Tactical Size Rotation in Switzerland

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JEL-Classification: G11, G17
Keywords: forecasting, size premium, Switzerland, factor models

1. 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.[1] 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.[2] Second, company-specific factors can pinpoint mispricing by the market.[3] 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.[4]

Tactical size rotation is based on the assumption that the variation of the size premium over time is predictable and correlates correspondingly with

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1 See Lucas, van Dijk and Kloek (2002) for a breakdown and discussion.

2 See Fama and French (1992), Fama and French (1993) and Lewellen (1999).

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

4 Chan, Karaceski and Lakonisch (2000) show that for the USA the usual size and value effects turned around in the period between 1990 and 1998.

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 smaller 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 and French style factors[5] value and size is frequently discussed together.[6] Nablantov, Bauer and Sprikhuizen-Kuyper (2006) and Cooper, Gulen and Vassalou (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 and Liodakis (1999) produced similar results to those of Cooper, Gulen and Vassalou (2001) for the UK. Bauer, Derwall and Molenaar (2004) 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.

2. Discussion 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) aggregates those stocks in the SPI universe with the highest market capitalisation. On the other hand, the SMI Mid (SMIM) comprises the 30 largest mid-cap stocks in the Swiss equity market that

5 See Fama and French (1992).

6 For new studies based on the simultaneous style rotation, see Amenc, Daphane, Malaise, and Martellini (2003) and Arshanapalli, Switzer and Panju (2007).

are not included in the SMI. [7] We calculate the size premium (SP) and the size index (SI) at time t in the following way:

$$SP_t = \ln\left(\frac{SMIM_t}{SMIM_{t-1}}\right) - \ln\left(\frac{SMI_t}{SMI_{t-1}}\right) \tag{1}$$

$$SI_t = (SI_{t-1})^{SP_t} \tag{2}$$

with $SI_{\text{January 1996}} = 100$. Illustration 1 shows SI and provides an overview of the varying performances of the shares of large companies compared with those of medium-sized companies. Furthermore, a trend calculated using the Hodrick-Prescott filter is added to the diagram.[8] A histogram of monthly SP in our sample from January 1996 until January 2009 is also shown. On average, the SMIM outperforms the SMI by about 0,26% per month. Nearly 55% of monthly SP are positive. 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. In particular at the beginning of the sample and after the TMT bubble burst, the equities of large companies outperformed those of the SMIM over a protracted time period. The empirical distribution of the excess return nevertheless was significantly greater at the tails than the normal distribution. This is signalled by a high kurtosis value of 7.36.

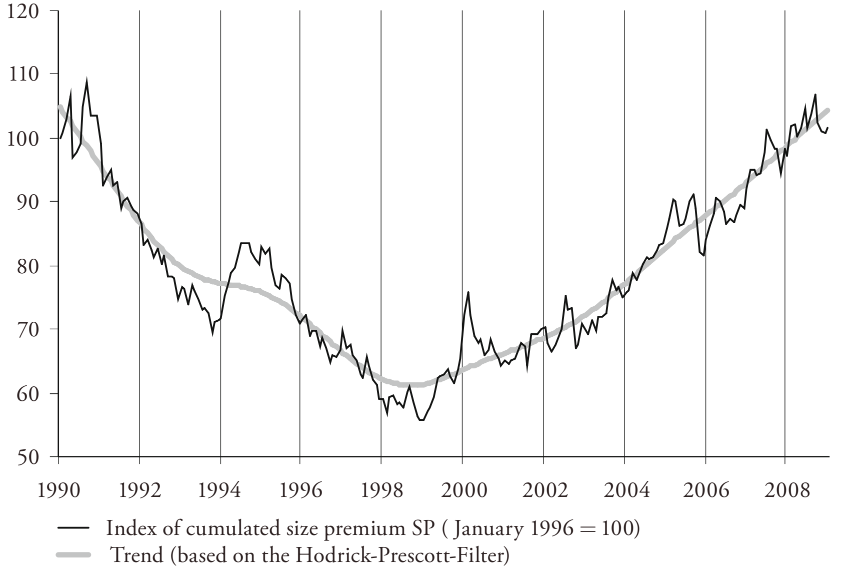
Our calculation is not immune to criticism. First, according to CARHART (1995), the size premium – as well as other risk factors – is calculated via zero-investment factor mimicking portfolios of individual stocks. In their calculation of the risk factors for the Swiss equity market, AMMANN and STEINER (2008) follow this approach.[9] Our definition of the size premium is chosen for one main advantage. In general, the paper examines the forecastability of the difference in returns between stocks of medium and large companies. An important criterion is that our results must be applicable in practical portfolio management.

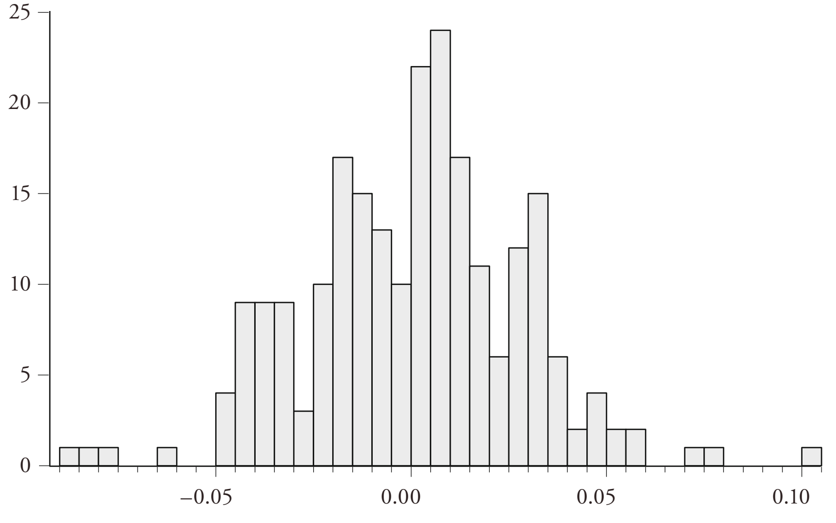
7 At the end of February 2009, the SPI comprised 228 stocks. At the same time the SMI included 20 and the SMI 30 stocks. The subscriber stocks were aggregated according to market capitalisation in order to calculate the three indices. On the basis of market capitalisation, the SMI (SMIM) stocks make up about 85.4% (8.9%) of the total SPI. The SMIM index has been available on Bloomberg since January 1996, the SMI Index much earlier.

8 See HODRICK and PRESCOTT (1997). The smoothing parameter lambda was set at 1440.

9 See AMMANN and STEINER (2008) for a detailed description of the methodology they use to calculate the risk factors.

Graph 1: The Size Premium





Histogramm of the monthly size premium SP

Therefore, transaction costs need to be taken into account. Since liquid and cheap futures are available on both indices, the profile of our SP over time can be replicated via long and short positions in the underlying futures. In contrast, using the methodology of Ammann and Steiner (2008) the long and the short part of the zero-investment portfolio have to be rebalanced monthly or at least frequently. In an illiquid environment like the Swiss market for small caps, such a procedure is very expensive.

Second, Ammann and Steiner (2008) construct risk factors beginning with January 1990. When analyzing their data set, we find that a structural positive size premium no longer exists. Using Monte-Carlo simulation, the authors show that their cumulative size premium (SMB) is not significantly different from zero at a 5% level. Their data show a period of a falling cumulative SMB in the 1990s, followed by a decade of a rising cumulative SMB. Therefore our sample could be biased and the proclaimed forecastability of the SP could be the result of a special cyclical environment. There are four arguments to address this point. First, the aim of our paper is to analyze the predictability of the return differential between two segments of the Swiss stock market over a horizon of one month. We do not address forecasts over longer horizons. With 157 data points we consider the size of our sample as sufficient. Additionally, we control for stationarity in the regressand and the regressors. This minimizes the danger of a biased sample. Second, due to the availability of very important explanatory variables like the Swiss PMI-index and especially the sales to price-ratio constructed with IBES-data, the sample period could not start before 1996. Third, ignoring the lack of important data, we could extend our data set by the data constructed by Ammann and Steiner (2008). A necessary condition for the legitimacy of this approach is the strong connection of both data sets in the joint sample period. When regressing SMB on SP, we get (1) a coefficient with a positive sign and a high significance level (t-value is 2.56) and (2) a rather small R-squared of 0.14. Additionally (3), in 32% of the months, SMB and SP show opposite signs in the common sample period. On the basis of these results, we conclude that a substitution of the two calculation methods is not possible.[10] Fourth, despite the concerns discussed above, we run our strategy with the data constructed by Ammann and Steiner (2008) beginning with 1990 as regressand. This reduces the number of possible regressors from 19 to 16. The results for two training periods turned out to be significantly positive, but not as good as for original

10 The detailed results from the regression analysis can be delivered by the author upon request.

data set with the smaller sample period. For one training period (48 months) the results are slightly negative.[11]

Third, explaining stock returns with time-series regression models has become a standard approach in literature. Several risk factors are used as regressors and account for a significant part in the variance of stock returns. Additionally to SMB and the excess return of the market (RMRF), the model applied by CARHART (1995) uses zero-investment mimicking portfolios for value (HML) and momentum (UMD). A necessary condition for the risk factors is that they are not correlated. Otherwise multicollinearity problems in the regression model would arise. In the approach used by AMMANN and STEINER (2008), this condition is fulfilled through the construction of the risk factors. Against this backdrop, our SP – when interpreting it as risk factor – could be biased. To address this problem, we run a regression of RMRF, HML and UMD on SP. We have found no significant influence of the regressors at the 5% level.[12]

From an economic standpoint, the aim of our analysis is not to construct a risk factor as an alternative to the standard SMB described in literature. As a risk factor, our SP has several weaknesses. In our analysis we focus on the predictability of the return differential between two sub-segments of the Swiss stock market. Our interpretation of SP is therefore mainly inspired by the work of NABLANTOV, BAUER and SPRIKHUIZEN-KUYPER (2006).

3. Potential Forecasting Factors

Now we must find variables that basically could have forecasting power for the SP. 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,[13] according to which smaller 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,[14] which makes it much more difficult

11 The detailed data of the strategy evaluation can be delivered by the author upon request.

12 However, there is weak evidence (10% level) for a significant coefficient of HML. The detailed results from this regression analysis can be delivered by the author upon request.

13 See GERTLER and GILCHRIST (1994) as well as BERNANKE and GERTLER (1999).

14 See CHAN and CHEN (1991) for the USA.

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.[15] Moreover, empirical studies see indicators of significant, varying risk premiums in bull and bear markets.[16] 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

15 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 occurred. Leistikow and Yu (2006) confirm the importance of the VIX in forecasting the size premium.

16 See Bhardwaj and Brooks (1993).

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.[17] 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 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.

4. 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.[18] 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

17 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.

18 The approach used is, in this respect, related to the method applied by Nablantov, Bauer and Sprikhuizen-Kuyper (2006). He permits the new addition or removal of economically sensible instruments at any point in time.

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.

5. 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[19] 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.[20]
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 a given error probability. The standard error is estimated on the basis of the Newey-West method.[21]
   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.

19 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 predefined error probability.

20 In this case, we include 19 explanatory variables and set a restriction of a maximum of 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.

21 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.

d. Is the model sufficiently stable? A CUSUM test of squares provides an answer.[22]
e. Are the instruments used correlated? An analysis of the variance inflationary factors is applied.[23]

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.[24]

6. Evaluating the Forecasts

The aforementioned 19 explanatory variables form the basis of the size premium forecast. In general our algorithm has three parameters that need to be fixed ex ante. The first one is the length of the training period. To check the robustness of our approach, we chose three training periods of 36 months (model 1), 48 months (model 2) and 60 months (model 3), respectively. The second parameter is the maximum number of instruments used in a forecasting model. We set this at three[25]. The last parameter is the confidence level of our statistical tests in the model selection procedure. We set the confidence level to 5%.

22 See BROWN, DURBIN and EVANS (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 by the expected value leads to a rejection of the null hypothesis. The table of significance lines can be found in JOHNSTON and DINARDO (1997). See CHU, STINCHCOMBE and WHITE (1996) for a discussion of the procedure for stability testing in econometric models.

23 See GREENE (2000), p. 257 ff.

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

25 This restriction is selected for reasons of 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.

Table 1: Results of the Forecasting Approach

	Model 1	Model 2	Model 3
Model details			
Start (first forecast)	4/1999	4/2000	4/2001
End (last forecast)	1/2009	1/2009	1/2009
# of Month (Total)	118	106	94
Training-Period	36	48	60
Max # of variables	3	3	3
# of Instruments	19	19	19
Level-of Confidence (Tests) (%)	5	5	5
Analysis of the forecasts			
Hit ratio (overall)	0.50	0.54	0.58
Top 33% size premiums	0.55	0.62	0.53
Middle 33% size premiums	0.50	0.59	0.67
Lowest 33% size premiums	0.45	0.44	0.57
Right forecasts: cumulative SP (%)	232	219	171
Wrong forecasts: cumulative SP (%)	161	125	114
Success ratio	1.45	1.75	1.50

Table 1 continued

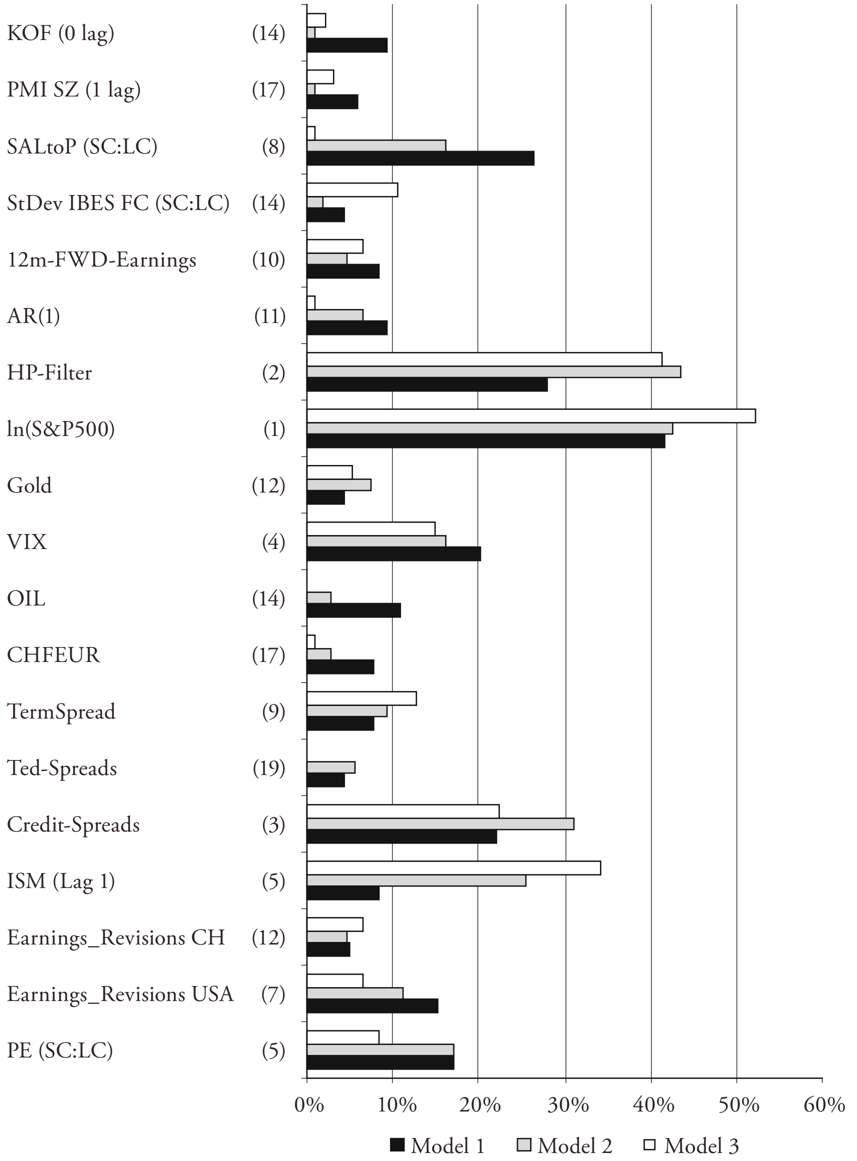
	Model 1			Model 2			Model 3		
10 largest size premiums (%)									
	month	*size premium*	*forecast*	*month*	*size premium*	*forecast*	*month*	*size premium*	*forecast*
1	1/2000	19.4	Hit	9/2001	–18.3	Hit	9/2001	–18.3	Hit
2	9/2001	–18.3	Hit	10/2008	–14.7	Hit	10/2008	–14.7	Hit
3	10/2008	–14.7	Hit	11/2000	–11.0	Hit	7/2001	–8.5	Hit
4	11/2000	–11.0	Hit	7/2001	–8.5	No hit	10/2005	–8.2	Hit
5	1/2000	9.1	Hit	10/2005	–8.2	No hit	10/2003	8.0	Hit
6	7/2001	–8.5	Hit	10/2000	–8.1	Hit	7/2004	–7.8	No hit
7	10/2005	–8.2	No hit	10/2003	8.0	Hit	11/2001	7.0	No hit
8	10/2000	–8.1	Hit	7/2004	–7.8	Hit	11/2007	–6.2	No hit
9	10/2003	8.0	Hit	11/2001	7.0	No hit	8/2003	–5.9	No hit
10	7/2004	–7.8	No hit	9/2000	7.0	Hit	2/2003	5.8	Hit
Key instruments									
1	ln(S&P500)			HP-Filter			ln(S&P500)		
2	HP-Filter			ln(S&P500)			HP-Filter		
3	SALtoP (MC:LC)			Credit-Spreads			ISM (Lag 1)		
4	Credit-Spreads			ISM (Lag 1)			Credit-Spreads		
5	VIX			PE (MC:LC)			VIX		

Our reference model (model 2) achieves 54% accuracy (table 1). If the realised size premiums are arranged by size, we notice two things. First, this approach is particularly good at anticipating major changes. The directions of seven 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 62%, the second third 59% and the last third 44% for model 2. Finally, we cumulate continuously compounded SP which the models forecast correctly (incorrectly). Each model reaches a positive net cumulative SP. The success ratio – defined as the quotient of right and wrong forecasts – is around 1.5 for all models. Overall, the results of the algorithm are promising.

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

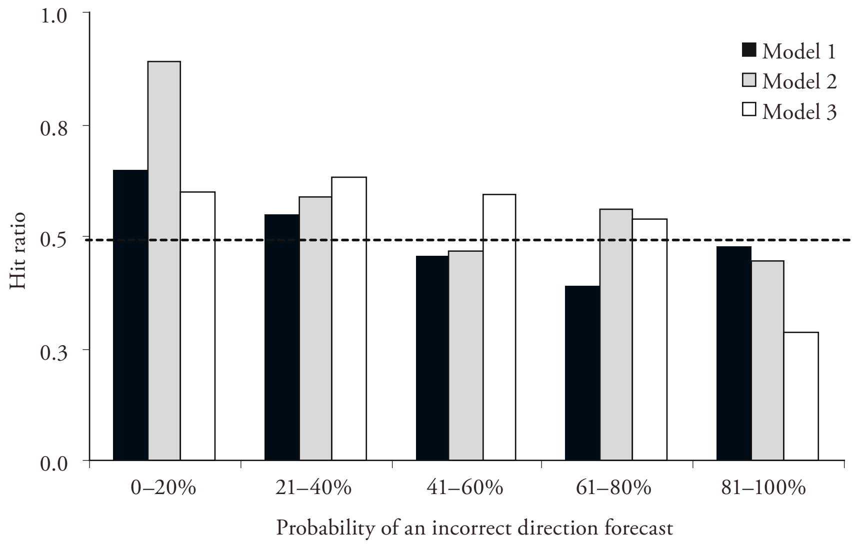
As we mentioned, one special aspect of our approach is that, in addition to the point forecast, conclusions about forecast confidence can also be drawn. In Illustration 3 all forecasts are distributed along the x-axis in five different quantiles. At the far left are the forecasts with the highest confidence (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 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.

Graph 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.

Graph 3: Hit Ratio and Forecast Confidence



7. Implementing the Strategy and Transaction Costs

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 SMI or the SMIM.

In general, the forecasts made by the model can be implemented by physically over- or underweighting certain stocks in a portfolio. The disadvantage of this approach is – as mentioned earlier in the paper – the size 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. 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 produces four different recommendations for the portfolio manager. In case 1 the forecasting model sends no signal in period $t-1$ but recommends a position in period t. In case 2 the positioning signal of period $t-1$ is confirmed in 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 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 benchmarks for our strategies are the SMI and the SMIM. At the end of each month the investor decides to invest fully in the benchmark – if no model signal occurs – or to invest in the benchmark and in a size position. The exposure of the size position 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. This somewhat arbitrary decision ensures that the tracking error of the strategy portfolio lies in the range between 2% and 3%. This is a reasonable tracking error budget for enhanced indexing strategies in institutional asset management.
3. All portfolio positions are valued at market prices. After a futures position is closed, there is a cash flow. If this is positive, then the resulting amount will 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.[26]

Table 2 shows the recommendation for the implementation in a given signal situation. In a first step we evaluate our three model variants without taking transaction costs into account. The start of the strategy is referred to the month of the first forecast and depends on the length of the training period. Table 3 shows the results. Our reference model 2 shows an annualised excess return of 2.1% p.a. and an information ratio of 0.73 (0.68) if the SMI (SMIM) serves as a benchmark.

26 Rolling a futures contract 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 (third Friday of the month).

Table 2: 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	$MV_t^L = 0.2PF_{t-1}(r_t^L - TAC)$ $MV_t^S = 0.2PF_{t-1}(r_t^S - TAC)$ $MV_t = MV_t^L - MV_t^S$	0	$PF_{t-1} \cdot r_t^{BM}$	PF_t
Case 2	$MV_t^L = MV_{t-1}^L \cdot r_t^L$ $MV_t^S = MV_{t-1}^S \cdot r_t^S$ $MV_t = MV_t^L - MV_t^S$	0	$PF_{t-1} \cdot r_t^{BM}$	PF_t
Case 3	$MV_t^L = 0.2(PF_{t-1} + CF_{t-1})(r_t^L - TAC)$ $MV_t^S = 0.2(PF_{t-1} + CF_{t-1})(r_t^S - TAC)$ $MV_t = MV_t^L - MV_t^S$	$CF_{t-1}^L = MV_{t-1}^L - TAC \cdot MV_{t-2}^L$ $CF_{t-1}^S = MV_{t-1}^S - TAC \cdot MV_{t-2}^S$ $CF_{t-1} = CF_{t-1}^L - CF_{t-1}^S$	$(PF_{t-1} + CF_{t-1})r_t^{BM}$	PF_t
Case 4	0	$CF_{t-1}^L = MV_{t-1}^L - TAC \cdot MV_{t-2}^L$ $CF_{t-1}^S = MV_{t-1}^S - TAC \cdot MV_{t-2}^S$ $CF_{t-1} = CF_{t-1}^L - CF_{t-1}^S$	$(PF_{t-1} + CF_{t-1})r_t^{BM}$	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

Table 3: Results of Various Strategies

	Model 1		Model 2		Model 3	
Backtest Details						
Start (first position)	4/1999		4/2000		4/2001	
End (last position)	1/2009		1/2009		1/2009	
# of month (total)	118		106		94	
Training-period	36		48		60	
Max # of variables	3		3		3	
# of instruments	19		19		19	
Level-of confidence (tests) (%)	5		5		5	
Underlying (futures position)	20% of Portfolio		20% of Portfolio		20% of Portfolio	
Performance Details						
Benchmark	SMI	SMIM	SMI	SMIM	SMI	SMIM
Return benchmark* (%)	–3.0	1.7	–3.8	–3.6	–3.9	–2.1
Return portfolio* (%)	–1.6	3.0	–1.8	–1.5	–2.4	–0.7
Excess return* (%)	1.4	1.4	2.1	2.1	1.4	1.4
Tracking error** (%)	3.2	3.2	2.8	3.1	2.7	2.9
Cumulative excess return (%)	14.3	13.3	18.2	18.5	11.3	11.1
Information ratio	0.45	0.43	0.73	0.68	0.53	0.48
Excess Return Evalutaion						
Beta	–0.04	–0.04	–0.03	–0.04	–0.03	–0.03
(*t*-stat)	–(1.51)	–(1.38)	–(1.71)	–(3.36)	–(1.30)	–(1.11)
Alpha (%)	1.32	1.46	1.93	2.00	1.32	1.39
(*t*-stat)	(1.16)	(1.28)	(2.31)	(2.03)	(1.29)	(1.29)
Excess Return Distribution						
Maximum (%)	4.4	3.9	3.2	4.0	3.3	3.9
Minimum (%)	–1.6	–1.7	–1.6	–1.8	–1.5	–1.6
Skewness	1.4	1.2	0.6	1.0	0.9	1.2
Kurtosis	7.0	6.2	4.4	6.4	5.5	7.5

* average monthly log-returns, annualized
** standard deviation of monthly excess returns, annualized

The cumulative excess return of our strategy is about 18% for model 2. But the other models also offer gratifying results.[27]

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 benchmark. The results suggest a very slight – and in each case negative – correlation between the market return and the excess return. The effects are, however, statistically significant only for model 2. On the other hand, the coefficients of the constants are – in the case of model 2 – highly significant and confirm the alpha potential of the strategies.[28]

How badly does the strategy's performance suffer if transaction costs are taken into consideration? To address this question, we take a look at the empirical transaction costs. We assume that the transaction costs are sufficiently approximated by the bid-ask spread.[29] An evaluation of the data 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. Slightly more than 70% of the calculated transaction costs are between 10 and 30 basis points. Sharp divergences are most likely due to errors in the data. 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 0.47 and an annual excess return of around 1.3% are expected.

27 The results raise the question of whether the method used basically supplies good results in both forecast directions. This is of special interest because our sample period shows a structural positive SP. Hence an additional strategy was evaluated in which investors are always positioned for a positive SP and behave analogously to the strategy discussed in the text. Such a one-sided investment strategy produces, in the case of model 2, an excess return of –0.84% p.a. and an information ratio of –0.27. The cumulative excess return over the sample is, in this case, –7.5%. The reason for these bad results is that the losses occur at the beginning of the sample, and in such a scenario it is very difficult to beat the benchmark with our strategy design. 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.

28 The t-values are adjusted according to the approach by Newey and West (1987). The alpha is defined as the coefficient of the constants multiplied by 12.

29 This assumption presumes that 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. A histogram of the transaction costs based on bid-ask spreads can be found in Appendix.

Table 4: Strategy Results under Different Assumptions for Transaction Costs (Model 2 with Benchmark SMI)

		Transaction costs SMIM futures		
		0.02%	0.05%	0.10%
Transaction costs SMIM futures	0.05%	17.3% (2.0%) **0.69**	17.0% (1.9%) **0.68**	16.4% (1.9%) **0.65**
	0.10%	16.6% (1.9%) **0.67**	16.3% (1.8%) **0.65**	15.8% (1.8%) **0.63**
	0.20%	15.4% (1.7%) **0.61**	15.0% (1.7%) **0.60**	14.5% (1.6%) **0.58**
	0.30%	14.1% (1.6%) **0.56**	13.7% (1.6%) **0.55**	13.2% (1.5%) **0.52**
	0.40%	12.8% (1.4%) **0.51**	12.4% (1.4%) **0.50**	11.9% (1.3%) **0.47**

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

8. Conclusions

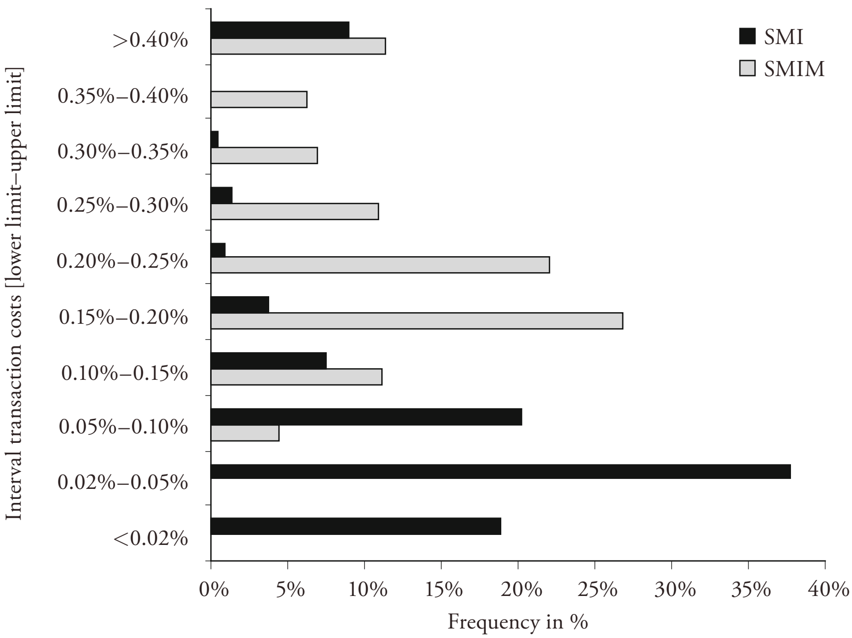
The size premium – in this study defined as the outperformance of the equities of medium-sized companies over those of large firms – is subject to sharp cyclical fluctuations over time. This empirical observation also holds true for Switzerland. This study explores the possibility of a tactical size rotation as an additional performance driver for active portfolio management. The study supports the hypothesis that the size premium is predictable to some extent, and supplements the existing empirical literature with results for Switzerland. The forecasts used come from a flexible forecasting approach based on time-variable multi-factor models. Our strategies provide gratifying information ratios for a maximum real-time period of about ten years. This result holds true for various specifications. Inclusion of an adequate level of transaction costs still permits significant positive excess returns.

The results show that risk variables such as the credit spread and the VIX, the performance of the S&P 500 and statistical variables such as trends calculated using a recursively calculated Hodrick-Prescott filter are 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 outdo traditional forecasting variables. The use of micro data as forecasting instruments for tactical size rotation is a new development. The modelling of an ex ante predictability of an incorrect forecast can, as we have shown, significantly improve the accuracy rate.

For further research, we 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.

Appendix

Graph: Breakdown of Transaction Costs* (Daily Data, 03/01/2006–02/11/2007)



Source: Bloomberg.
* transaction costs are shown as a % of the investment.

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SUMMARY

The size premium, defined as the return differential between shares of small and large companies, is subject to cyclical fluctuations. This study examines the predictability of this premium for the Swiss stock market applying a new and flexible forecasting approach. Our strategies provide promising information ratios. The results show that risk variables (VIX, TED spread, etc.), the performance of the S&P 500 and statistical variables such as AR(1) terms or trends prove to be successful forecasting variables in our algorithm. Furthermore, variables that sum up the consensus estimates of equity analysts (IBES) make valuable forecast contributions.