differ across the models. Each month, we estimate the factor models using extending samples from June 1984 onwards. We make the first forecasts in June 1989. Panel A gives the results if we have perfect foresight on the optimal (in a linear context) factor payoffs of Size and book-to-market. Panels B and C show the findings relating to a value and a large cap investment style, respectively. Panels D through G show results obtained from time-dependent models for the factor loadings, and Panel H makes use of macroeconomic variables to model the dynamics in the factor loadings. The average and the standard deviation of the equally weighted market index (benchmark) are 3.78 and 9.57, respectively.

Panel B shows that investing in stocks with particular B / P ratios produced mixed results. Returns on Portfolios 1, 2 and 5 are slightly above the benchmark return 1.14, while the reverse holds for Portfolios 3 and 4. This points to similar

Table 5
Investment results from quarterly return factor models

	Panel A: Perfect foresight					Panel B: Fixed B / P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	9.11	6.64	6.01	4.89	3.50	4.26	3.83	3.41	3.35	4.03
Standard deviation	11.6	10.1	9.69	10.2	9.50	11.3	8.57	8.63	9.72	11.8
Tracking error volatility	4.50	2.52	2.33	1.57	1.80	4.37	2.17	1.86	1.97	4.53
Turnover indicator	30.5	24.6	22.1	20.3	23.5	70.6	59.9	58.5	64.1	75.6
0th order LPM	0.05	0.13	0.15	0.28	0.50	0.50	0.60	0.63	0.57	0.40
1st order LPM	0.09	0.12	0.09	0.21	0.84	1.29	0.80	0.80	1.00	1.71
2nd order LPM	0.17	0.23	0.08	0.23	2.08	6.09	1.71	2.75	2.85	10.20

	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	4.17	3.77	3.45	3.37	4.12	3.79	3.56	3.91	3.36	3.48
Standard deviation	6.97	8.82	9.89	10.9	13.0	6.85	7.24	8.08	8.84	9.66
Tracking error volatility	4.43	1.84	1.46	2.16	4.86	5.11	3.66	2.39	1.69	1.60
Turnover indicator	87.8	76.8	67.6	62.2	65.2	64.1	54.9	49.7	45.3	41.4
0th order LPM	0.42	0.45	0.50	0.55	0.55	0.40	0.42	0.40	0.47	0.50
1st order LPM	1.47	0.62	0.73	1.05	1.50	1.68	1.34	0.71	0.76	0.75
2nd order LPM	10.8	1.78	1.59	3.12	6.24	15.7	8.60	2.44	2.12	1.50

	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	4.16	4.00	3.77	3.95	3.56	3.37	3.31	3.83	3.42	3.42
Standard deviation	6.81	7.05	7.60	9.06	8.94	10.7	8.73	9.44	9.30	9.71
Tracking error volatility	5.11	3.84	2.89	2.01	1.80	5.92	3.17	2.62	1.86	1.52
Turnover indicator	62.0	45.2	38.3	33.2	30.8	34.1	24.6	21.7	21.6	22.0
0th order LPM	0.53	0.53	0.57	0.47	0.60	0.55	0.63	0.55	0.63	0.55
1st order LPM	1.67	1.30	1.15	0.71	0.78	2.32	1.33	0.97	0.91	0.81
2nd order LPM	13.7	7.64	3.74	1.65	1.81	23.0	6.66	3.27	2.12	1.72

	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	3.82	3.47	3.43	3.38	3.35	5.38	4.17	3.98	3.63	3.39
Standard deviation	8.75	8.32	8.83	9.60	9.51	7.85	8.05	8.81	9.46	9.94
Tracking error volatility	5.58	3.63	2.55	1.77	2.24	5.62	3.92	2.73	2.08	2.12
Turnover indicator	33.9	28.3	25.0	22.8	26.1	62.6	51.6	46.2	42.6	41.7
0th order LPM	0.45	0.50	0.55	0.50	0.63	0.35	0.42	0.47	0.53	0.57
1st order LPM	2.18	1.45	1.09	0.91	1.09	1.50	1.34	0.96	0.86	1.02
2nd order LPM	17.4	8.83	4.26	2.33	3.45	11.3	7.23	3.16	2.39	2.79

findings as in Chan et al. (2000). Panel *C* shows that a large-Size investment style outperformed passive index tracking, while a small-cap strategy underperformed. Panels D through G provide evidence that it is possible to outperform the equally weighted index using simple statistical approaches for style rotation. Except for Portfolios 5 of the autoregressive approach (1.11) and the pooling approach (1.13), all returns lie above the benchmark return of 1.14. The Business Cycle method in Panel H gives the highest value added. The return on the top 20% of predicted positive returns (Portfolio 1) clearly exceeds the return on the market index (and all other style rotation schemes). The same holds for the next 40% of stocks

Table 6
Quarterly risk analysis: market risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	3.81[a]	1.51[c]	0.95	−0.62	−1.73	−0.63	−0.78	−1.39	−1.95	−2.16
Market $\boldsymbol{\beta}$	1.27	1.22	1.19	1.34[a]	1.25[b]	1.14	1.06	1.12	1.27[b]	1.55[a]
R^2	0.54	0.66	0.69	0.77	0.78	0.45	0.68	0.75	0.77	0.79
	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	−0.33	−1.23	−1.91	−1.96	−1.46	−0.57	−0.91	−0.80	−1.63	−1.65
Market $\boldsymbol{\beta}$	1.02	1.18[c]	1.29[b]	1.28[c]	1.36	0.98	1.01	1.09	1.17[c]	1.22[c]
R^2	0.97	0.81	0.77	0.62	0.50	0.92	0.87	0.82	0.79	0.71
	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	−0.06	−0.33	−0.69	−1.13	−1.26	−1.46	−1.37	−1.05	−1.62	−1.74
Market $\boldsymbol{\beta}$	0.93	0.97	1.01	1.20[b]	1.12	1.12	1.08	1.14	1.19	1.23[c]
R^2	0.84	0.84	0.79	0.79	0.71	0.49	0.68	0.65	0.73	0.72
	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	−1.07	−1.41	−1.57	−1.83	−1.80	1.49[c]	−0.15	−0.86	−1.44	−1.86
Market $\boldsymbol{\beta}$	1.14	1.14[c]	1.17[c]	1.24[b]	1.22[c]	0.83	0.96	1.13	1.20	1.26[c]
R^2	0.77	0.85	0.80	0.76	0.74	0.50	0.64	0.74	0.73	0.72

This table shows the results from the regression of quarterly portfolio returns on a constant and returns on an market-capitalization-weighted market index. Estimates for the constant and slope parameters are denoted by Jensen's α and market $\boldsymbol{\beta}$, respectively. The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. For Panels A and D through H, the portfolios q, $q=1,\dots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels, where we use a one-sided test for $\alpha > 0$ and a two-sided test for $\boldsymbol{\beta} \neq 1$. The symbol R^2 denotes the coefficient of determination.

Table 7
Quarterly risk analysis: the FF risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	5.44[a]	2.87[a]	2.07[a]	0.54[b]	−0.62	0.77[b]	0.04	−0.45	−0.49	−0.10
FF_{Rm}	1.17	1.14[c]	1.13[c]	1.27[a]	1.18[a]	1.06	1.01	1.06	1.19[a]	1.43[a]
FF_{HML}	0.25[c]	0.12	0.19[b]	0.14[a]	0.09	0.61[a]	0.35[a]	0.17[a]	−0.12[b]	−0.57[a]
FF_{SMB}	0.98[a]	0.77[a]	0.68[a]	0.68[a]	0.62[a]	1.04[a]	0.60[a]	0.58[a]	0.70[a]	0.79[a]
R^2	0.87	0.92	0.93	0.97	0.96	0.97	0.98	0.97	0.97	0.97

	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	−0.26	−0.29	−0.57	−0.00	0.91[b]	−0.34	−0.40	0.05	−0.68	−0.39
FF_{Rm}	1.02	1.12[a]	1.21[a]	1.17[a]	1.22[a]	0.96	0.98	1.04	1.12[a]	1.14[a]
FF_{HML}	0.10[a]	0.07	0.02	0.04	0.21[b]	−0.04	0.05	0.05	0.13[a]	0.13[b]
FF_{SMB}	0.08[a]	0.53[a]	0.71[a]	1.04[a]	1.35[a]	0.10[c]	0.30[a]	0.47[a]	0.56[a]	0.72[a]
R^2	0.99	0.96	0.97	0.99	0.96	0.92	0.95	0.96	0.98	0.96

	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	−0.19	−0.17	−0.12	−0.41	−0.29	−0.47	−0.52	−0.01	−0.53	−0.52
FF_{Rm}	0.94	0.96	0.97	1.16[a]	1.06	1.07	1.03	1.08	1.12[a]	1.16[a]
FF_{HML}	0.28[a]	0.29[a]	0.21[a]	0.25[a]	0.24[a]	0.37[b]	0.24[b]	0.31[a]	0.17[a]	0.17[a]
FF_{SMB}	0.07	0.22[a]	0.40[a]	0.51[a]	0.63[a]	0.71[a]	0.57[a]	0.70[a]	0.66[a]	0.73[a]
R^2	0.90	0.96	0.96	0.97	0.97	0.74	0.90	0.95	0.97	0.98

	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	−0.81	−0.69	−0.48	−0.55	−0.44	1.98[b]	0.78	0.16	−0.08	−0.40
FF_{Rm}	1.13	1.10	1.11[b]	1.17[a]	1.14[b]	0.80[c]	0.91	1.07	1.12[b]	1.17[a]
FF_{HML}	0.06	−0.02	−0.04	0.03	−0.04	0.28[c]	0.08	0.06	−0.02	−0.02
FF_{SMB}	0.17	0.36[a]	0.54[a]	0.68[a]	0.69[a]	0.40[a]	0.53[a]	0.56[a]	0.71[a]	0.76[a]
R^2	0.79	0.92	0.95	0.96	0.95	0.67	0.83	0.91	0.94	0.95

This table shows the results from the regression of quarterly portfolio returns on a constant (FF_{α}) and the Fama and French risk factors. These factors are a market return factor (FF_{Rm}), a return differential of high B/P minus low B/P firms (FF_{HML}), and a return differential of small minus big firms (FF_{SMB}). The latter two are orthogonalized with respect to (FF_{Rm}). The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. The Portfolios q, $q = 1,\ldots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels, where we use a one-sided test for $FF_{\alpha} > 0$, a two-sided test for $FF_{Rm} \neq 1$, and two-sided tests for $FF_{HML} \neq 0$ and $FF_{SMB} \neq 0$. The symbol R^2 denotes the coefficient of determination.

(Portfolios 2 and 3). Moreover, the returns are monotonically decreasing from Portfolio 1 through 5: weaker ex-ante predicted winners also show a weaker ex-post performance. The return of Portfolio 1 vis-à-vis Portfolio 5 for Panel H is not offset by a corresponding increase in risk if we consider standard deviations or the probability on a negative tracking error. The risk only shows if we consider tracking errors or lower partial moments of orders 1 and 2.

To test whether the forecasting power of Size and B/P as shown in Panel A of Table 2 generates significant risk-corrected excess returns, we use the following test. We perform a time-series regression of the portfolio returns on a constant and the return of a market index. This is the standard market model, where, in general, the constant and slope parameter are denoted by Jensen's α and the market $\boldsymbol{\beta}$, respectively. Following the standard approach, see for example Lewellen (1999), we use a market capitalization weighted index return. The parameter estimates are given in Panel A of Table 3. The table also contains the test results for the null hypotheses that $\alpha > 0$ (one-sided) and $\boldsymbol{\beta} \neq 1$(two-sided). The results indicate that Jensen's α remains significantly positive for Portfolios 1 through 3 in Panel A after correcting for market risk. The market $\boldsymbol{\beta}$'s are higher than 1, but only for Portfolio 4 the difference is significant. Panels B through G of Table 3 show no evidence of significant risk-corrected excess returns. All α's are negative, except for Portfolio 1 in Panels F and G. For Panel H, most conclusions remain similar. The risk-corrected return of $\alpha = 0.30$ is statistically significant at the 10% level. It is the only statistical significant entry for α in the table besides Panel A. Again, α's in Panel H gradually decline if the ex-ante predicted performance of the stocks is weaker. With a few exceptions, the R^2's of the market model are generally relatively high, indicating that the model captures an important part of the variation in portfolio returns.

The market model is only one of the many potential risk models that explain return differentials. The three-factor model of Fama and French (1993) is another well-known model, see, e.g., Daniel and Titman (1997) and Lewellen (1999). The risk factors in this model are (i) a market return factor (FF_{Rm}); (ii) a return differential of a portfolio consisting of high B/P stocks minus a portfolio of low

Notes to Table 8:
This table contains return and risk statistics for several investment strategies. Every 6 months, we construct five equally weighted portfolios given the return forecasts that we obtain from factor models. The portfolios contain only stocks for which the return forecasts are positive. We use Size and book-to-market ratios as factors. The factor loadings differ across the models. Each month, we estimate the factor models using extending samples from June 1984 onwards. We make the first forecasts in June 1989. Panel A gives the results if we have perfect foresight on the optimal (in a linear context) factor payoffs of Size and book-to-market. Panels B and C show the findings relating to a value and a large cap investment style, respectively. Panels D through G show results obtained from time-dependent models for the factor loadings, and Panel H makes use of macroeconomic variables to model the dynamics in the factor loadings. The average and the standard deviation of the equally weighted market index (benchmark) are 7.58 and 10.51, respectively.

B/P stocks (FF_{HML}) and (iii) a return differential of a portfolio consisting of small stocks minus a portfolio consisting of big stocks (FF_{SMB}). The latter two are orthogonalized with respect to FF_{Rm}. As in Lewellen (1999), all these portfolios

Table 8
Investment results from semi-annual return factor models

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	19.0	11.4	9.61	8.17	7.31	8.83	7.48	6.98	6.86	7.74
Standard deviation	16.5	9.86	9.13	10.3	10.1	14.7	10.1	9.44	9.70	13.0
Tracking error volatility	10.3	4.05	2.98	2.81	3.43	6.98	3.10	2.52	2.56	6.98
Turnover indicator	10.2	10.0	9.0	9.4	15.8	59.9	48.8	46.9	52.4	64.7
0th order LPM	0.10	0.15	0.25	0.50	0.50	0.45	0.55	0.60	0.60	0.40
1st order LPM	0.12	0.26	0.24	0.86	1.56	2.21	1.33	1.14	1.41	2.66
2nd order LPM	0.18	0.89	0.49	2.58	7.27	16.4	3.75	5.13	5.26	25.9
	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	8.12	7.20	6.21	5.77	10.6	7.39	6.81	7.26	6.39	7.40
Standard deviation	7.13	8.95	10.6	12.0	17.1	13.6	11.2	10.5	9.97	10.3
Tracking error volatility	5.69	2.95	2.16	2.58	8.61	9.47	6.05	3.14	2.12	2.68
Turnover indicator	82.4	68.0	56.0	48.7	50.8	38.5	28.4	24.8	25.7	29.0
0th order LPM	0.45	0.40	0.70	0.80	0.45	0.45	0.55	0.45	0.70	0.45
1st order LPM	1.63	1.30	1.77	2.23	1.77	3.89	2.65	1.49	1.50	1.17
2nd order LPM	13.3	5.78	5.55	8.33	11.0	46.9	21.9	6.24	5.25	4.00
	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	9.30	8.41	7.45	7.39	6.86	12.9	9.82	8.41	7.98	6.92
Standard deviation	13.0	9.60	10.1	11.0	10.4	15.2	11.6	9.44	10.4	10.1
Tracking error volatility	10.4	5.12	3.55	3.06	2.23	8.42	3.75	4.04	2.52	2.59
Turnover indicator	36.8	23.4	18.1	17.9	17.2	32.4	19.8	16.9	16.1	17.2
0th order LPM	0.40	0.45	0.50	0.40	0.70	0.30	0.35	0.55	0.40	0.65
1st order LPM	3.47	1.65	1.39	1.24	1.34	1.10	0.59	1.17	0.88	1.38
2nd order LPM	44.6	10.7	7.79	5.55	3.52	5.98	1.61	3.67	2.56	4.77
	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	6.82	6.93	6.63	5.98	6.10	12.2	9.31	7.26	6.24	5.54
Standard deviation	11.8	10.4	10.6	10.1	10.5	10.1	9.20	9.31	9.48	10.2
Tracking error volatility	7.67	4.72	3.28	2.31	2.81	7.51	4.29	3.01	3.45	3.47
Turnover indicator	15.0	12.6	11.2	12.9	20.7	39.7	30.6	26.1	25.3	25.0
0th order LPM	0.60	0.60	0.75	0.75	0.70	0.30	0.50	0.60	0.70	0.65
1st order LPM	3.34	1.99	1.82	2.00	2.00	0.74	0.77	1.29	2.18	2.65
2nd order LPM	32.7	12.6	7.03	6.91	8.05	2.28	1.72	5.36	10.5	14.1

Table 9
Semi-annual risk analysis: market risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	9.59[b]	2.98	1.15	−1.03	−1.65	−0.77	−1.47	−2.16	−2.47	−3.85
Market $\boldsymbol{\beta}$	1.10	0.93	0.94	1.06	1.02	1.12	1.02	1.05	1.08	1.45[c]
R^2	0.23	0.46	0.54	0.53	0.52	0.29	0.51	0.62	0.63	0.64
	Panel C: Fixed Size method					**Panel D: Pooling method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	−0.51	−1.70	−3.25	−4.86	−0.39	−3.51	−3.46	−2.28	−2.36	−1.53
Market $\boldsymbol{\beta}$	0.97	1.01	1.10	1.29	1.36	1.33	1.23	1.11	0.99	1.02
R^2	0.94	0.65	0.55	0.59	0.32	0.49	0.61	0.56	0.49	0.49
	Panel E: Averaging method					**Panel F: Autoregressive method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	2.03	0.22	−1.47	−2.96	−2.62	2.08	0.18	−0.02	−1.30	−2.35
Market $\boldsymbol{\beta}$	0.75	0.90	1.02	1.25	1.11	1.32	1.13	0.94	1.07	1.07
R^2	0.16	0.43	0.50	0.65	0.57	0.39	0.48	0.50	0.53	0.57
	Panel G: Random walk method					**Panel H: Business cycle method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	−3.99	−3.53	−3.75	−3.55	−3.37	5.42[b]	0.67	−2.28	−2.91	−3.73
Market $\boldsymbol{\beta}$	1.32	1.26	1.25	1.11	1.11	0.67	0.97	1.12	1.05	1.07
R^2	0.62	0.73	0.71	0.61	0.56	0.22	0.56	0.73	0.62	0.55

This table shows the results from the regression of semi-annual portfolio returns on a constant and returns on an market-capitalization-weighted market index. Estimates for the constant and slope parameters are denoted by Jensen's α and Market $\boldsymbol{\beta}$, respectively. The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. For Panels A and D through H, the portfolios q, $q=1,\ldots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels, where we use a one-sided test for $\alpha>0$ and a two-sided test for $\boldsymbol{\beta}\neq 1$. The symbol R^2 denotes the coefficient of determination.

are value weighted[3]. The results in Panel A of Table 4 indicate that not only a market risk factor, but also the size and book-to-market risk factors capture variation in the portfolio returns. We test whether the factor loading of FF_{Rm} is

[3] The general conclusions on the stability and robustness of the excess (risk-corrected) returns on the business cycle style rotation scheme remain unaltered if we use equally weighted rather than value-weighted indices. This also holds for the conclusions on the non-robustness of the alternative style rotation schemes.

Table 10
Semi-annual risk analysis: the FF risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	12.7[a]	5.42[a]	3.31[a]	0.87	0.61	1.15[b]	−0.42	−0.33	0.27	0.19
FF_{Rm}	0.88	0.76[c]	0.79[b]	0.93	0.86	0.99	0.95	0.92	0.89[c]	1.16
FF_{HML}	0.28	−0.01	−0.00	0.14	0.02	0.63[a]	0.35[a]	0.07	−0.16[a]	−0.59[a]
FF_{SMB}	1.16[a]	0.74[a]	0.66[a]	0.68[a]	0.70[a]	1.03[a]	0.57[a]	0.61[a]	0.73[a]	0.84[a]
R^2	0.70	0.86	0.92	0.91	0.87	0.99	0.96	0.95	0.98	0.93

	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	−0.25	0.00	−0.65	−1.60	3.39[b]	−0.77	−0.51	−0.00	0.25	0.60
FF_{Rm}	0.95	0.89	0.92	1.06	1.09	1.14	1.02	0.95	0.80[b]	0.86
FF_{HML}	0.05	0.03	−0.00	−0.11[c]	0.34[b]	−0.31	−0.33[b]	0.03	0.02	0.12
FF_{SMB}	0.12[a]	0.54[a]	0.80[a]	0.93[a]	1.40[a]	0.63[b]	0.68[a]	0.72[a]	0.82[a]	0.74[a]
R^2	0.97	0.92	0.95	0.97	0.93	0.61	0.83	0.90	0.97	0.92

	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	1.41	0.74	0.32	−0.95	−0.05	3.89[c]	2.39[c]	1.35	0.90	−0.05
FF_{Rm}	0.79	0.86	0.89	1.10	0.92	1.19	0.97	0.84	0.92	0.91
FF_{HML}	0.87[a]	0.42[a]	0.17[c]	0.05	−0.02	0.37	0.15	0.18	0.09	0.01
FF_{SMB}	0.41[c]	0.45[a]	0.67[a]	0.65[a]	0.77[a]	0.81[a]	0.78[a]	0.55[a]	0.74[a]	0.71[a]
R^2	0.72	0.86	0.90	0.92	0.95	0.73	0.88	0.84	0.93	0.93

	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	−3.23	−2.00	−1.27	−1.31	−0.96	6.03[a]	2.36[b]	−0.71	−1.13	−1.42
FF_{Rm}	1.27	1.15	1.07	0.95	0.93	0.63[c]	0.85	1.00	0.93	0.91
FF_{HML}	0.15	0.00	−0.15[c]	0.01	0.01	0.45[b]	0.04	0.03	0.04	−0.01
FF_{SMB}	0.34	0.47[a]	0.66[a]	0.70[a]	0.75[a]	0.50[b]	0.55[a]	0.51[a]	0.57[a]	0.70[a]
R^2	0.71	0.88	0.95	0.95	0.91	0.70	0.83	0.95	0.89	0.89

This table shows the results from the regression of semi-annual portfolio returns on a constant (FF_{α}) and the Fama and French risk factors. These factors are a market return factor (FF_{Rm}), a return differential of high B/P minus low B/P firms (FF_{HML}), and a return differential of small minus big firms (FF_{SMB}). The latter two are orthogonalized with respect to (FF_{Rm}). The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. The Portfolios q, $q=1,\ldots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels, where we use a one-sided test for $FF_{\alpha} > 0$, a two-sided test for $FF_{Rm} \neq 1$, and two-sided tests for $FF_{HML} \neq 0$ and $FF_{SMB} \neq 0$. The symbol R^2 denotes the coefficient of determination.

different from one and whether the factor loadings of FF_{HML} and FF_{SMB} are significantly different from zero. All three tests are two-sided. Tests on $FF_{\alpha} > 0$ are again one-sided. Most parameter estimates in Panel A, including the risk-corrected returns FF_{α}, are significant at the one percent level. The coefficient of determination ranges from 0.84 for Portfolio 1 to 0.95 for Portfolio 4, which suggests a good fit of the model. This is in accordance with expectations, as Panel A assumes optimal linear predictors are used, i.e., perfect foresight regarding the optimal factor loadings λ_{it} in Eq. (10). Under less than perfect foresight, Panels B through H show that most FF_{α}s are insignificant or negative. There are three exceptions with respect to significance of FF_{α}. Investing in the 20% stocks with the highest B/P values generated significant risk-corrected returns. Also Portfolio 2 of the Random Walk model leads to a significant FF_{α}. Both of these did not show up under the alternative risk correction in Table 3. Finally, the top quintile (Portfolio 1) of the Business Cycle approach generates a statistically significant FF_{α}. This is robust to the way of risk-correction, compare Table 3. Note that both the Jensen's α's and the FF_{α}s for the Business Cycle model are substantially higher than those of the other models (excepting Panel A). Moreover, the coefficients of FF_{SMB} and FF_{HML} differ substantially across models. We conclude that the Business Cycle method generates the best overall performance before and after risk correction. The difference between the perfect foresight setting and the other models remains relatively large. Hence, only a limited fraction of the variation in the effects of Size and B/P can be forecasted by our approaches.

5.2. Quarterly returns

Table 5 provides the results when rebalancing takes place after a buy and hold period of 3 months. The methodology and structure of the tables for quarterly returns are similar to those for monthly returns. Panel A of Table 5 shows that perfect (linear) forecasting skills with respect to the (linearly) optimal loadings λ_{it} on Size and B/M is highly rewarding for the 3-month investment horizon. The return on Portfolio 1, for example, is about 533 basis points higher than that on an

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Notes to Table 11:
This table contains return and risk statistics for several investment strategies. Every 12 months, we construct five equally weighted portfolios given the return forecasts that we obtain from factor models. The portfolios contain only stocks for which the return forecasts are positive. We use Size and book-to-market ratios as factors. The factor loadings differ across the models. Each month, we estimate the factor models using extending samples from June 1984 onwards. We make the first forecasts in June 1989. Panel A gives the results if we have perfect foresight on the optimal (in a linear context) factor payoffs of Size and book-to-market. Panels B and C show the findings relating to a value and a large cap investment style, respectively. Panels D through G show results obtained from time-dependent models for the factor loadings, and Panel H makes use of macroeconomic variables to model the dynamics in the factor loadings. The average and the standard deviation of the equally weighted market index (benchmark) are 17.57 and 9.65, respectively.

equally weighted portfolio. The average returns on Portfolios 2 through 4 are higher than that on the benchmark portfolio and gradually decline, while the return for Portfolio 5 falls short of the benchmark. The standard deviations of the portfolios are higher than that of the benchmark portfolio, except for Portfolio 5

Table 11
Investment results from annual return factor models

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	36.5	25.4	17.5	15.4	14.3	18.5	15.9	16.8	17.3	19.4
Standard deviation	13.5	12.3	13.5	10.4	12.5	13.8	11.7	10.1	7.95	13.6
Tracking error volatility	7.43	5.32	6.02	4.35	4.57	7.42	5.34	2.75	3.70	10.41
Turnover indicator	13.8	13.3	15.4	16.4	16.4	48.3	40.8	37.9	43.4	52.3
0th order LPM	0.00	0.10	0.60	0.60	0.60	0.50	0.70	0.50	0.50	0.40
1st order LPM	0.00	0.20	2.13	3.14	3.67	2.70	2.87	1.59	1.63	3.49
2nd order LPM	0.00	0.41	12.1	17.7	28.9	22.2	18.0	5.18	7.70	40.1
	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	17.0	14.6	12.6	13.5	30.0	26.0	20.2	17.7	14.4	13.9
Standard deviation	8.24	9.42	8.33	11.8	14.3	13.9	12.7	13.5	10.4	11.7
Tracking error volatility	5.23	1.87	3.63	2.79	7.27	8.72	5.56	5.09	2.75	3.15
Turnover Indicator	79.1	62.0	50.0	41.8	40.5	33.4	23.5	18.9	18.3	20.7
0th order LPM	0.50	1.00	0.90	0.90	0.10	0.30	0.30	0.60	0.80	0.90
1st order LPM	2.50	2.98	5.27	4.17	0.13	0.67	1.04	1.79	3.33	4.00
2nd order LPM	13.8	12.0	35.0	23.3	0.17	2.12	4.04	9.90	16.7	21.2
	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	23.3	20.4	16.5	16.3	17.8	23.0	18.0	16.5	13.8	13.3
Standard deviation	15.1	12.2	11.9	12.9	13.4	19.7	13.0	11.7	9.78	7.41
Tracking error volatility	10.0	5.92	4.55	4.00	5.20	14.9	6.93	4.03	2.63	4.17
Turnover indicator	34.0	20.8	16.5	16.0	14.2	22.1	16.6	16.2	18.5	20.5
0th order LPM	0.20	0.20	0.50	0.70	0.60	0.40	0.30	0.60	0.90	0.70
1st order LPM	2.01	0.98	2.19	2.49	1.77	3.63	2.56	2.36	3.89	4.61
2nd order LPM	22.5	6.27	13.8	11.1	7.56	38.5	27.1	10.7	20.4	33.1
	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
Performance	32.5	23.2	17.0	13.9	12.9	27.5	20.5	17.0	15.2	13.6
Standard deviation	16.4	14.1	11.2	11.1	9.45	15.8	12.1	9.77	10.4	10.8
Tracking error volatility	11.0	5.98	3.82	2.84	4.06	10.1	5.74	3.02	2.61	2.36
Turnover indicator	16.2	14.9	14.4	14.4	15.2	25.0	16.6	14.0	11.9	14.1
0th order LPM	0.00	0.30	0.60	0.90	0.90	0.20	0.30	0.40	0.70	0.90
1st order LPM	0.00	0.27	1.83	3.74	4.71	0.18	0.61	1.48	2.75	4.04
2nd order LPM	0.00	0.36	9.01	20.9	36.5	0.16	1.71	5.63	11.2	20.5

again. Downside-risk measures are increasing in the portfolio number, with the exception of Portfolio 3. The turnover indicator shows that 30.5% of Portfolio 1 is not sold on average. This figure is lower for the other portfolios.

In Panels B through G, 12 out of 30 portfolios outperform the benchmark return of 3.78%. By far the largest outperformance, however, is generated by Portfolio 1 in Panel *H*. This is consistent with the earlier results for monthly data. Again, we also find a monotonic relation across the returns of five portfolios for the Business Cycle model. The only other method satisfying this criterion for quarterly data is the Random Walk method. Consistent with the monthly results, the standard deviation and 0th order lower partial moment for Panel H as measures of risk generally decrease with the stated return, whereas the converse holds for the tracking error volatility and the lower partial moments of orders 1 and 2.

As before, we also consider risk-corrected returns using both the market model and the three factor Fama and French model. The results are in Tables 6 and 7, respectively. The Jensen's α's in Panel A of Table 6 are only positive and significant for Portfolios 1 and 2. Perfect foresight about the optimal linear loadings for Size and B/P would lead to significant average returns only for clear predicted winners. In the remaining panels, only Portfolio 1 for Panel H generates a significantly positive Jensen's α. This corroborates the results for monthly holding periods. The positive α comes with a market $\boldsymbol{\beta}$ that is insignificantly below 1. By contrast, fixed B/P and Size strategies (Panels B and C) typically come with market $\boldsymbol{\beta}$'s exceeding 1. Table 7 gives the FF_{α}s. Panel A illustrates that perfect foresight on the optimal loadings of Size and B/P would lead to significantly positive risk-corrected returns for four out of five portfolios. Panels B and C show that for quarterly data we obtain the familiar pattern documented in the literature: high B/P and small Size strategies outperform the benchmark after correcting for risk. The reported FF_{α}s are, however, much lower than for the Business Cycle approach if we concentrate on the clearest predicted winners, i.e., Portfolio 1 for Panels B and H and Portfolio 5 for Panel C. Moreover, it is interesting to note that Panel H now has three positive entries, although only one is statistically significant. Only Panel B has two positive entries, one of which is very close to zero (0.04). It is also interesting to see that the factor loadings are very different between the portfolios with significant FF_{α}s. The fixed B/P and Size strategies come with market $\boldsymbol{\beta}$'s (FF_{Rm}) of 1.06 and 1.22, respectively. These exceed unity. By contrast, the Business Cycle approach generates a market $\boldsymbol{\beta}$ that is significantly below 1. Also the loadings on the other risk factors, especially FF_{SMB}, differ substantially. The fit of the risk model for Portfolio 1 in Panel H is not as good as for the fixed investment styles, suggesting that there may be another risk factor that is not accounted for in the FF framework.

5.3. Semi-annual and annual returns

Tables 8, 9 and 10 show return statistics and risk measures for portfolios that are actively rebalanced twice a year using one of our forecasting methods.

Similarly, Tables 11, 12 and 13 present the results for annual holding periods. As before, the only modeling approach showing a consistent behavior across rebalancing periods and methods for risk-correction is the Business Cycle approach. The clear predicted winners (Portfolio 1 of Panel H) show significant excess return before and after risk-correction. Moreover, ex-post performance declines if the portfolio contains stocks with a weaker ex-ante predicted performance. Again, the market $\boldsymbol{\beta}$ for Portfolio 1 in Panel H is below unity. Finally, the R^2's of the Fama–French factor model regressions (Tables 10 and 13) are substantially lower for the Business Cycle model than for the fixed-Size and fixed-B/P strategies,

Table 12
Annual risk analysis: market risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	22.9[a]	10.1[c]	−2.44	0.15	−3.59	3.58	0.12	2.27	2.34	1.74
Market $\boldsymbol{\beta}$	0.63	0.75	1.12	0.75	0.96	0.72	0.80	0.70	0.73	0.94
R^2	0.20	0.34	0.64	0.48	0.53	0.25	0.43	0.42	0.71	0.44
	Panel C: Fixed Size method					**Panel D: Pooling method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	0.65	−0.43	−1.02	−3.74	14.5[b]	7.02	4.28	0.12	−2.03	−1.84
Market $\boldsymbol{\beta}$	0.84[c]	0.73	0.63	0.91	0.77	1.04	0.81	0.94	0.84	0.79
R^2	0.93	0.54	0.49	0.52	0.27	0.48	0.35	0.43	0.59	0.40
	Panel E: Averaging method					**Panel F: Autoregressive method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	7.14	3.45	2.32	−0.73	1.18	1.01	0.09	−0.16	−1.87	0.27
Market $\boldsymbol{\beta}$	0.82	0.88	0.67	0.89	0.86	1.28	0.96	0.86	0.78	0.58[c]
R^2	0.26	0.45	0.28	0.43	0.38	0.37	0.46	0.49	0.58	0.53
	Panel G: Random walk method					**Panel H: Business cycle method**				
Quintile	1	2	3	4	5	1	2	3	4	5
Jensen's α	17.2[b]	7.04	2.12	−2.35	−1.38	12.6[c]	3.93	2.06	−0.51	−2.54
Market $\boldsymbol{\beta}$	0.76	0.82	0.72	0.83	0.68	0.73	0.86	0.73	0.79	0.82
R^2	0.19	0.31	0.39	0.51	0.44	0.19	0.46	0.51	0.52	0.51

This table shows the results from the regression of annual portfolio returns on a constant and returns on an market-capitalization-weighted market index. Estimates for the constant and slope parameters are denoted by Jensen's α and Market $\boldsymbol{\beta}$, respectively. The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. For Panels A and D through H, the portfolios q, $q=1,\ldots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% ([a]), 5% ([b]) and 10% ([c]) levels, where we use a one-sided test for $\alpha > 0$ and a two-sided test for $\boldsymbol{\beta} \neq 1$. The symbol R^2 denotes the coefficient of determination.

Table 13
Annual risk analysis: the FF risk model

	Panel A: Perfect foresight					Panel B: Fixed B/P method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	21.0^{a}	8.91^{a}	−2.82	−0.16	−4.16	3.33^{b}	0.11	1.51	1.54	−0.43
FF_{Rm}	0.72	0.81	1.14	0.77	0.99	0.74^{b}	0.80	0.73^{b}	0.77^{b}	1.05
FF_{HML}	−0.18	0.07	0.28	0.28^{c}	0.26	0.64^{a}	0.47^{b}	0.16	−0.13	-0.84^{a}
FF_{SMB}	1.45^{a}	1.07^{a}	0.56^{c}	0.50^{c}	0.70^{b}	0.74^{a}	0.40	0.78^{a}	0.58^{a}	1.15^{a}
R^2	0.83	0.89	0.90	0.88	0.91	0.98	0.90	0.96	0.96	0.93
	Panel C: Fixed Size method					Panel D: Pooling method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	0.48	−1.16	−1.70	−4.57	13.0^{a}	6.44	2.77	−1.39	−2.64	−3.04
FF_{Rm}	0.85^{c}	0.77^{c}	0.66^{c}	0.95	0.85	1.07	0.88	1.01	0.87	0.85
FF_{HML}	0.03	0.06	0.03	0.16^{c}	0.02	0.25	−0.06	−0.09	0.11	0.04
FF_{SMB}	0.17^{c}	0.67^{a}	0.61^{b}	0.85^{a}	1.35^{a}	0.71	1.24^{a}	1.21^{a}	0.62^{b}	1.06^{a}
R^2	0.97	0.92	0.85	0.97	0.87	0.77	0.90	0.89	0.90	0.96
	Panel E: Averaging method					Panel F: Autoregressive method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	6.61^{c}	3.26	1.56	−2.20	−0.39	−0.94	−1.03	−0.95	−2.68	−0.06
FF_{Rm}	0.85	0.89	0.71^{b}	0.96	0.94	1.37	1.01	0.90	0.82	0.60^{b}
FF_{HML}	0.53^{c}	0.46^{b}	0.32^{b}	−0.08	−0.12	−0.28	−0.02	0.10	−0.02	0.12
FF_{SMB}	0.90^{b}	0.55^{b}	0.92^{a}	1.19^{a}	1.24^{a}	1.43^{c}	0.94^{b}	0.76^{b}	0.68^{b}	0.39^{c}
R^2	0.84	0.93	0.96	0.94	0.89	0.63	0.78	0.83	0.88	0.82
	Panel G: Random walk method					Panel H: Business cycle method				
Quintile	1	2	3	4	5	1	2	3	4	5
FF_{α}	14.6^{a}	5.62^{a}	1.16	−3.13	−2.09	10.8^{b}	2.63	1.16	−1.13	−3.43
FF_{Rm}	0.89	0.89	0.77	0.87	0.71	0.82	0.92	0.78	0.82	0.87
FF_{HML}	−0.36	0.12	0.06	0.10	0.07	0.06	−0.11	−0.03	0.16	0.08
FF_{SMB}	1.87^{a}	1.31^{a}	0.87^{b}	0.76^{b}	0.67^{b}	1.54^{a}	1.02^{a}	0.75^{a}	0.67^{a}	0.82^{a}
R^2	0.85	0.97	0.84	0.89	0.81	0.85	0.86	0.88	0.93	0.94

This table shows the results from the regression of annual portfolio returns on a constant (FF_{α}) and the Fama and French risk factors. These factors are a market return factor (FF_{Rm}), a return differential of high B/P minus low B/P firms (FF_{HML}), and a return differential of small minus big firms (FF_{SMB}). The latter two are orthogonalized with respect to (FF_{Rm}). The portfolio returns result from applying several forecasting methods. Panels A through H relate each to a particular method. The Portfolios q, $q=1,\ldots,5$, are obtained after ranking the positive return forecasts from a particular method and dividing up into quintiles. Portfolio 1 is based on stocks with the strongest ex-ante predicted outperformance. Significance is denoted by superscripts at the 1% (^{a}), 5% (^{b}) and 10% (^{c}) levels, where we use a one-sided test for $FF_{\alpha} > 0$, a two-sided test for $FF_{Rm} \neq 1$, and two-sided tests for $FF_{HML} \neq 0$ and $FF_{SMB} \neq 0$. The symbol R^2 denotes the coefficient of determination.

indicating that an additional risk factor to the Fama–French model may be needed to explain returns.

5.4. Synthesis and robustness

We conclude from the previous analyses that a rotating Size and B/P-based investment style based on a Business Cycle approach is able to generate significant excess returns. These returns are robust to the holding period of stocks and to the way of risk-correction. The more conventional fixed investment styles, like one based on small Sizes or high B/P values, may also generate significant (risk-corrected) returns, but the results are not as robust to the way of risk-correction or the choice of holding period. Purely statistical approaches to style rotation are not very promising: they either underperform with respect to the benchmark, or the detected outperformance is (more than) offset by an increase in risk.

In order to check the robustness of the Business Cycle approach further, we also used a market-capitalization-weighted index. In addition, Portfolios 1 through 5 were constructed using market-capitalization weights. This is somewhat more in line with the way how portfolios are constructed in practice. The results (not reported here) are robust to this change. Clear predicted ex-ante winners using the Business Cycle approach generate significant excess returns, irrespective of the market model or FF way of risk correction. The results are consistent across holding periods, except for annual frequencies. For annual rebalancing, the excess (risk-corrected) return is still positive, but may become insignificant. This may, however, be due purely to the limited number of annual observations (Eq. (10)) given our data set.

As indicated in Section 3, outliers may be a potential hazard in analyses with this type of data. In order to check for the sensitivity of the results to outliers, we cross-sectionally Winsorized Size and B/P values. This means that we define boundary values for each variable and cross section. The boundaries equal the cross-sectional median plus or minus four times a robustly estimated standard deviation. If an observation falls above the upper or below the lower boundary, respectively, it is reset to the boundary value. This mitigates the potential bias of outliers in a standard regression setting, see for example Hampel et al. (1986). The returns are not Winsorized. Again, the results are robust: clear predicted winners using the Business Cycle style rotation scheme show a consistent and robust excess performance across holding periods and ways of risk-correction.

6. Concluding remarks

This paper develops a framework for capturing the time-varying impact of firm characteristics like size and book-to-price on excess returns. We showed that both the magnitude and direction of this impact displayed considerable time-variation.

Using standard statistical techniques, however, did not help in predicting the future direction of impact. By contrast, by linking the impact to macroeconomic conditions through the term structure and a business cycle leading indicator, we found significant and robust excess returns to portfolios of clear predicted winners. The returns were robust to various ways of risk-correction, choice of holding period, way of portfolio construction, and outlier control. Standard small-Size and high book-to-market investment strategies were not robust in this respect. Our results add a further dimension to the current anomaly versus risk compensation debate for explaining reported excess returns from Size and book-to-market investment strategies. In particular, by allowing for rotating investment styles over time, we examine whether the excess returns are in effect the manifestation of a more dynamic asset pricing model. The robustness of the resulting excess returns on a rotating investment scheme that is consistent with such a dynamic asset pricing model, contrasts with the less robust patterns found for conventional Size and book-to-market investment strategies.

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Appendix A. Bias correction for Section 4.4

Here, we derive the bias correction for the autoregressive modeling approach of Section 4.4. Note that if we write $\hat{\gamma}_t = \gamma_t + \xi_t$ with ξ_t and η_t uncorrelated zero-mean random variables, one easily derives the following relations. For Φ, we have

$$\Phi = \mathrm{Cov}(\gamma_t, \gamma_{t-1})\left[\mathrm{Cov}(\gamma_{t-1})\right]^{-1}. \tag{A1}$$

By contrast, if $\hat{\Phi}$ is the parameter in the model with all γ_t's replaced by $\hat{\gamma}_t$'s, we have

$$\hat{\Phi} = \mathrm{Cov}(\hat{\gamma}_t, \hat{\gamma}_{t-1})\left[\mathrm{Cov}(\hat{\gamma}_{t-1})\right]^{-1} \approx \mathrm{Cov}(\gamma_t, \gamma_{t-1})\left[\mathrm{Cov}(\gamma_{t-1}) + \bar{V}_{t-1}\right]^{-1}$$
$$= \Phi\,\mathrm{Cov}(\gamma_{t-1})\left[\mathrm{Cov}(\gamma_{t-1}) + \bar{V}_{t-1}\right]^{-1} \tag{A2}$$

where

$$\bar{V}_{t-1} = \sum_{s=1}^{t-1} \mathrm{Cov}(\xi_t)/(t-1). \tag{A3}$$

Note that the persistency in γ_t is generally under-estimated if Φ is estimated based on $\hat{\gamma}_t$. The numerators in Eqs. (A1) and (A2) are the same, while the denominator in Eq. (A2) is larger. Note that ξ_t can be interpreted as the estimation error of $\hat{\gamma}_t$. Using standard asymptotic theory, it follows that $n_t^{1/2}(\hat{\gamma}_t - \gamma_t)$ is (asymptotically) normally distributed with mean zero and covariance matrix $\mathbf{V}_t$. Here, n_t is the number of firms in cross-section t. The covariance matrix $\mathbf{V}_t$ is estimated consistently by the OLS covariance matrix of $\hat{\gamma}_t$, and can be directly plugged into Eq. (A3). Using the estimates of $\bar{V}_{t-1}$ and $\hat{\Phi}_t$, we can rewrite Eq. (A2) to obtain the following bias-corrected estimate of Φ,

$$\tilde{\Phi}_t = \hat{\Phi}\mathrm{Cov}(\hat{\gamma}_{t-1})\left[\mathrm{Cov}(\hat{\gamma}_{t-1}) - \bar{V}_{t-1}\right]^{-1}, \tag{A4}$$

where we have used the equality $\mathrm{Cov}(\hat{\gamma}_{t-1}) = \mathrm{Cov}(\gamma_{t-1}) + \bar{V}_{t-1}$ to substitute the unobserved $\mathrm{Cov}(\gamma_{t-1})$ by the observed $\mathrm{Cov}(\hat{\gamma}_{t-1}) - \bar{V}_{t-1}$. Note that the estimate $\tilde{\Phi}_t$ of Φ depends on t, i.e., on the time the forecast is made. This implies that the parameter estimates of the autoregressive model (A1) are updated recursively as the forecasting period progresses. Given $\tilde{\Phi}$, the constant term in Eq. (7) is estimated as

$$\tilde{\mu}_t = \sum_{s=1}^{t-1}\left(\hat{\gamma}_s - \tilde{\Phi}_t\hat{\gamma}_{s-1}\right)/(t-1).$$

Also note that the bias correction is quite small if the cross-sectional dimension is sufficiently large. This is due to the fact that the cross-sectional estimators are consistent, such that the measurement error problem and associated bias disappear if the cross-sectional dimension grows indefinitely.

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