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Tactical Size Rotation in Switzerland

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The size premium, defined as the outperformance of equities of small and medium-sized companies compared with the shares of large companies, is subject to strong cyclical fluctuations over time. This study examines the predictability of this premium for the Swiss stock market. The forecasts used are developed applying a flexible forecasting approach that is based on time variable multi-factor models. Our strategies provide information ratios significantly greater than 1 for a maximum real-time application of a good seven years. The results show that risk variables such as the credit spread and TED spread, the performance of the S&P 500 and statistical variables such as AR(1) terms or trends calculated using the Hodrick-Presscot filter prove to be successful forecasting variables in our algorithm. Furthermore, variables that sum up the consensus estimates of equity analysts (IBES) for various size portfolios can sometimes make valuable forecast contributions.

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Introduction

The size effect is defined as the empirical observation that the equities of small companies – measured in terms of market capitalisation – generate average returns that are systematically higher than those of the CAPM benchmark. Banz (1981) was the first to point out this phenomenon. The theoretical literature proposes at last three different theories explaining the longer-term excess returns of, on the one hand, small-cap companies and, on the other, value stocks.[i] First, company-specific variables can be taken as proxies for risk factors. From this standpoint, the higher returns should considered compensation for higher risks. Companies with the same characteristics should, against this background, show the same sensitivity to various macro-economic factors.[ii] Second, company-specific factors can pinpoint mispricing by the market.[iii] Third, different classes of companies profit to different degrees from unanticipated technological innovations. However, structural excess returns are also subject to significant fluctuations over time. We can repeatedly identify periods in which premiums deviate from their usual patterns.[iv]

Tactical size rotation is based on the assumption that the trend in the size premium over time is predictable and correlates correspondingly with fundamental, macro-economic and/or technical information. Depending on the forecast, investors benefit if they adopt a tactical over- or underweighting of the equities of small companies in a portfolio relative to the benchmark. The aim of these active strategies is to generate excess returns compared with a passive benchmark strategy.

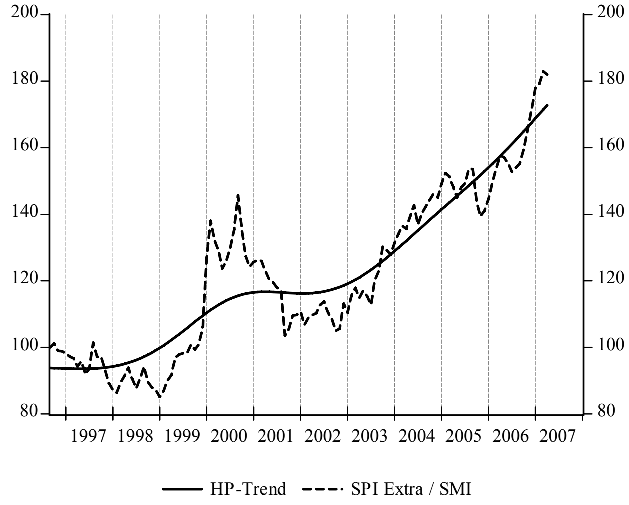
In the literature, the tactical positioning as regards the two Fama/French style factors[v] value and size is frequently discussed together.[vi] Nablantov et. al. (2006) and Cooper et. al. (2001) provide positive results for style rotation strategies in the USA, with the latter study providing stronger evidence of the predictability of the size premium compared with the value premium. Levis und Lidorski (1999) produced similar results to those of Cooper et. al. (2001) for the UK. Bauer et. al. (2002) find indications of profitable style rotation strategies in Japan – provided transaction costs are low.

This study supplements the existing research in three ways. First, the selected approach – a synthesis of traditional forecasting models and statistical approaches– is innovative. Second, as far as we know, we are the first to examine tactical size rotation for the Swiss stock market. Third, we have expanded the data categories by aggregative analysts' data supplied by IBES. This study is organised as follows. First we make a statistical descriptive analysis of the size premium in Switzerland, define the forecasting variables used in the back test and explain their selection. Then we introduce and discuss the forecasting process used. This is followed by some comments on the definition of the optimal model. Then we examine the forecast performance of our approach in various specifications and evaluate the success of tactical size strategies. We conclude the study with some thoughts about transaction costs and implementation as well as a summary.

Descriptive analysis of the size premium

The Swiss stock market as a whole is best depicted using the Swiss Performance Index (SPI). The Swiss Market Index (SMI), on the other hand, aggregates those stocks in the SPI universe with the highest market capitalisation.[vii] Last but not least, the SPI Extra (SPIEX) includes all the SPI shares that are not in the SMI.

Illustration 1: The size premium and some statistics



	Size Premium
Mean	0.5%
Median	0.7%
Maximum	19.3%
Minimum	-11.4%
Std. Dev.	3.6%
Skewness	0.87
Kurtosis	8.42
Jarque-Bera	171.75
Probability	0.0%

Illustration 1 shows the ratio of the SPIEX relative to the SMI (September 1996 = 100) and provides an overview of the varying performance of the shares of large companies compared with those of small companies. Furthermore, it also shows a trend calculated using the Hodrick-Prescott filter.[viii] Using a sample of ten years, the SPIEX shows much higher returns than the SMI. This historical observation basically underscores the hypothesis of a systematic size premium. Certainly the trend of this index we constructed is exposed to cyclical fluctuations. At the beginning of the sample in particular and after the TMT bubble burst, the equities of large companies outperformed those of the SPIEX companies over a protracted time period. On average, however, the SPI Extra's returns were around 0.5% better per month than those of the SMI. The empirical distribution of the excess return nevertheless had a significantly greater distribution at the tails compared with the normal distribution. This is signalled by the high kurtosis value of 8.4.

Potential forecast factors[ix]

Now we must find variables that basically could have forecasting power for the size premium. Its cyclical behaviour suggests a correlation between the economic cycle and the "size cycle". This hypothesis is based on the theory of the financial accelerator,[x] according to which small companies are more affected by the credit and economic cycles than their large counterparts. The literature basically offers two explanations for these empirically proven differences in sensitivity. First, the product range of small companies has a comparatively low diversification. As a consequence, orders and earnings fluctuate more than at large companies. Second, smaller companies have higher debt levels,[xi] which makes it much more difficult and more expensive for them to borrow in tough times. These hypotheses stand up in an empirical examination in the USA. Moon and Burnie (2002) confirm the hypothesis that the size effect is manifested first and foremost in a phase of economic upswing. In periods of economic downturn, on the other hand, no size premium was observed. In order to identify the cycle, we use the Swiss purchasing manager index, the economic barometer of KOF Swiss Economic Institute and the US ISM index.

Financial market data that describe investors' appetite for risk and the general state of the financial and goods markets should also have a high degree of forecasting accuracy. If appetite for risk decreases, investors then as a rule favour large, transparent companies. An indicator of appetite for risk is, first, the credit spread. It describes the compensation in return that investors demand for the purchase of bonds with lower credit ratings compared with those with higher ratings. Second, the TED spread shows the risk premium that is paid on the interbank money market for the provision of short-term loans. It can be observed in the difference between a market interest rate and an interest rate for loans with identical maturities that are controlled by the central bank. A third risk premium is the so-called term spread. It is derived from a short-term and a long-term interest rate and describes the compensation demanded by investors for accepting inflation and interest rate risks. Appetite for risk can also be approximated using volatility measures. The most prominent indicator for the anticipated fluctuation range is the VIX, which shows the option premiums demanded by investors in the US stock market. Various empirical studies show the – at least short-term – forecasting power of this indicator for the size effect.[xii] Moreover, empirical studies see indicators of significant, varying risk premiums in bull and bear markets.[xiii] We use the US S&P 500 to show stock market trends. Furthermore, we analyse the forecast accuracy of the price of oil and gold and the exchange rate of the CHF to the EUR.

Factors that evaluate information from equity analysts constitute an additional category of potential forecasting variables. There are two variants. First (changes in) analysts' forecasts regarding expected earnings (12-month forward earnings) can provide indications about varying earnings growth in both segments of the stock market. Confidence data, such as the standard deviation of all earnings forecasts for a corporation for the current fiscal year, provide information about the variety of opinions dominating the market regarding a company's business outlook. Furthermore, it is conceivable that figures which target relative valuations can help make forecasts.[xiv] Many studies confirm the forecasting performance of various value factors. An example is the oft-quoted study by Fama and French (1998). We measure the valuation based on the sales to price and earnings to price ratios. In order to calculate all the ratios named in this paragraph, in a first step, we list all the available companies of the SPI at every point in time based on their market capitalisation. For the 30% of the companies with the largest (smallest) market capitalisation, we calculate an average ratio. The variable used in making the forecast is the quotient of both ratios.

Last but not least, size premiums, delayed by one month, and a recursive trend calculated recursively with the help of the Hodrick-Prescott filter are used as explanatory variables. Both time series should help capture the cyclicality of the size premium.

The forecasting process

Our forecasts for the size premium are based on multivariate factor models. The concrete method of model construction is distinguished by several special characteristics. First, we permit dynamic selection of the forecasting factors and thus acknowledge the empirical fact that financial market figures react to different variables at different times.[xv] Second, our use of rolling forecasting periods permits the instruments used to have an influence that varies in strength over time. In addition to the flexible factor selection, this approach mitigates the problem of instabilities. Third, our method solves the multicollinearity problems between the instruments that change over time by constantly testing the instrument combinations used for partial redundancy. Compared with purely statistical methods, our approach has the advantage that the instruments used and their relative impact are visible at all times. Against this background the forecasts are no black box.

The approach used is distinguished by its dynamic structure. Each permissible combination of lagging instruments forms the basis for the forecast of the size premium at any time. If the algorithm selected the optimal combination, the forecast for the size premium is made based on the empirically estimated coefficients on the one hand and the current, explanatory variables on the other. In the subsequent period, the entire process is repeated. Hence it is possible that a selected model will only be used once for a forecast and will be replaced by a superior one already one period later.

Definition of the optimal model

At any point in time an optimal model is selected from all the potential combinations of instruments. The selection process fulfils the following standardised mechanism:

1. First the time series properties of the instruments and the size premium are evaluated in the training period using an ADF test[xvi] and, if appropriate, differences are calculated until all data series can be qualified as stationary.

2. All possible instrument combinations are considered. The stipulation of a maximum number of instruments per model limits the number of combinations to be tested.[xvii]

3. Each potential combination defines a regression model. The standardised quality check successively answers the following questions:

    a. Should a constant be included in the regression? An increase in the adjusted R^2 related to a significant coefficient argues in favour of the inclusion of a constant.

    b. Are all regression coefficients statistically significant? This decision is made based on an error probability of 5%. The standard error is estimated on the basis of the Newey-West method.[xviii]

    c. What are the distribution properties of the model's residuals? The null hypothesis of a normal distribution is tested using the Jarque-Bera test.

    d. Is the model sufficiently stable? A CUSUM test of squares provides an answer.[xix]

    e. Are the instruments used correlated? An analysis of the variance inflationary factors is applied.[xx]

4. A two-step process is used to select the best model. The quality is shown via a score based on the above test procedure. For models with the same quality score, the adjusted R^2 determines the best combination.

Once the optimal model has been found, a forecast for the size premium in the coming period is made. Moreover, the forecasting risk is evaluated. For this we interpret the point forecast of the model as the expected value of a normal distribution. The variance around the expected value can ex ante be easily derived with the help of the standard error of the regression model.

We define the forecasting risk as the cumulative probability of an incorrect directional forecast.[xxi]

Evaluating the forecasts

The aforementioned 19 explanatory variables form the basis of the size premium forecast. We set the maximum number of instruments used in a forecasting model at three[xxii] and test our algorithm for robustness for the three training periods of 36 months (model 1), 48 months (model 2) and 60 months (model 3).

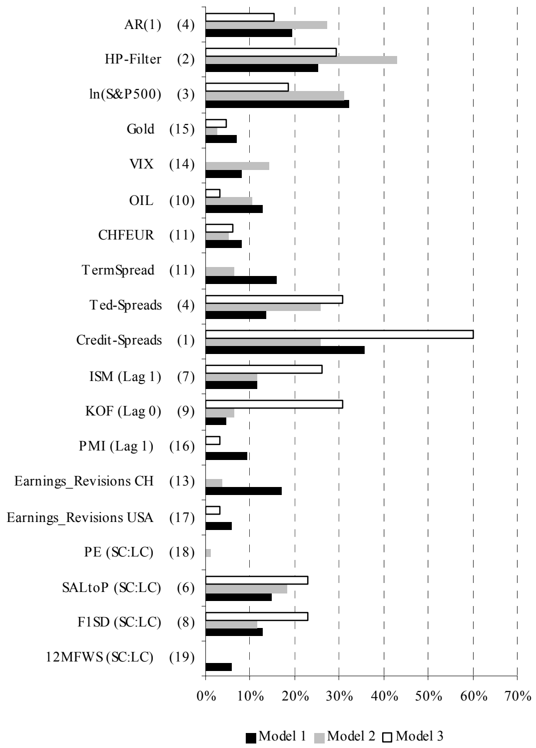
Table 1: Results of the forecasting approach

	Model 1			Model 2			Model 3		
Model details									
Backtest period - start	February 00			November 00			November 01		
Backtest period - duration (in months	88			78			66		
Training period (in months)	36			48			60		
Max. number of variables	3			3			3		
Number of evaluated instruments	19			19			19		
Analysis of the direction forecasts									
Hit ratio	0.60			0.58			0.57		
Chi squared test: critical value	2.93			1.43			0.58		
Chi squared test: p value	0.09			0.23			0.45		
Top 33% size premiums	0.72			0.57			0.68		
Middle 33% size premiums	0.62			0.64			0.63		
Lowest 33% size premiums	0.46			0.54			0.52		
10 largest size premiums									
	9/2001	-12.2%	Hit	9/2001	-12.2%	Hit	12/2002	6.8%	Hit
	2/2000	8.5%	Hit	12/2002	6.8%	Hit	10/2005	-6.5%	Hit
	10/2000	-7.5%	No hit	10/2005	-6.5%	Hit	8/2003	6.3%	No hit
	9/2000	7.3%	Hit	8/2003	6.3%	No hit	10/2003	5.8%	Hit
	12/2002	6.8%	Hit	10/2003	5.8%	No hit	2/2003	4.5%	No hit
	10/2005	-6.5%	Hit	2/2003	4.5%	No hit	7/2004	-4.2%	No hit
	8/2003	6.3%	No hit	7/2004	-4.2%	No hit	1/2007	4.0%	Hit
	11/2000	-5.9%	Hit	1/2007	4.0%	Hit	11/2006	3.7%	Hit
	10/2003	5.8%	Hit	11/2001	3.8%	Hit	2/2002	-3.6%	Hit
	2/2003	4.5%	Hit	11/2006	3.7%	Hit	10/2002	-3.5%	Hit
Key instruments									
1	Credit spreads			HP filter			Credit spreads		
2	S&P 500			S&P 500			Kof		
3	HP filter			AR (1)			TED spreads		
4	AR (1)			Credit spreads			HP filter		
5	Earnings revisions CH			TED spreads			ISM (lag 1)		

Our reference model (model 1) achieves 60% accuracy (table 1). A comparably restrictive chi squared test[xxiii] rejects the null hypothesis of similar odds as a coin toss with an error probability of 9%.

If the realised size premiums are arranged by size, we notice two things. First, this approach is particularly good at anticipating major changes. The direction of eight of the ten largest changes were correctly forecast. Second, the forecast performance for the larger changes was generally better than for the smaller ones. The rate of accuracy in the one-third with the largest changes was 72%, the second third 62% and the last third 46%.

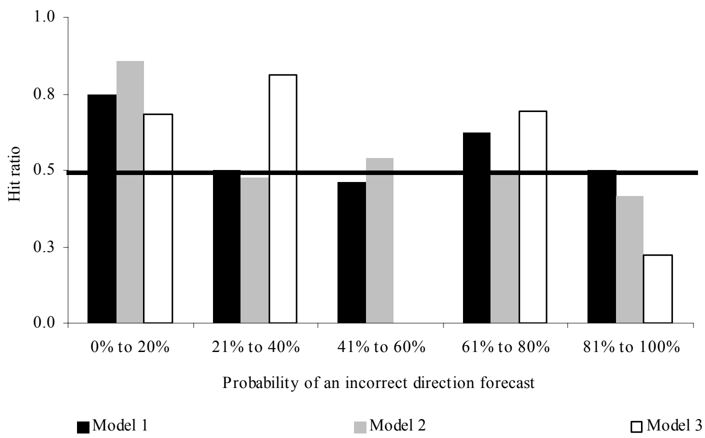
Illustration 2: Application of individual instruments in % of the maximum forecasting steps



Note: The rankings in parentheses refer to the average ranking based on the three model variants.

Which instruments does the algorithm select most frequently to make the forecasts? In the case of model 1, the credit spreads, the changes of the S&P 500, the earnings revisions for the Swiss stock market and the indicators for modelling the trend dominate. According to Illustration 2, the application of instruments can be described basically as robust versus various model specifications.

Illustration 3: Hit ratio and forecast confidence



As we mentioned, one special aspect of our approach is that, in addition to the point forecast, conclusions about forecast confidence can also be drawn. In Illustration 3 all forecasts are distributed along the x-axis in five different quantiles. At the far left are the forecasts with the highest confidence (probability of an incorrect direction forecast between 0% and 20%), and at the far right those with the lowest confidence (probability of an incorrect direction forecast between 80% and 100%). The hit ratio is displayed on the y-axis. The chart shows the basic relationship between forecast confidence and the hit ratio. In the quantile at the far left, the accuracy rate is significantly higher for all three model specifications than in that at the far right. Inclusion of forecast confidence can thus improve the general forecast performance as it provides supplementary information on the point forecast.[xxiv]

Evaluating the investment strategies

Much more decisive from the investor's standpoint, however, is how much additional (risk-adjusted) return can be expected when applying our tactical size rotation versus a passive benchmark investment in the SPI. In this regard we evaluate a strategy in which the investor has the option of over- or underweighting the SPIEX. For the forecast of outperformance (underperformance) of the SMI versus the SPIEX, a tactical weighting of 100% (60%) SMI and 0% (40%) SPIEX is selected.[xxv]

Table 2: Results of various strategies

	Perfect foresight	Passive strategy	Model 1	Model 2	Model 3
Start	2/2000	2/2000	2/2000	11/2000	11/2001
Random sample size	88	88	88	78	66
Excess return	9.3%	2.8%	3.7%	2.3%	3.7%
Tracking error	2.2%	3.6%	2.4%	2.0%	1.9%
Information ratio	4.24	0.77	1.52	1.13	1.93
Beta	-0.03	-0.02	-0.03	-0.03	-0.02
(t-stat)	(1.51)	(0.42)	(1.84)	(2.14)	(1.10)
Alpha	7.4%	2.2%	3.0%	2.0%	2.6%
(t-stat)	(6.85)	(1.44)	(3.37)	(2.33)	(2.85)
Skewness	2.95	0.02	0.47	0.43	0.74
Kurtosis	14.91	6.78	5.65	4.45	4.87
Minimum	0.0%	-3.8%	-2.1%	-1.2%	-1.2%
Maximum	4.2%	4.2%	2.8%	2.2%	2.2%
Quantile 10%	0.1%	-0.9%	-0.5%	-0.6%	-0.3%
Quantile 1%	0.0%	-3.2%	-1.8%	-1.2%	-1.2%
Cum. excess return	91.4%	22.1%	30.7%	15.8%	22.3%

Table 2 shows the results of the strategy when our three model variants are taken into consideration. Furthermore, the results are shown given a perfect foresight and permanent overweighting of the SPIEX with a weighting of 40% (passive strategy). Our reference model 1 shows an annualised excess return of 3.7% p.a. and an information ratio of 1.52. It is interesting to note the comparison with a passive strategy that assumes a systematic outperformance by the SPIEX against the SMI. In this case the relative and risk-adjusted performances are smaller.[xxvi]

Can the outperformance of the approach be attributed to the systematic acceptance of market risks? This question can be answered by a simple regression analysis which explains the outperformance of each strategy with a constant and the return of the SPI. The results suggest a very slight – and in every case negative – correlation between the market return and the excess return. The effects are, however, only statistically significant in a few strategies. On the other hand, the coefficients of the constants are highly significant and confirm the alpha potential of the strategies.[xxvii]

The analysis of the distribution of the excess returns provides interesting results in view of negative extreme events. Here our strategy shows an improvement compared with a permanent overweighting of medium-sized and small equities, as the minimum, 1% quantile and 10% quantile show. Our forecasting algorithm proves to be robust in various training periods which can be seen in a comparison of the results of model 2 and model 3.[xxviii]

Implementing the strategy and transaction costs

In general, the model forecasts can be implemented via physical over- or underweighting of certain stocks in a portfolio. The disadvantage of this approach is the magnitude of the transaction costs, which in this case are reflected in the size of the bid-ask spread and in the market impact that transactions in less liquid market segments have. Furthermore, the forecasts can also be implemented via derivatives and an investment in the SPI. Nevertheless, today there are no derivatives available on the SPIEX. Indirectly, however, there is the option to build up exposure in small and mid caps via derivatives on the SMIM index (SMIM) – it includes the 30 largest SPI stocks based on market capitalisation that are not included in the SMI. Futures contracts on the SMI have been available for some time. A necessary condition to implement this variant, namely a high correlation between the SMIM and the SPIEX, is given (Illustration 4). The correlation coefficient of the monthly returns of the two indices from January 1996 to August 2007 is 0.97. Overall, there was a diverging sign of the index return in only 8.5% of the months, and these cases the returns are exceptionally low.

Illustration 4: Monthly returns SMIM vs. SPIEX

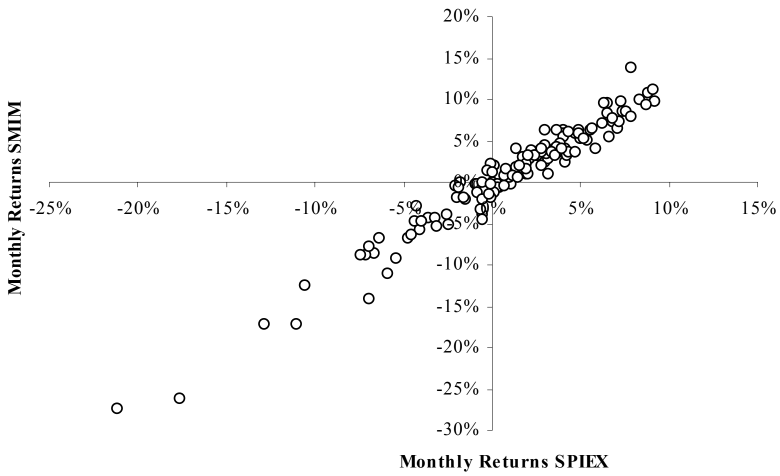


Table 3: Implementation of the model signals with transaction costs

	Market value of open positions (MV_t) (1)	**Cash flow from closing a position (CF_{t-1})** (2)	**Investment benchmark** (3)	**Total portfolio (PF_t)** (1) + (3)
Case 1	$MV_t^L = 0.2*PF_{t-1} * (r_t^L\text{-TAC})$ $MV_t^S = 0.2*PF_{t-1} * (r_t^S\text{-TAC})$ $MV_t = MV_t^L - MV_t^S$	0	$PF_{t-1} * r_t^{BM}$	PF_t
Case 2	$MV_t^L = MV_{t-1}^L * r_t^L$ $MV_t^S = MV_{t-1}^S * r_t^S$ $MV_t = MV_t^L - MV_t^S$	0	$PF_{t-1} * r_t^{BM}$	PF_t
Case 3	$MV_t^L = 0.2*(PF_{t-1} + CF_{t-1}) * (r_t^L\text{-TAC})$ $MV_t^S = 0.2*(PF_{t-1} + CF_{t-1}) * (r_t^S\text{-TAC})$ $MV_t = MV_t^L - MV_t^S$	$CF_{t-1}^L = MV_{t-1}^L - TAC* MV_{t-2}^L$ $CF_{t-1}^S = MV_{t-1}^S - TAC* MV_{t-2}^S$ $CF_{t-1} = CF_{t-1}^L - CF_{t-1}^S$	$(PF_{t-1} + CF_{t-1}) * r_t^{BM}$	PF_t
Case 4	0	$CF_{t-1}^L = MV_{t-1}^L - TAC* MV_{t-2}^L$ $CF_{t-1}^S = MV_{t-1}^S - TAC* MV_{t-2}^S$ $CF_{t-1} = CF_{t-1}^L - CF_{t-1}^S$	$(PF_{t-1} + CF_{t-1}) * r_t^{BM}$	PF_t

TAC= transaction costs, $r^{L(S)}$ = return long (short) trade, $r^{L(S)}$ = return long (short) trade, MV_t = futures positions, $MV_t^{L(S)}$ = market value long (short) trade, r_t^{BM} = return BM, PF_t = portfolio, CF_t = cash flow

A variant of the implementation against this backdrop is a zero investment strategy, in which a short (long) position in SMI futures corresponds with a long (short) position of the same size in SMIM futures. The advantage of such an overlay structure is that an exposure is possible according to the prediction of the size premium without changing the underlying portfolio.

In this type of implementation, the model makes four different recommendations for the portfolio manager. In case 1 the forecasting model sends no signal in the period t-1 but recommends a position in the period t. In case 2 the positioning signal of period t-1 is confirmed in the period t. In case 3 the trade from period t-1 must be reversed in the subsequent period t. Finally, case 4 considers a situation in which a trade is open in period t-1 but the model does not make a recommendation for the subsequent period. Our implementation calculation which takes into consideration transaction costs is based on the following assumptions.

1. Using the end-of-the-month values for the instruments, our algorithm calculates the signals for the recommended position in the subsequent period. We assume that the open positions can be closed at exactly the same time – and hence at the same price.

2. The benchmark for our strategy is the SPI. At the end of each month the investor can invest in a size position. The exposure is determined by the value of the portfolio at this time. Our calculations are based on the assumption that the contract volumes of the long and short side account for 20% of the portfolio.

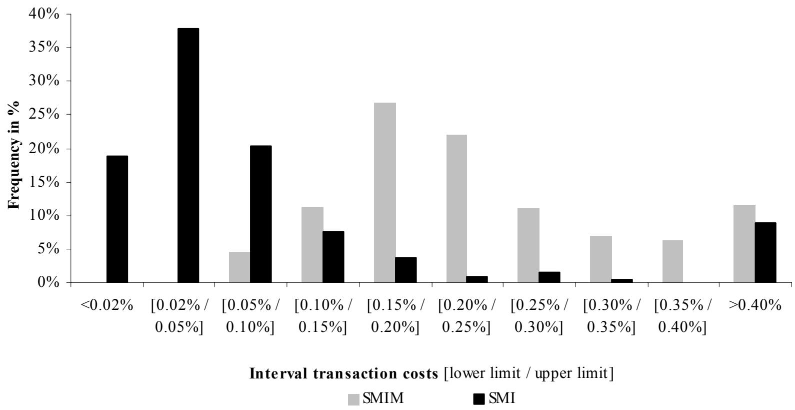
3. The portfolio consists of a passive benchmark investment and open futures positions that are valued at market prices. After the futures positions are closed, there is a cash flow. If this is positive, then the resulting amount will henceforth be added to the

passive benchmark investment. If the amount is negative, then the benchmark portfolio will be reduced by this amount.

4. Transaction costs accrue on both sides upon entering the contracts and when closing them. In conjunction with the market conditions, we assume that there are no transaction costs in the case of a rolled contract.[xxix]

Table 3 shows the recommendation for the implementation in a given signal situation. In order to answer the question of how much the performance of the strategy suffers if transaction costs are taken into consideration, we now take a look at the empirical transaction costs. We assume that the transaction costs are sufficiently approximated by the bid-ask spread.[xxx] In Illustration 5 the transaction costs incurred since the beginning of 2006 are shown as a % of the investment. This is based on the daily Bloomberg data. The evaluation shows that a good three quarters of the applicable transaction costs were less that 10 basis points for the SMI futures segment, and around half are less than five basis points. As expected, the market for SMIM futures is less liquid. A good 70% of the calculated transaction costs are between 10 and 30 basis points. Sharp divergences are most likely due to errors in the data.

Illustration 5: Breakdown of transaction costs (daily data, 03.01.2006 – 02.11.2007)



This result calls for an evaluation of the implementation taking into consideration various levels of transaction costs. Table 4 shows the results. The strategy proves highly profitable in practical implementation too. Even assuming high transaction costs, information ratios of at least 0.50 and an annual excess return of around 1.5% are expected.

Conclusion

The size premium – defined as the outperformance of the equities of small and medium-sized companies compared with those of large firms – is subject to sharp cyclical fluctuations over time. This empirical observation is also true for Switzerland. This study explores the possibility of a tactical size rotation as an additional driver of performance for active portfolio management.

Table 4: Breakdown of transaction costs (daily data, 03.01.2006 – 02.11.2007)

Transaktionskosten SMIM-Futures		Transaktionskosten SMIM-Futures		
		0.02%	**0.05%**	**0.10%**
	0.05%	14.7% (2.0%) **0.71**	14.4% (2.0%) **0.69**	13.8% (1.9%) **0.66**
	0.10%	14.1% (1.9%) **0.68**	13.8% (1.9%) **0.66**	13.3% (1.8%) **0.63**
	0.20%	13.0% (1.8%) **0.63**	12.7% (1.8%) **0.61**	12.2% (1.7%) **0.58**
	0.30%	12.0% (1.6%) **0.57**	11.6% (1.6%) **0.55**	11.1% (1.5%) **0.53**
	0.40%	10.9% (1.5%) **0.52**	10.5% (1.5%) **0.50**	10.0% (1.4%) **0.47**

Normal print: cumulative return, in parentheses: annualised return, bold print: information ratio

The study supports the hypothesis that the size premium is somewhat predictable and supplements the existing empirical literature with results for Switzerland. The forecasts used come from a flexible forecasting approach that is based on time-variable multi-factor models. Our strategies provide information ratios significantly greater than 1 for a maximum real-time period of a good seven years. This result is true for various specifications. Inclusion of a sensible level of transaction costs still permits significant positive excess returns.

The results show that risk variables such as the credit spread and TED spread, the performance of the S&P 500 and statistical variables such as AR(1) term or trends calculated using the Hodrick-Presscot filter prove to be successful forecasting variables in our algorithm. Furthermore, variables that encompass the consensus estimates of equity analysts (IBES) for various size portfolios at times make valuable forecasting contributions. Specifically the aggregated sales to price ratios and ratios on the dispersion of analyst opinions outdo traditional forecasting variables. The use of micro data as a forecasting instrument for tactical size rotation are a new development, as far as this author is aware. The modelling of an ex ante predictability of an incorrect forecast can, as we have shown, significantly improve the accuracy rate.

For other studies, we would recommend integrating information on forecast confidence in the positioning decision. Size instruments constructed based on micro data also have the potential to improve the performance of the tactical size rotation.

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Footnotes

[i] See Lucas et. al. (2001) for a breakdown and discussion.

[ii] See Fama and French (1992), Fama and French (1993) and Lewellen (1999).

[iii] Lakonishok, Shleifer and Vishny (1994) find indications that the excess returns can be traced back to incorrect extrapolation of historical equity returns.

[iv] Chan et. al (1999) show that for the USA the usual size and value effects turned around in the period between 1990 and 1998.

[v] See Fama and French (1992).

[vi] For new studies based on the simultaneous style rotation, see Martellini et al. (2003) and Arshanapalli et. al. (2007).

[vii] At the end of November 2007, 226 stocks comprised the SPI. At the same time the SMI included 20 stocks. The subscriber stocks were aggregated according to market capitalisation in order to calculate the two indices. On the basis of market capitalisation, the SMI stocks comprise 84.7% of the total SPI (at the end of November 2007).

[viii] See Hodrick and Prescott (1997). The smoothing parameter lambda was set at 1440.

[ix] When using the data, delays were taken into consideration so that only the information that was available at the time of the forecast was used in the forecasting model. In this way we eliminate a "look ahead bias".

[x] See Gertler and Gilchrist (1994) as well as Bernanke and Gertler (1999).

[xi] See Chan and Chen (1991) for the USA.

[xii] Copeland and Copeland (1999) show that after days with advances, VIX large cap portfolios performed significantly better than small cap portfolios. On days of declining prices, the opposite occurs. Leistikow and Yu (2006) confirm the importance of the VIX in forecasting the size premium.

[xiii] See Bhardwaj and Brooks (1993).

[xiv] The calculations of the valuation ratios are also based on estimates by equity analysts (IBES). The advantage of the data over balance sheet data – for example, from the Worldscope database – is that it is not revised and is available at an early date.

[xv] The approach used is, in this respect, related to the method applied by Nalbantov et. al. (2006). He permits the new addition or removal of economically sensible instruments at any point in time.

[xvi] Augmented Dickey-Fuller test according to Dickey and Fuller (1979). The critical values are based on MacKinnon (1996). The selection of the lags used is based on the Akaike information criterion, in which a maximum number of 10 lags are studied. The ADF regressions are estimated using constants. The rejection of the non-stationarity null hypothesis is based on a 5% error probability.

[xvii] In this case, we include 19 explanatory variables and set a restriction of a maximum 3 variables for the forecasting model. This results in 19 models with exactly one variable, 171 models with exactly two variables ("2 of 19") and 969 models with exactly 3 variables. Overall, at each forecasting timepoint, 1169 models are undergoing the testing process.

[xviii] See Newey and West (1987). This process ensures an estimate of the standard error that allows for the autocorrelation and the heteroskedasticity in the residuals.

[xix] See Brown et al. (1975). The test is based on the cumulative sum of recursive estimated residuals and tests the null hypothesis of stable parameters. Exceeding the confidence limits (5%) by the expected value leads to a

rejection of the null hypothesis. The table of the significance lines can be found in Johnston and DiNardo (1997). See Chu. et. al. (1996) for a discussion of the procedure for stability testing in econometric models.

[xx] See Greene (2000), p. 257 ff.

[xxi] A simple example should illustrate this procedure. The algorithm supplies at time t, for example, a point forecast of 6% outperformance by the SPIEX against the SMI. The forecasting model used shows a historical standard deviation of 8%. The probability of an underperformance by the SPIEX against the SMI is, in this case, estimated at almost 23%.

[xxii] This restriction is selected for reasons of the calculation time requirement. When the maximum variables are raised from 3 to 4, the number of the models evaluated at each point of time rises from 1159 to 5035. This corresponds with a calculation time requirement per back test that is higher by a factor of 4.3.

[xxiii] When the maximum variables are increased from 3 to 4, the number of models evaluated at each point in time increases from 1159 to 5035. This corresponds with a factor of 4.3 höheren zeitlichen Rechenbedarf per back test.

[xxiii] See Diebold and Lopez (1996).

[xxiv] The forecasts are distributed as follows in the confidence quantiles in model 1. 32% of the forecasts are in quantile 1, 16% in quantile 2, 15% in quantile 3, 18% in quantile 4 and 18% in quantile 5. The information on forecast confidence is not used further in the following procedures. One reason is that the author prefers not to introduce additional degrees of freedom.

[xxv] This strategy corresponds with a variable overweighting of the SPIEX, since the SPIEX's share of the SPI fluctuates – measured on the first trading day of a year – between around 25% in 1997 and around 9% in 2002. At the beginning of 2007 the share was at just under 13%. (Source: http://www.swx.com/market/indices/historical_baskets_de.html.)

[xxvi] This raises the question of whether the method used basically supplies good results in both forecast directions. Hence an additional strategy was evaluated in which investors can only overweight the SPIEX. In the event that a positive size premium is forecast, the latter behaves analogous to the strategy discussed in the text (weighting SMI 60%, weighting SPIEX 40%). Given the opposite forecast, the investor dispenses with a bet and invests completely in the benchmark (SPI). Such a one-sided investment strategy produces, in the case of model 1, an excess return of 3.0% p.a. and an information ratio of 1.33. The cumulative excess return over the sample is, in this case, at 24.4%. The results of this one-sided strategy are therefore poorer than with the option of a position in both directions. Hence, the forecasting algorithm generates an outperformance in phases of both positive and negative size premiums. This result applies for all three of the evaluated model variants.

[xxvii] The shown (amounts of the) t values are adjusted according to the Newey and West approach (1987). The alpha is defined as the coefficient of the constants multiplied by 12.

[xxviii] A comparison between model 1 and model 2 shows that the use of a training period of 60 months rather than 36 months improves the risk-adjusted performance. However, the varying size of the random sample must be considered. The shorter sample represents a phase of lower volatility. The lower tracking error is thus also the main reason for the increase in the risk-adjusted performance. If one applies model 1 solely to the shorter sample, this produces an information ratio of 2.18.

[xxix] Rolling a future contracts means that an open position is not held until the month of the delivery obligation but rather must be closed sooner and transferred into a new position (with the same direction) with contracts that expire at the next deadline. Rolling is only discussed when the same position is held. Basically, contracts on the SMI and the SMIM are offered for delivery in March, June, September and December (3rd Friday of the month).

[xxx] This assumption presumes that the the transaction does not result in any market impact. Furthermore, the costs shown here refer to the "first" transaction. For example, if the demanded volume is very large, then not all contracts can be traded at this price (market depth). In this case, the bid-ask spreads widen in "later" market transactions.

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