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Forecasting of interest rates using neural network models

by

A. Din

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Abstract

During the past couple of years, interest rates around the world have declined to very low levels and there is a quest in the financial community for better understanding the dynamics of this situation. In the paper, the development of the monthly Libor and Swap rates are investigated over a 10 year period (1993-2002) in relation to a number of potentially important factors. For the case of Swiss interest rates, these factors include a range of rates for different maturities, gross domestic product, inflation rate and exchange rates.

Interest rate forecasting models are developed which endeavour to include the statistically most significant factors defined in terms of time lag changes of individual time series as well as of relative movements of different maturity rates. The models are constructed on the basis of back propagation neural networks involving one hidden layer of 5-10 nodes. Model validation is done for a period covering the past 5 years with the model retraining carried out every 3 months.

The results for forecasting the Libor 3 month rate and the Swap 5 year rate on a forecasting horizon of 12 months show a quite good directional reliability. The directional movement is forecasted correctly in 83% of the months of the validation period. The quality of the models for the Libor 3 month rate and the Swap 5 year rate on a forecasting horizon of 3 months is somewhat lower, with only 61-63% of accuracy in the directional forecasting. Overall, the absolute predicted rates are quite close to the real rates.

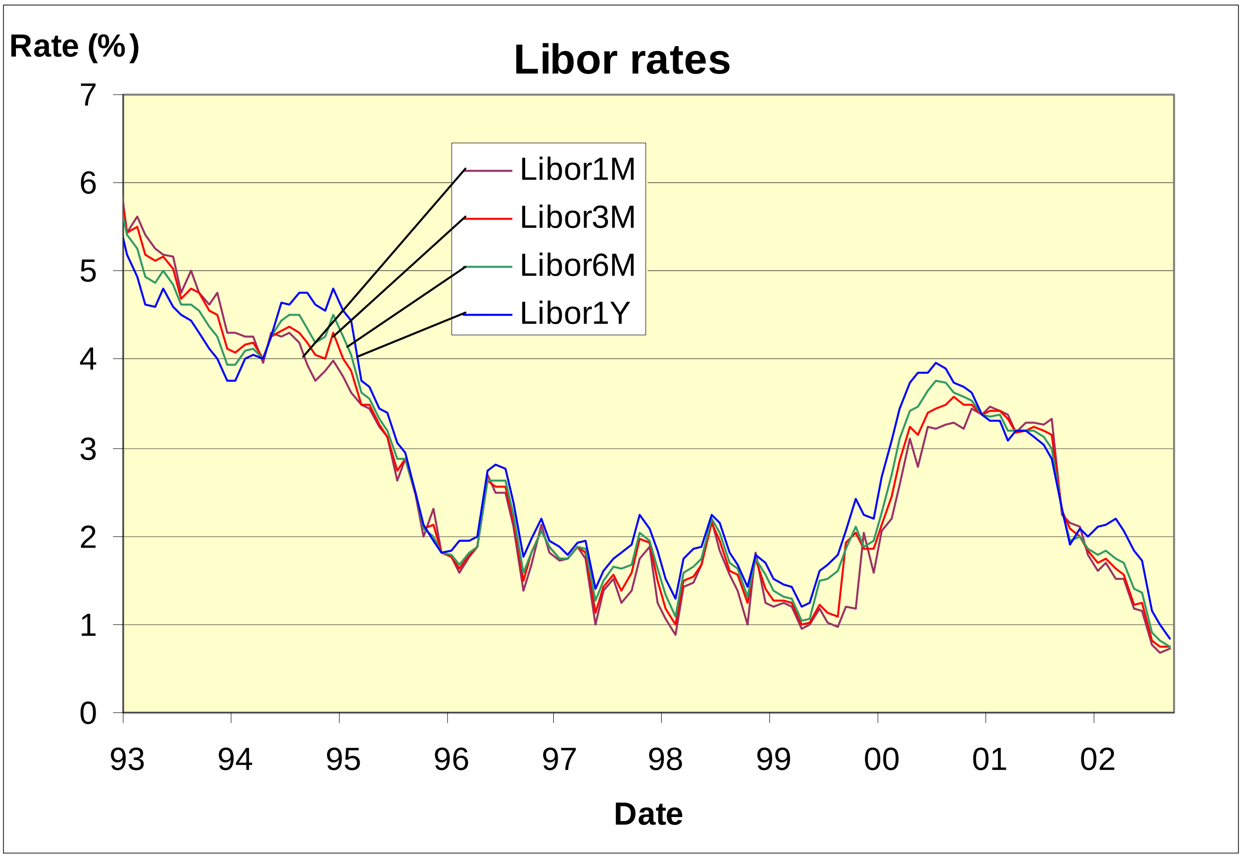
Geneva Research Collaboration
Rue de Veyrot 12, CH-1217 Geneva, Switzerland
Phone: +41-22-9891280
E-mail:info@genevaresearch.org, Web: www.genevaresearch.org

1. Data inputs for interest rate forecasting

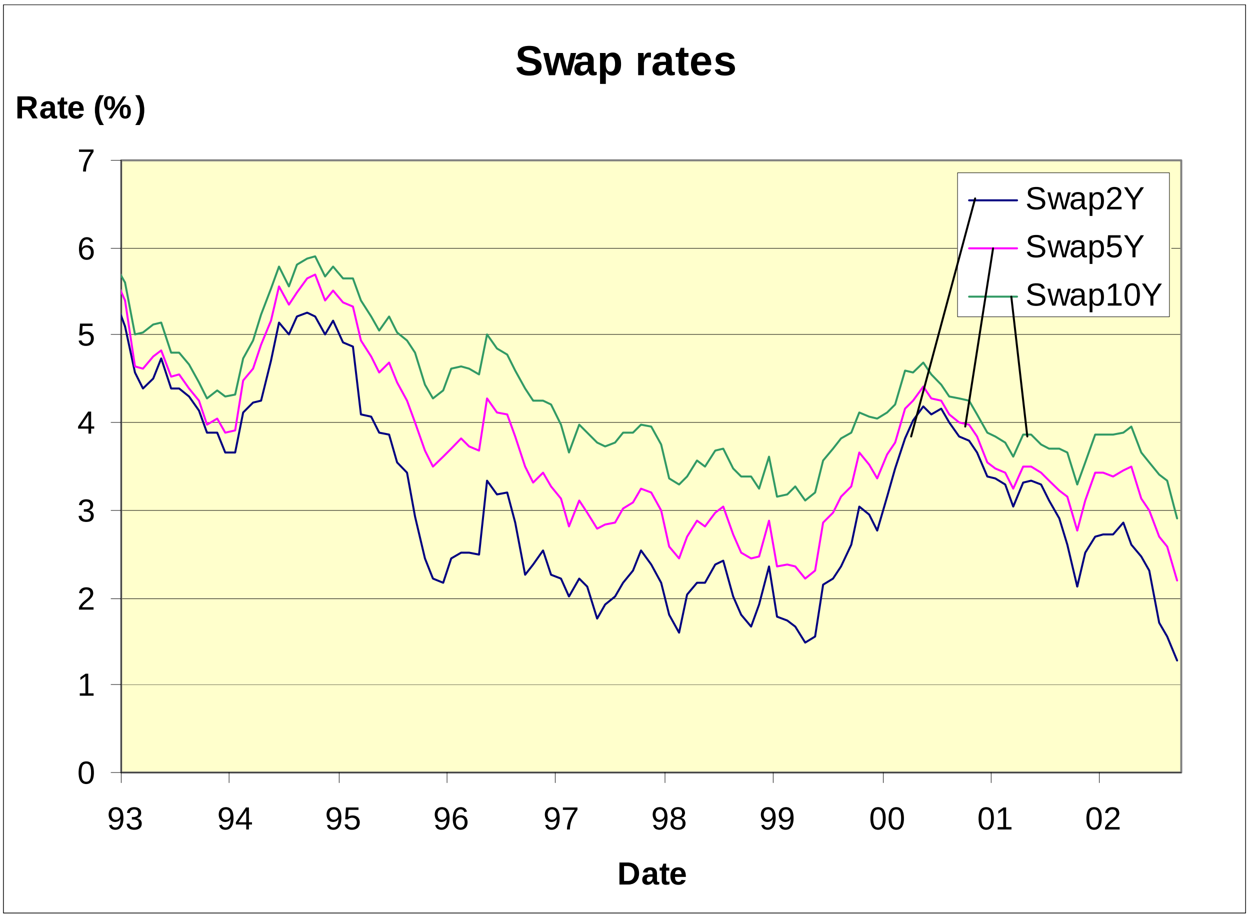
Historically, the forecasting of interest rates has been treated with standard tools of econometry in the framework of general macro-economic modelling. Different inputs such as gross domestic product, consumer price index, and foreign exchange rates may be used to construct forecasting models within linear or non-linear approaches to modelling (see e.g. Brace 1997, Franses 1998, Granger 1993, Granger 1986, Harvey 1990, Taylor 1994).

This paper focuses on the forecasting of Libor and Swap rates of different maturities on a forecasting horizon of 3 to 12 months. These instruments have been the subject of much work during the past years (see e.g. Jamshidian 1997, Sidenius 1998) and have lately been under special scrutiny because of the precipitous drop of interest rates which has hit Europe as well as the USA and Japan. Thus there is quest for better understanding the dynamics of interest rates so as to have a good grasp on the factors which may be keeping rates close to zero as well as on possible circumstances which might lead to a rebound.

In the next section, artificial neural network models will be developed and applied to analyse the past 10 years of data for 3 month Libor rates and 5 year Swap rates. Other maturities may be treated within a similar approach and in fact they are all considered as possible inputs to the modelling. The following diagrams show the behaviour of monthly Libor and Swap rates during the considered period.



Libor rates for maturities 1, 3, 6 and 12 months



Swap rates for maturities 2, 5 and 10 years

It is seen that the Libor rates follow each other rather closely and also show different features of short and long rates crossing, which are interesting phenomena from the point of view of rate dynamics. The Swap rates are also strongly correlated but show less complex relative features.

The data input is presented as a time series of monthly data even if daily data may sometimes be available. Because other data of relevance for forecasting, such as consumer price indices and gross domestic product, are available with a lower frequency, the monthly period was chosen as the most convenient. This means that the number of data points available during the considered 10 year history is rather limited which clearly is a drawback in constructing forecasting models that may be tested extensively. On the other hand, it may be argued that including more historical data for constructing models may not necessarily be helpful because of recent fundamental changes in the macro-economic framework

The following data inputs have been chosen for modelling the Libor and Swap rates:

- Libor rates
- Swap rates
- Interbank rates
- Bond rates
- Swiss inflation rates
- Swiss GDP
- USD/CHF exchange rate

Other data could potentially be relevant and clearly the Swiss data could be substituted, or complemented, by other national economy data. It should be remarked that the GDP data is only quarterly data which has to be recast as monthly data in the same way as the other inputs.

The problem to be addressed is how construct and test models based on these inputs for forecasting the Libor 3 month rate and Swap 5 year rate on a 3 and 12 month horizon.

2. Construction of neural network models

The standard approach of using linear econometric models for addressing such a problem has often turned out to be inadequate and therefore the paper will examine the possibility of using the more complex non-linear methodology represented by artificial neural networks. The value for economic time series modelling of using non-linear models, in general, and neural networks, in particular, has been demonstrated in many different cases (see e.g. Anders 1999, Azoff 1994, Bishop 1995, Casdagli 1989, Dayhoff 1990, Harvey 1990, Haykin 1999, Refenes 1995).

The present paper uses a standard feed-forward back propagation neural network approach (see Rummelhart 1986). A selection process, using different statistical methods and genetic algorithms, was applied to identifying the most relevant inputs. The considered inputs are the basic raw inputs as well as derived data such as increments, time lags, non-linear transformations, and relative parameters, following standard methods of model construction as well as some more recent ones (see e.g. Kearns 1997, Ripley 1995). There are many examples of successfully applying specification strategies, see for example Anders 1999, involving two stages: 1) the selection of the optimal number of hidden units with a fully connected neural network; 2) the reduction of the number of input connections. This paper emphasizes the identification of certain relative series variables and their time lags which appear to be important for the dynamics.

Neural networks are a very convenient class of predictive models because they provide a non-parametric method of constructing a non-linear model based on learning from a selected past history. Their key feature (described for example in Haykin 1999) is constituted by the architectural structure involving nodes in hidden layers, activation functions and weights. It is a fundamental goal that models should be robust and therefore the number of free parameters should be small, i.e. the models should have. as few parameter transformations and hidden nodes as possible. The price to pay for the flexibility and versatility of neural network models is often that they are more difficult to interpret than the simpler linear regression methods.

Starting from a large set of potentially interesting variables, between 50 and 100 raw inputs and derived parameters, a pruning is carried out through a cascading process of variable selection using both standard statistical methods as well as genetic algorithms. This results in a reduction of approximately 10 variables for each of the 4 forecasting problems at hand, the Libor 3 month rate on a 3 and 12 months horizon, and the Swap 5 year rate on a 3 and 12 months horizon. Only relative changes of the input parameters are considered and the forecast output is also expressed as a relative change. For example, for the case of the Libor 3 month rate on a 12 month horizon, the objective is to predict the % change of the rate 12 months later with respect to the current level.

All the data of the considered 10 year period is used for this preliminary generic analysis. However, this does not conflict with the objective of implementing an acceptable model validation process. The selected input variables for the four different models are listed in the table below.

MODEL	**SWAP5Y+12M**	**SWAP5Y+3M**	**LIB3M+12M**	**LIB3M+3M**
Output	D+12M(SWAP5Y)	D+3M(SWAP5Y)	D+12M(LIB3M)	D+3M(LIB3M)
Validation periods	12 times 3M	17 times 3M	12 times 3M	17 times 3M
Correct direction	83%	61%	83%	63%
ANN model type	1 hidden layer	1 hidden layer	1 hidden layer	1 hidden layer
	of 5-10 nodes	of 5-10 nodes	of 5-10 nodes	of 5-10 nodes
Inputs	10	10	9	8
	D-12M(LIB1M)	D-3M(LIB1M)	D-12M(LIB1M)	D-3M(LIB1M)
	D-12M(LIB1Y)	D-1M(LIB1Y)	D-1M(LIB3M)	D(LIB6M/3M)
	D-1M(SWAP10Y)	D(LIB1M/1Y)	D(LIB6M/3M)	D-1M(LIB3M)
	D-12M(SWAP10Y)	D-1M(SWAP5Y)	D-1M(Swap2Y)	D-3M(Swap2Y)
	D(SWAP10Y/2Y)	D(SWAP10Y/2Y)	D-12M(Swap2Y)	D-1M(Bond10Y)
	D-1M(Bond10Y)	D-3M(SWAP10Y/2Y)	D-12M(CHPrice)	D-3M(CHIBK3M)
	D-3M(Bond10Y)	D-1M(Bond10Y)	GDP3M	D-1M(USDCHF)
	D-12MCHIBK9M	D-3M(Bond10Y)	D-1M(USDCHF)	D-3M(USDCHF)
	D-12M(CHPrice)	D-3M(CHIBK9M)	D-12M(USDCHF)	
	GDP3M	D-1M(USDCHF)		

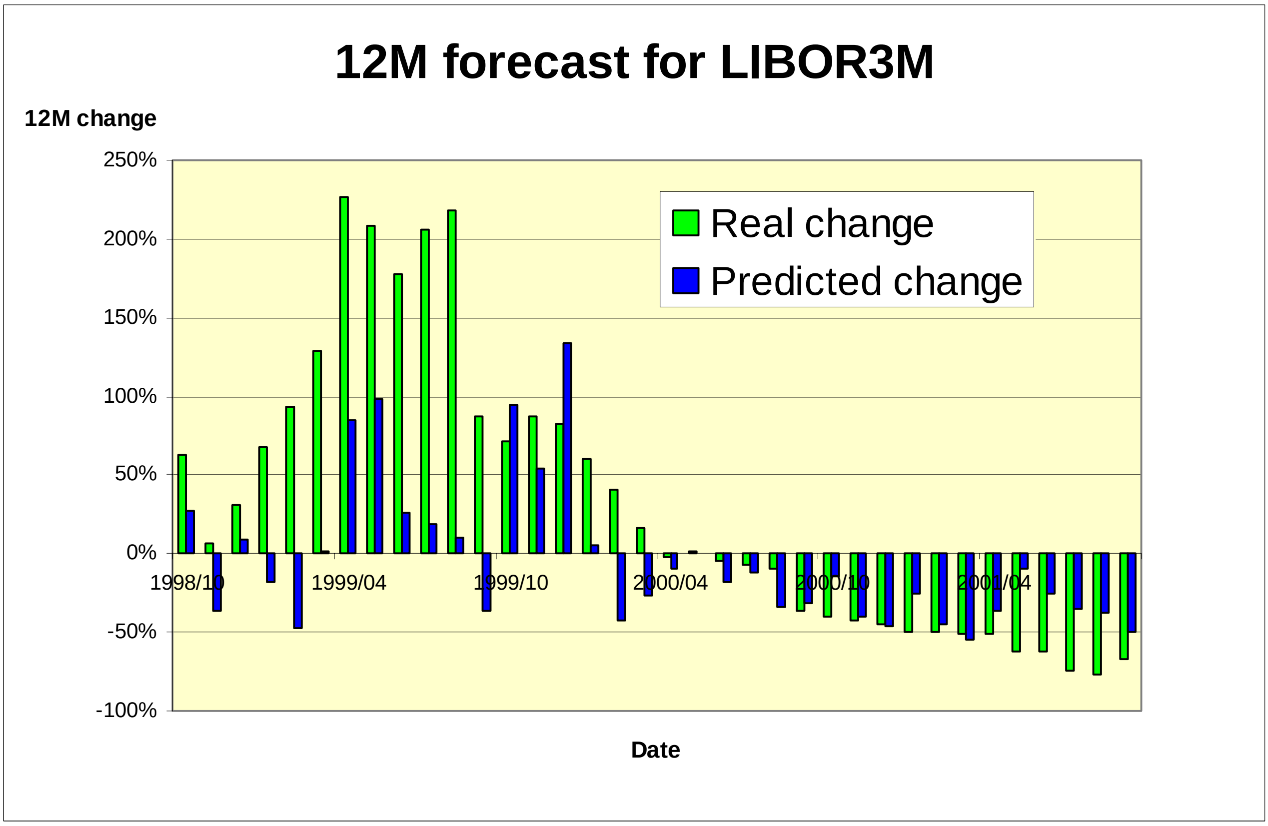
Model structure and results

The model construction is done in steps, starting the back testing in 1998 with a forecasting period of 3 months using the historical data of the past 5 years, i.e. 60 months 1993-98. After 3 months, a neural network retraining is carried out with input data from a displaced 5 year window involving the same ensemble of input parameters. The process is repeated so as to include the latest considered 2002 data, altogether providing 12-17 validation periods of 3 month length, depending on the forecast horizons of 3 or 12 months, during the period 1998-2002.

The training and testing of the models are carried out in a standard fashion of feed-forward networks with a correlation function taken as error measure. The adopted models all involve 5-10 nodes in one hidden layer. The objective of constructing models which are as robust as possible is thus addressed by reducing the basic input parameters to a reasonable minimum (around 10) and to select a rather low nom of hidden nodes in one hidden layer only.

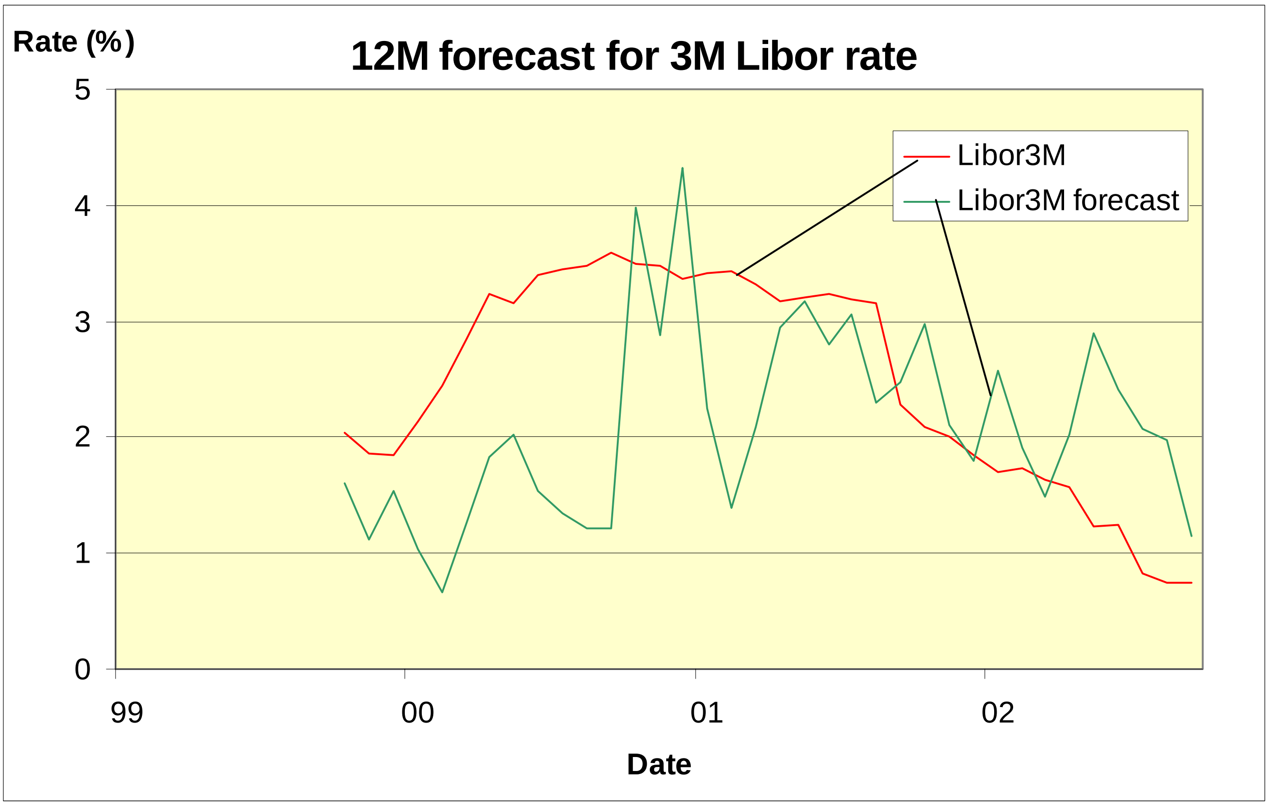
3. Model results

The objective of the models is to predict the absolute value of the rate change over the selected forecasting horizon. It would also have been possible to try to predict only the direction of the change, i.e. the rate moving either up or down, but for the case at hand this does not appear to lead to better models. However, from the point of view of summarizing the results of the 12-17 models developed for each problem during the period 1998-2002, it is still useful to explicitly feature the directional prediction. This is done below for the forecasting of the 3 month Libor rate on a 12 month horizon with predictions provided every month.



Neural network model for 3 month Libor rate changes on a 12 month horizon

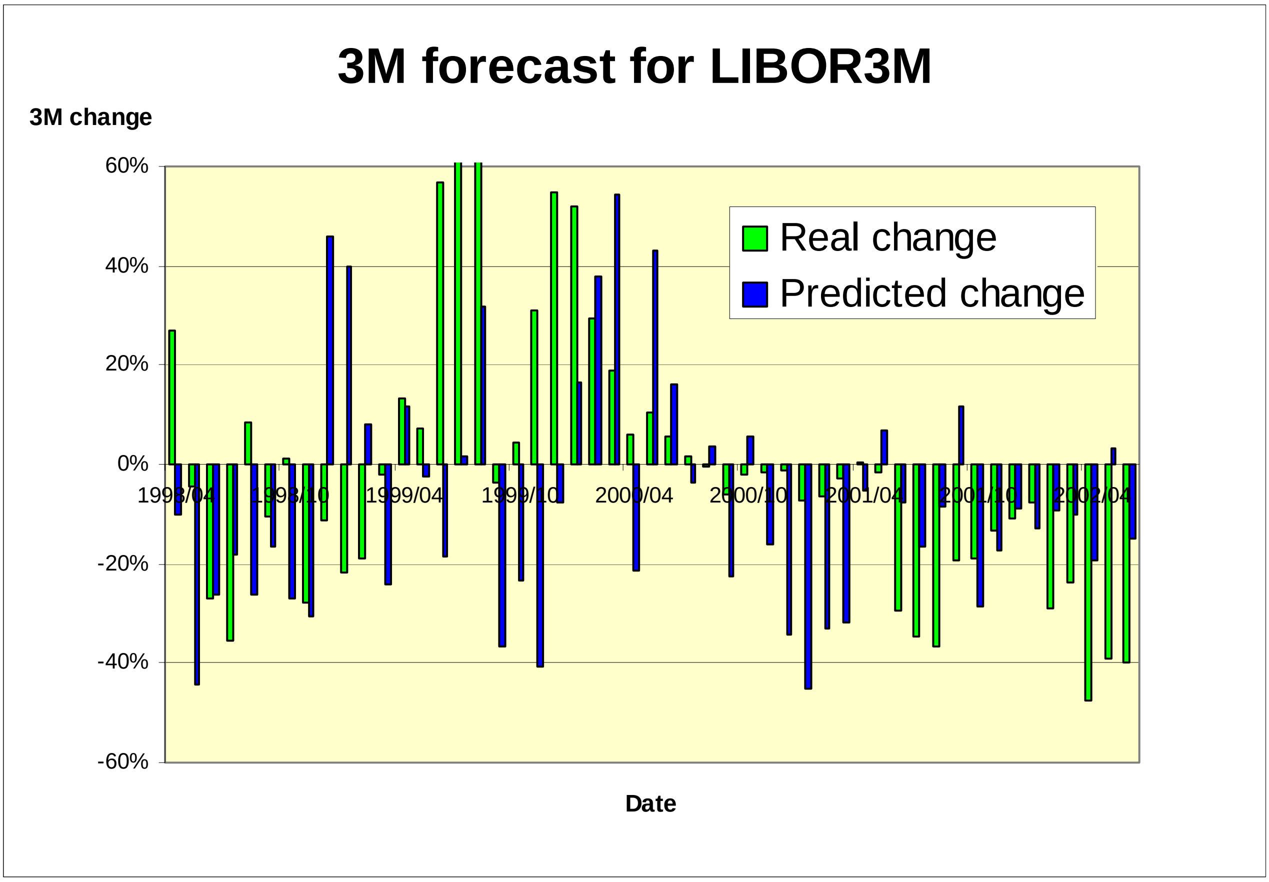
The table in the previous section indicates that the prediction of the direction of the change in the 3 month Libor rate was correct in 83% of the months during 1998-2002. Nevertheless, the above graph also shows that the absolute prediction of the change is quite often well off the mark. This is illustrated in the graph of the absolute real rate and the absolute predicted rate.



Neural network model for 3 month Libor absolute rates on a 12 month horizon

In the beginning of the period the model prediction is much below the real value but later it is somewhat closer.

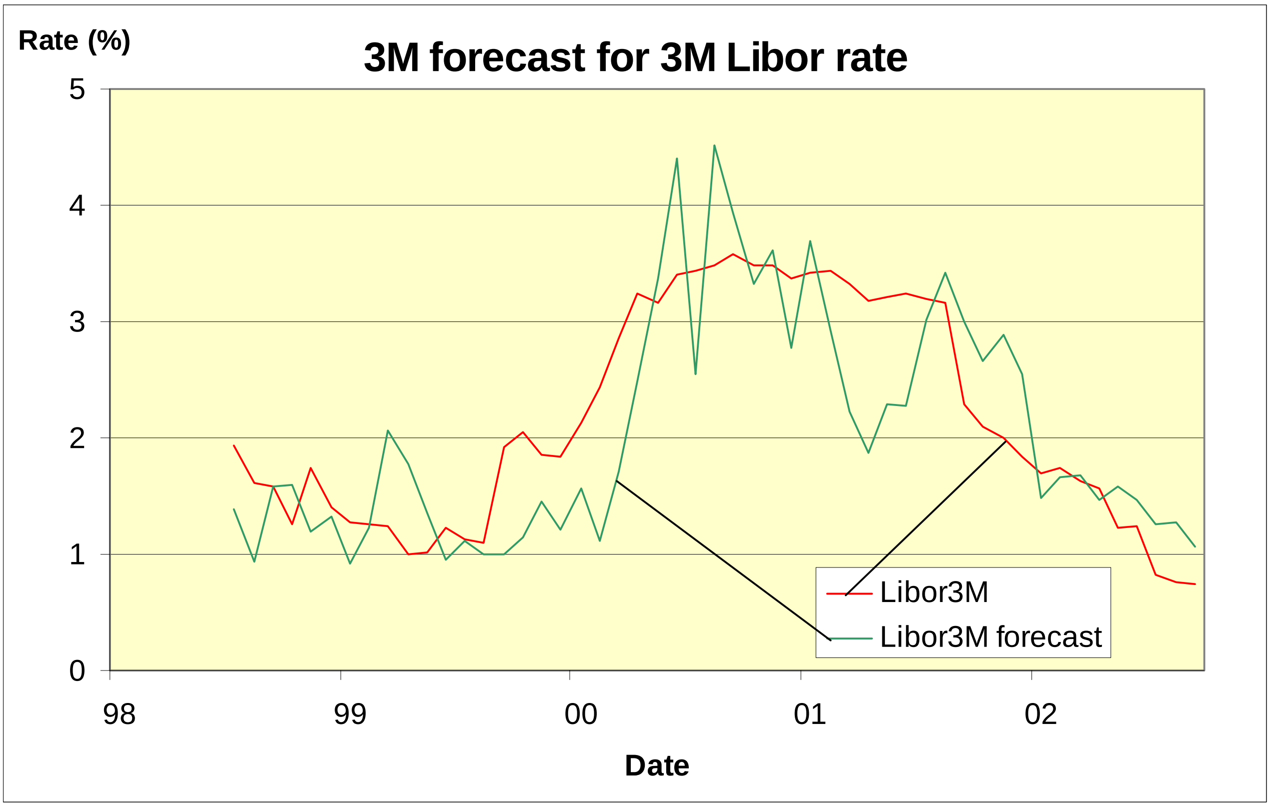
The model results for the 3 month Libor rate on a 3 month horizon are presented in the graph below. The directional prediction quality of the model is substantially lower than the one for the 12 month Libor rate with only 63 % of the predictions being correct over the 1998-2002 period (as listed in the table of section 2). There is clearly a higher variability in the data to be predicted and as a result the neural network model quite often does not adapt correctly to changes.



Neural network model for 3 month Libor rate changes on a 3 month horizon

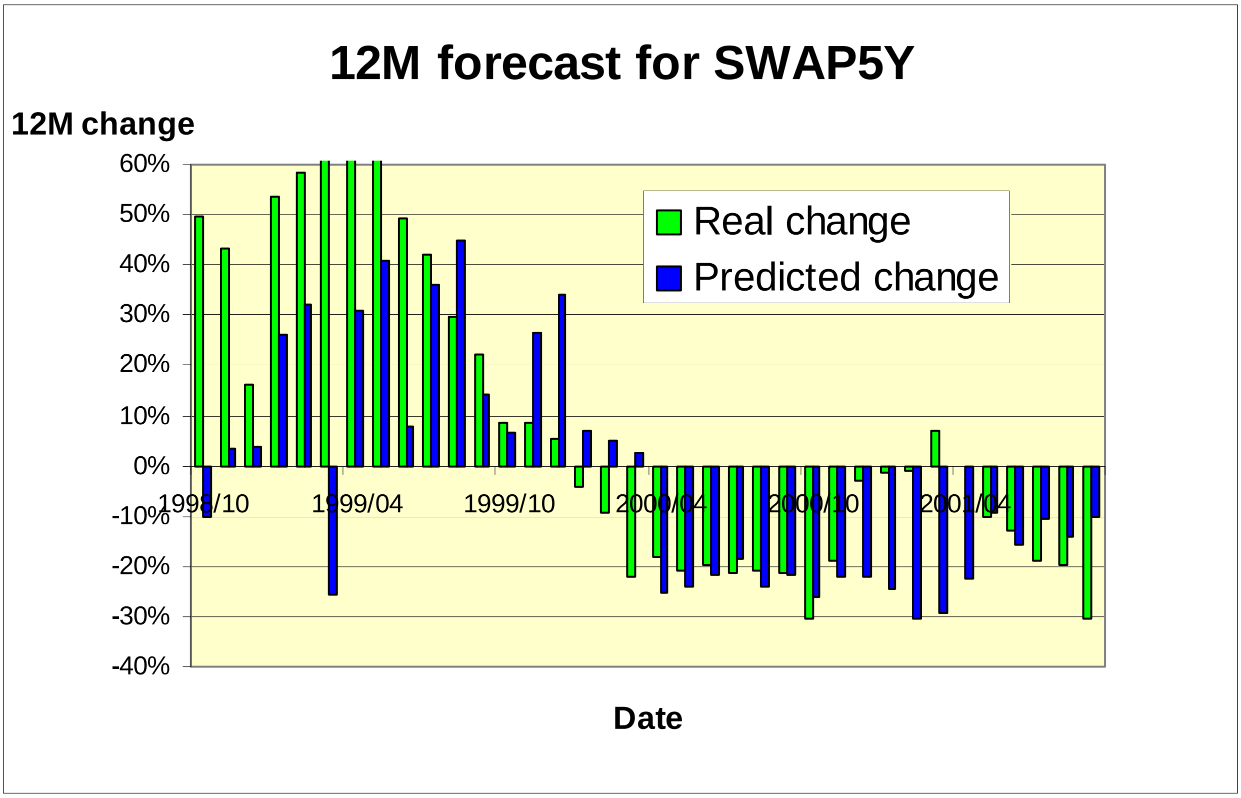
Since the variability of the rate changes is higher for the 3 month Libor rate, the question could be raised about whether it might be possible to focus on models for predicting the directional change only, and not the absolute change. Preliminary results show that this does not in any straightforward way lead to a significant improvement in the forecast precision. However, this does of course not mean that it is impossible to find an alternative input parameter setup and model type which would be able to produce better results.

In fact, the graph of the absolute real and predicted rate shows that the prediction remains rather close to the real rate during the whole period.



Neural network model for 3 month Libor absolute rates on a 3 month horizon

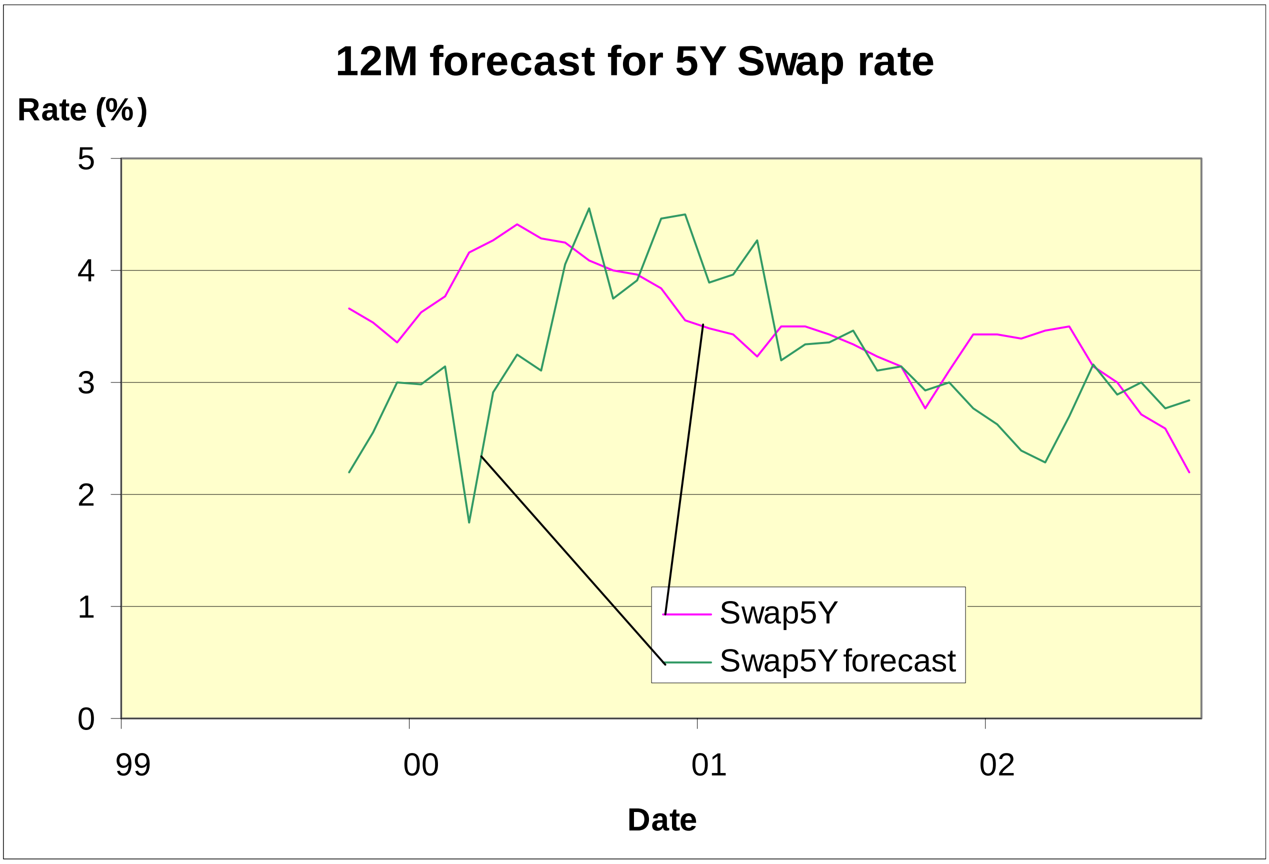
The model results for the 5 year Swap rate on a 12 month horizon are presented in the graph below. The directional model quality is as high as for the 3 month Libor rate on a 12 month horizon with 83 % of the directional being correct over the 1998-2002 period (as listed in the table of section 2).



Neural network model for the 5 year Swap rate on a 12 month horizon

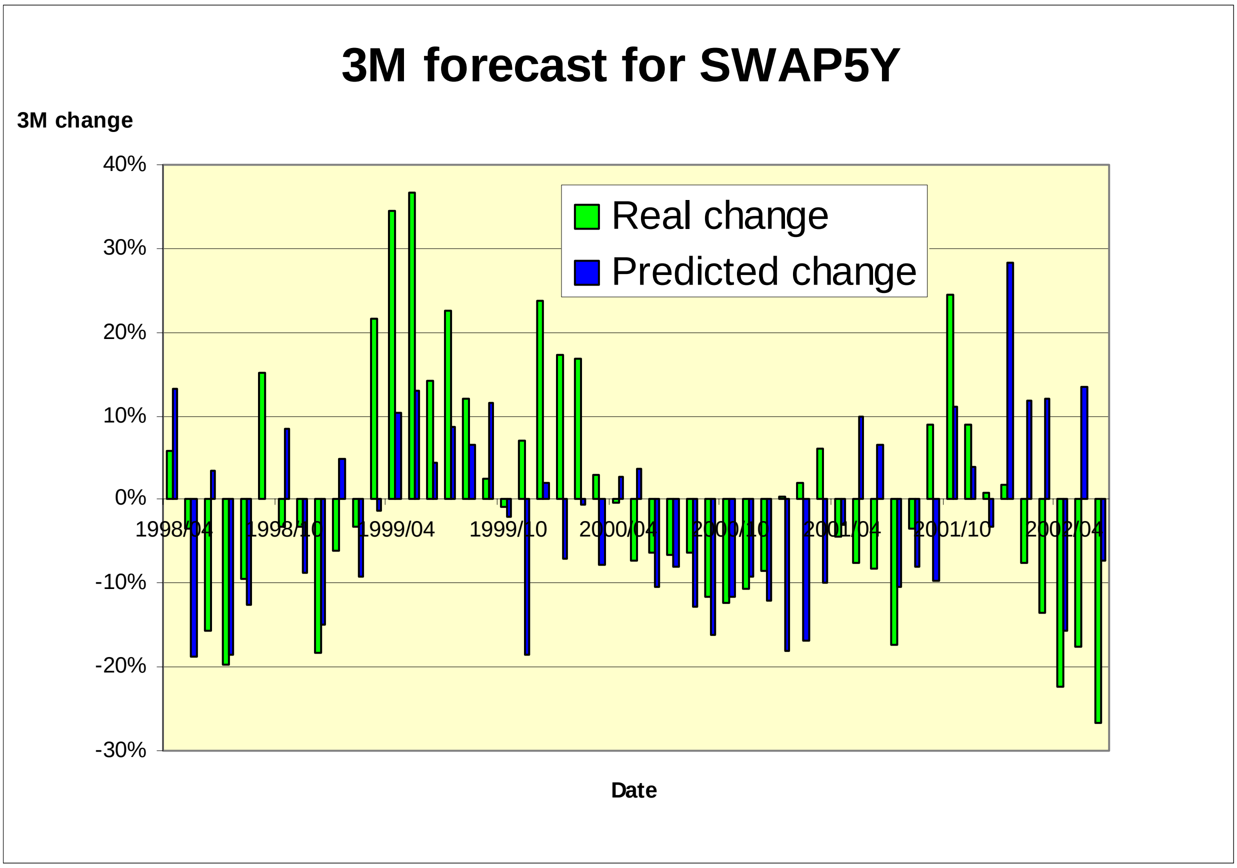
As it was the case for the 3 month Libor rate, it is seen that the structural change to a general downtrend during 2000 is captured by the model rather quickly. Since then the model results have been quite robust.

The prediction of the absolute values of the changes is rather approximate. The absolute predicted rate is below the real rate in the beginning of the period but is fairly close the end of the period.



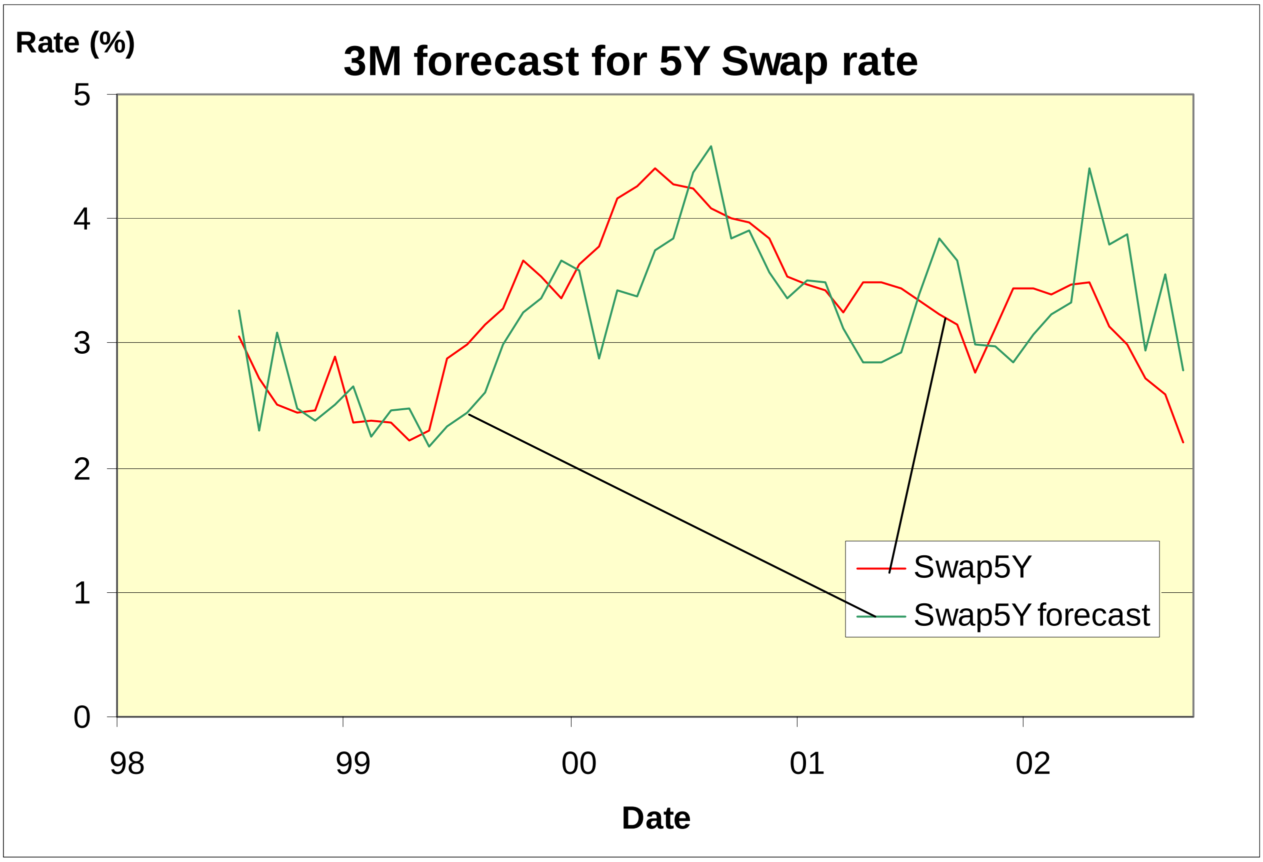
Neural network model for 5 year Swap absolute rates on a 12 month horizon

The model results for the 5 year Swap rate on a 3 month horizon are presented in the graph below. The directional model quality is substantially lower with only 61 % of the predictions being correct over the 1998-2002 period (as listed in the table of section 2). There is clearly a higher variability in the data to be predicted and as a result the neural network model quite often does not adapt correctly to changes.



Neural network model for the 5 year Swap rate on a 3 month horizon

The prediction of the absolute values of the changes is rather approximate. However, overall the absolute predicted rate follows the real rate quite closely over the whole period.



Neural network model for 5 year Swap absolute rates on a 3 month horizon

It may be instructive to make a statement about the sensitivity of the predictions to the specific inputs of the different neural network models. However, since the models are non-linear it is not as simple to describe this sensitivity as for linear regression models.

The table below provides the average value of the input variable derivative for one representative model of each of the four groups. The signs and relative sizes of these sensitivities may be valuable for better understanding the overall importance of the model inputs.

5YSwap+12M	Weights	5YSwap+3M	Weights	3MLibor+12M	Weights	3MLibor+3M	Weights
D-12M(LIB1M)	-0.3521	D-3M(LIB1M)	0.2028	D-12M(LIB1M)	0.4632	D-3M(LIB1M)	0.9420
D-12M(LIB1Y)	0.2075	D-1M(LIB1Y)	-0.8881	D-1M(LIB3M)	0.6845	D(LIB6M/3M)	0.0058
D-1M(SWAP10YM)	-0.0137	D(LIB1M/1Y)	0.4322	D(LIB6M/3M)	0.1726	D-1M(LIB3M)	0.1046
D-12M(SWAP10YM)	-0.4026	D-1M(SWAP5YM)	1.6079	D-1M(Swap2Y)	-0.5091	D-3M(Swap2Y)	-0.6935
D(SWAP10Y/2Y)	0.3269	D(SWAP10Y/2Y)	-0.7099	D-12M(Swap2Y)	0.4815	D-1M(Bond10Y)	-0.4713
D-1M(Bond10Y)	-0.1550	D-3M(SWAP10Y/2Y)	0.4513	D-12M(CHPrice)	0.2074	D-3M(CHIBK3M)	0.7502
D-3M(Bond10Y)	0.6291	D-1M(Bond10Y)	-1.0262	GDP3M	0.0242	D-1M(USDCHF)	-0.2280
CHIBK9M	-0.9798	D-3M(Bond10Y)	0.0091	D-1M(USDCHF)	-0.2197	D-3M(USDCHF)	-0.3837
D-12M(CHPrice)	-0.3250	D-3M(CHIBK9M)	0.1303	D-12M(USDCHF)	-0.3652		
GDP3M	0.0088	D-1M(USDCHF)	-0.1621				

Input sensitivities of the neural network models

4. Conclusions

It appears that the Libor and Swap rates on a longer horizon, i.e. 12 months, may be described quantitatively in the framework of neural network models in a quite satisfactory way in what concerns the directional change. A success rate of the order of 80% for the directional change might be of some practical value. The prediction for the absolute magnitude of the rate change is very approximate in the beginning of the considered period and fairly good later in the period.

For the Libor and Swap rates on a shorter horizon, i.e. 3 months, the quality of the directional change prediction is somewhat lower. However, the absolute rate prediction is rather close to the real rate during the whole period.

The model approach to forecasting Libor and Swap rates as described above may carried over to the full range of maturities 1-12 month Libor rates and 1-10 year Swap rates on the forecasting horizons of 3, 6, 9 and 12 months which are commonly used. For each model construction, it is necessary to follow a similar procedure of initial filtering and selection of potentially important input data and step wise back testing of a relatively simple neural networks with as few parameters as possible.

It would of course be possible to apply a similar neural network construction using short frequency data, i.e. daily data. This would make good sense for the 3 month Libor rates, for example, for the prediction of which the longer term input variables (GDP and inflation rate) do not play a significant role.

In so far as such models are of operational interest to the financial community, it is relatively easy to implement the described neural network models in a simple, user friendly setting, for example using forecasting functions embedded in the framework of an Excel spreadsheet.

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