International Conference
24th Mini EURO Conference
"Continuous Optimization and Information-Based Technologies in the Financial Sector"
(MEC EurOPT 2010)
June 23–26, 2010, Izmir, TURKEY

ISBN 978-9955-28-598-4
R. Kasımbeyli, C. Dinçer, S. Özpeynirci and L. Sakalauskas (Eds.): MEC EurOPT 2010
Selected papers. Vilnius, 2010, pp. 5–10

OPTIMIZED CALIBRATION OF CURRENCY MARKET STRATEGIES

Mustafa Onur Çağlayan[1], **János D. Pintér**[2]

[1]*Faculty of Economics and Administrative Sciences;* [2]*Faculty of Engineering*
Özyeğin University, Kusbakisi Caddesi, No. 2, 34662 Altunizade, Üsküdar – Istanbul
E-mail: [1]*mustafa.caglayan@ozyegin.edu.tr;* [2]*janos.pinter@ozyegin.edu.tr*

Abstract: We propose a new financial indicator and risk metric embedded in a currency trading model to assist investors in currency markets. Since our model is highly nonlinear, we utilize global optimization technology to maximize the performance of the currency basket, based on our selection of key decision variables. We introduce the model and present numerical results based on actual market data.

Keywords: Quantitative financial model development; Currency markets; Globally optimized trading strategy; Numerical results.

1. Introduction

The differences in interest rates between countries have always played an important role for investors when making an investment decision in currency markets. The strategy of buying the currency of the country with the higher interest rate and simultaneously selling the currency of the country with the lower interest rate, which is also known in financial markets as the "carry trading strategy", is often perceived as one of the most popular trading strategies in currency markets. While this type of a strategy can bring very good returns over the years, another key financial factor that needs to be kept in mind at all times is the volatility of the currency pair in question. We have developed an indicator which we name Interest Rate Differentials Adjusted for Volatility (IRDAV), to capture both the interest rate differentials and the volatility of the currency pairs in a single indicator. We measure IRDAV for each currency pair in our analysis as the ratio of one-month London Inter-Bank Offer Rate (LIBOR) interest rate differential between the high-yielding and low-yielding currencies to the annualized standard deviation of the daily exchange rate returns. This measure uses the same concept as the well-known Sharpe ratio (SR) defined by

$$SR = \frac{(r_p - r_f)}{\partial r_p}. \qquad (1)$$

In (1) r_p is the return on the asset or portfolio p, r_f is the risk-free rate and ∂r_p is the standard deviation of returns from asset or portfolio p. For further background and application, we refer to Sharpe (1966, 1975, 1992), Treynor and Black (1973), and Bodie, Kane, and Marcus (1993). Under positive market conditions, buying a currency with high interest rate and simultaneously selling a currency with low interest rate, after adjusting for volatility of the currency pair in question can generate significant positive returns. However, when crisis situations evolve, investors exit such money making strategies suddenly: as a result, significant losses can occur. In an effort to minimize these potential losses, we also developed a risk metric that evaluates the total risk by looking at various risk indicators across different markets. We use this risk metric to get timely signals of evolving crises and to flip the strategy from long to short in a timely fashion, to prevent losses and make further gains even during crisis periods.

Since our model is highly nonlinear (multi-modal), and for all practical purposes it can be perceived as a "black box" computational procedure, we need to utilize suitable global optimization technology and software to maximize the performance of the currency basket, based on our selection of key decision variables. Specifically, we use the LGO solver suite for global-local optimization with a direct link and interface to handle our Excel based currency trading model.

2. Model Description

For each currency pair included in this analysis, we calculate IRDAV as the interest rate differential between the high-yielding and low-yielding currencies, divided by the annualized standard deviation of the daily exchange rate returns calculated over a six-month period.

$$IRDAV = \frac{(i_A - i_B)}{\partial_{FXa/FXb}} . \tag{2}$$

In (2) i_A is the high(er) interest rate in country A, i_B is the low(er) interest rate in country B, and $\partial_{FXa/FXb}$ is the annualized standard deviation of the daily exchange rate returns between countries A and B. For further background, we refer to Çağlayan and Giacomelli (2005), Çağlayan (2003), Çağlayan and Giacomelli (2003), Çağlayan, and Kantor (2001, 2002), Normand *et al*. (2004). The major market currency pairs included in the sample are determined according to the liquidity and transaction volume of the Foreign Exchange (FX) pairs in currency markets. At the beginning of each month, we rank these currency pairs according to their IRDAV values, and we pick the top IRDAV-ranked FX pairs to compose the currency basket, where each currency pair in the basket receives an equal portfolio weight. The top IRDAV-ranked FX pairs constitute our basket for the month considered until new rankings are computed at the beginning of the following month. The positive "carry" positions in the basket are held until our risk metric (computed daily) reaches a certain threshold value, whereupon the basket is flipped to negative "carry" positions. In currency markets, timing the change from normal markets' *"search for yield"* status to crisis periods' *"flight to quality"* status is a crucial subject. Hence, investors need to be aware of sentiment changes in financial markets to better protect themselves against a sharp decline in the performance of positive "carry" trades. We attempt to gauge the timing of these sentiment shifts in the financial markets with our *risk metric*. In order to measure risk across a wide spectrum of markets, this risk metric includes six different proprietary risk measures, each representing a unique risk for liquidity, credit markets, emerging markets, equity markets, commodity markets, and currency markets. All of the chosen risk measures have given timely signals when to exit positive "carry" positions, and to reverse these positions – thereby making further gains even during crisis periods. To be more specific regarding the construction of the risk metric, on a daily basis, we first calculate Z-scores (number of standard deviations away from a 3-month average) for each of the six individual risk measures mentioned above:

$$Z_i = \frac{(RM_t^i - \mu_t^i)}{\partial RM_t^i} . \tag{3}$$

In (3) RM_t^i is the risk measure i in month t, μ_t^i is the 3-month rolling average of the risk measure i in month t, and ∂RM_t^i is the 3-month standard deviation of the risk measure i in month t. Then, we take the weighted average of the six selected Z_i scores to come up with the final daily reading on our risk metric. The weights on the individual risk measures that define each measure's importance in the overall risk metric will be calculated by using global optimization, to maximize the performance of the currency basket. The threshold overall Z score level, upon which the basket positions are flipped to negative carry from positive carry will also be optimized. One can argue that (due to their financial background) the six risk measures used in constructing the risk metric are not independent. The optimized weights attempt to take care of this problem, since optimization can potentially give a zero weighting to a risk indicator that is highly correlated with another measure but that does not perform as well as the other risk measure. The generic optimization approach would work also for other risk metric constructions in which certain parameters need to be optimized after their overall effect is evaluated by the ("black box") model.

In addition to the outlined general information about the formation of the basket and the risk metric, our model incorporates all the specifications for a full currency trading model, including transaction costs, stop-loss levels, and take take-profit levels. The reported returns are all transaction cost adjusted in the tables presented later on. Specifically, the model deducts 0.05% return from each trade in the basket, a realistic assumption given the size of the bid-ask spreads for most of the major currency pairs. Moreover, the model calculates the drawdown from the peak of returns and the accumulated returns from the bottom of returns to use stop-loss and take-profit levels efficiently. We prefer to apply stop-losses and takeprofits on the basket rather than on the individual currency pairs so that an extraordinary performance (negative or positive) in one of the currency pairs can be compensated by the performance of other pairs in the basket, without triggering stop-loss and take-profit signals frequently. Once a stop-loss or take-profit signal is triggered on the basket portfolio, however, the model requires a certain number of days to wait before re-entering the trades again. Since from a financial perspective there is no definite "scientific" answer on what a stop-loss or take profit level should be, and on how many days should one wait before re-entering trades after a stop-loss or take-profit level, we will let global optimization to determine those trade parameters as well, in order to maximize the overall performance of the currency basket. We define the information ratio *IR*

$$IR = \frac{R_{IRDAV}}{\partial R_{IRDAV}}. \tag{4}$$

Here R_{IRDAV} is the annualized and compounded full sample period return from IRDAV currency basket and ∂R_{IRDAV} is the annualized standard deviation of daily returns from IRDAV currency basket for the full sample period 1998–2009. Our proprietary Currency Trading Model (CTM can be summarized as follows.

Objective: max $IR = \frac{R_{IRDAV}}{\partial R_{IRDAV}}$; calculated from the Excel implementation of the CTM.

Constraint: $\sum_{i=1}^{6} w_i = 1$; w_i is the weight that risk measure *i* receives in the risk metric.

Decision variables, with corresponding (given) lower and upper bounds:

ncpl≤ncp≤ncpu; rmtl≤rmt≤rmtu; $0 \le w_i \le 1$ i=1,..,6; sll≤sl≤slu; tpl≤tp≤tpu; ndsl≤nds≤ndsu; ndtl≤ndt≤ndtu.

Here *ncp* is the number of currency pairs to be included in the basket; *rmt* is risk metric threshold level where positions are switched from "positive carry" to "negative carry", or vice versa; w_i are the weights of our six risk measures that appear in the aggregated risk metric; *sl* is the stop-loss level; *tp* is the take-profit level; *nds* is the number of days to wait after stop-loss; *ndt* is the number of days to wait after take-profit. The lower and upper bounds are denoted by adding *l* and *u* to the corresponding variable name.

CTM has been implemented in Excel as a stand-alone computational procedure with direct parameter sampling (input-output) possibility, but without access to gradient information. The embedded model functions leading to the calculation of the objective function are all continuous. In our numerical tests it has also become obvious that this "black box" model is multi-modal. Due to its outlined key features, the solution of CTM requires derivative-free global optimization software. Therefore, we use the Lipschitz Global Optimizer (LGO) software with a direct link to Excel to solve it.

3. Global Optimization of "Black Box" System Models with LGO

3.1. Problem Statement

We shall consider the continuous global optimization (CGO) model

$$min\, f(x) \quad \text{subject to}\ x \in D := \{x:\ l \le x \le u \quad g_j(x) \le 0 \quad j=1,...,m\}. \tag{5}$$

In (5) we apply the following notation and assumptions:

$x \in \mathbf{R}^n$ — n-dimensional real-valued vector of decision variables,
$f: \mathbf{R}^n \to \mathbf{R}$ — continuous (scalar-valued) objective function,
$D \subset \mathbf{R}^n$ — non-empty set of feasible solutions, a proper subset of $\mathbf{R}^n$,
$l \in \mathbf{R}^n$, $u \in \mathbf{R}^n$ — component-wise finite lower and upper bounds imposed on x,
$g: \mathbf{R}^n \to \mathbf{R}^m$ — m-vector of continuous constraint functions.

Without going into technical details which are outside of the scope of the present discussion, we note that the concise model formulation (5) covers many special cases. This specifically includes also the financial model discussed here, since we assume (only) a continuous model structure without requiring any further specifics of the actual model which may be a "black box".

3.2. The LGO Software Package for Nonlinear (Global and Local) Optimization

Let us briefly review the LGO solver suite that has been designed to address also "black box" problems as discussed above. In development since the late 1980's, LGO is currently available for a range of compiler platforms (C, C++, C#, Fortran), with seamless links to several optimization modeling languages (AIMMS, AMPL, GAMS, MPL), and to the leading high-level technical computing systems Maple, Mathematica, and MATLAB. For algorithmic and implementation details not discussed here, we refer to Pintér (1996, 2009, 2010a).

The overall design of LGO is based on the combination of global and local search strategies, with corresponding theoretical convergence properties. LGO hence can be used for both global and local (continuous nonlinear) optimization. Let us point out that LGO's derivative-free design is markedly different from other nonlinear optimization software packages that require explicit analytical model information to support model parsing and function type specific operations (such as rigorous bounding procedures). Of course, we do not claim that one design is "universally superior" to the other. A model function decomposition-parsing-bounding based approach supports the precise solution of a range of GO models which, however, have to be defined "only" in terms of a given set of possible component functions. In contrast to this approach, the design of LGO allows the handling of "black box" problems that will remain outside of the scope of the analytical global optimization approaches. In numerical practice LGO's global search options generate a global solution estimate(s) that is (are) refined by the seamlessly following local search mode(s). The expected practical result of using LGO – barring numerical problems caused by a "tricky" multimodal objective and/or difficult feasible set, poor model scaling, etc. which could impede any nonlinear optimization software – is a global and local search based high-quality feasible solution that meets at least the local optimality criteria. (The latter are theoretically guaranteed only under standard local smoothness conditions). At the same time, one should keep in mind that no global (or other) optimization software will "always" work satisfactorily, with default settings and under resource limitations such as time, model function evaluation, or other preset usage limits. Extensive numerical tests and an increasing range of practical applications demonstrate that LGO and its platform-specific implementations can find a close numerical approximation of the global solution not only when using standard "academic" GO test problems, but also in far more complicated, sizeable GO models.

3.3. The Excel-LGO Software Implementation

Recently, we developed an LGO solver link to Microsoft Excel with an easy-to-use worksheet interface to assist users in the model formulation process. Excel-LGO is described by the software documentation (Pintér, 2010b): therefore we only mention some key facts here. (We wish to point out, however, that the Excel-LGO link development is entirely independent from the Excel Premium Solver platform development by Frontline Systems.)

In order to use Excel-LGO, users need to have access to a personal computer with the following software: Microsoft Windows XP, Vista (or a more recent version); Microsoft Office 2003 or 2007 (or a more recent version), installed with .NET Programmability Support; and Microsoft .NET version 2 (or a more recent version). A typical (recommended) installation structure is shown below.

C:\EXCEL-LGO

\Documentation	Includes the User's Guide and optional technical notes;
\Models	Test examples and user models, in subdirectories;
\Work	Installation directory for the Excel-LGO runtime files.

4. Numerical Results and Discussion

The numerical results obtained for our IRDAV basket clearly show a significant improvement in the information ratio (*IR*) based performance of our currency basket after the optimization. Before doing formal optimization, by manually selecting values for the key decision variables, we were able to increase the information ratio of the IRDAV basket for the entire 1998–2009 sample period up to 1.81. Table 1 below shows the annual performance of the IRDAV basket as well the performance for the full sample period, together with manually selected values for the key decision variables, before the optimization.

Next, we present our optimization results in Table 2. One can see a very clear improvement in the performance of the IRDAV basket when the selected decision variable values are determined by global optimization. Specifically, if the decision variable values are determined by the LGO software, then we see that the objective function value has increased significantly to 2.71 (from 1.81) for the sample period 1998–2009. In the world of finance, this is an eye-opening 50% improvement in the overall performance of the currency basket. Table 2 shows the annual performance of the IRDAV basket as well the performance for the full sample period, together with the optimized values for the decision variables. The computational effort related to the optimization is over 19 hours on a (current average capability) laptop computer. This is due to two factors. First, the number of decision variables is 12: hence one should attempt a thorough global search in a 12-dimensional decision space. Based on our experience with LGO and other global optimization software, a direct sampling effort with tens or hundreds of thousands of sample points seems reasonable. Second, the function evaluations themselves are rather expensive, since each decision vector setting needs to be evaluated by the Excel implementation of the CTM. We also tried to use local optimization only from several starting points: the results clearly indicated that the "black box" model is indeed highly multi-modal.

Table 1. Performance of the IRDAV basket before optimization

	Annual Return (%)	Std. Deviation (%)	Information Ratio
1998	16.01	6.40	2.50
1999	9.18	4.91	1.87
2000	4.88	4.50	1.08
2001	7.59	5.26	1.44
2002	15.62	4.67	3.35
2003	12.95	5.00	2.59
2004	5.55	4.84	1.15
2005	8.51	3.96	2.15
2006	9.47	4.18	2.26
2007	13.28	7.63	1.74
2008	12.95	9.37	1.38
2009	15.52	8.50	1.83
1998–2009 Sample	10.90	6.01	1.81
Key Decision Variables		**Risk Metric Weights**	
Number of pairs in basket:	5	RM1:	0.1667
Risk Metric threshold:	1.25	RM2:	0.1667
Stop-loss level:	–2.50	RM3:	0.1667
Take-profit level:	8.00	RM4:	0.1667
Number of days to wait after stop-loss:	5	RM5:	0.1667
Number of days to wait after take profit:	1	RM6:	0.1667

Table 2. Performance of the IRDAV basket after global optimization

	Annual Return (%)	Std. Deviation (%)	Information Ratio
1998	15.55	4.12	3.78
1999	10.97	4.16	2.64
2000	4.76	3.95	1.21
2001	11.10	3.48	3.19
2002	13.12	3.59	3.66
2003	19.15	4.16	4.61
2004	12.57	4.22	2.98
2005	9.37	2.68	3.50
2006	8.49	3.45	2.46
2007	11.77	4.94	2.38
2008	6.53	6.83	0.96
2009	30.05	7.66	3.92
1998–2009 Sample	12.61	4.65	2.71

Key Decision Variables		Risk Metric Weights	
Number of pairs in basket:	12	RM1:	0.206
Risk Metric threshold:	1.73	RM2:	0.000
Stop-loss level:	–1.84	RM3:	0.073
Take-profit level:	13.88	RM4:	0.264
Number of days to wait after stop-loss:	12	RM5:	0.000
Number of days to wait after take profit:	15	RM6:	0.457

6. Conclusions

In this paper we have introduced a new model to assist investors in currency markets and discussed its subsequent calibration by global optimization. Since the model has been developed using Excel, we have used the Excel-LGO software to optimize our selection of key decision variables. After an introduction to the model, we presented detailed numerical results based on actual market data. From a practical optimization point of view, our results show the validity of the approach followed. From the point of view of the financial application area, we have been able to produce a high-quality trading strategy that is applicable in currency markets. Our forthcoming research work will expand upon the current model and its results, with the objective to make available a robust and efficient tool for financial decision making.

Acknowledgements

We wish to acknowledge the valuable contributions of Baris C. Sal and Frank J. Kampas to the Excel-LGO software link development project.

References

Bodie, Z.; Kane, A., and Marcus, A. J. 1993. *Investments*, 2nd Edition. Richard D. Irwin, Homewood, IL.

Çağlayan, M. O. 2003. Alternative LCVI Trading Strategies, *JPMorgan Investment Strategies* 8: 1–6.

Çağlayan, M. O. and Giacomelli, D. 2003. Finding Lower-risk FX Carry Trades, *JPMorgan Foreign Exchange Research Note* 1–2.

Çağlayan, M. O. and Giacomelli, D. 2005. Trading JPMorgan's Carry-to-Risk Currency Model in G-10 and Emerging Markets, *JPMorgan Foreign Exchange Research Note* 1–16.

Çağlayan, M. O. and Kantor, L. 2001. New LCPI Trading Rules: Introducing FX CACI, *JPMorgan Investment Strategies* 3: 1–6.

Çağlayan, M. O. and Kantor, L. 2002. Using Equities to Trade FX: Introducing the LCVI, *JPMorgan Investment Strategies* 7: 1–4.

Normand, J.; Çağlayan, M. O.; Ko, D.; Panigirtzoglou, N., and Shen, L. 2004. JPMorgan's FX and Commodity Barometer, *JPMorgan Investment Strategies* 10: 1–32.

Pintér, J. D. 1996. *Global Optimization in Action*. Kluwer Academic Publishers, Dordrecht.

Pintér, J. D. 2009. Software Development for Global Optimization. In: Pardalos, P. M. and T. F. Coleman, eds. *Global Optimization: Methods and Applications*, p. 183–204. *Fields Institute Communications Vol. 55*. Published by the American Mathematical Society, Providence, RI.

Pintér, J. D. 2010a. *LGO – A Model Development and Solver System for Nonlinear (Global and Local) Optimization. User's Guide.* (Current version) Distributed by Pintér Consulting Services, Inc., Canada. For professional information summary. Available from Internet: <http://www.pinterconsulting.com>.

Pintér, J. D. 2010b. *Spreadsheet-Based Modeling and Nonlinear Optimization with Excel-LGO – User's Guide*. (With technical contributions by B.C. Sal and F.J. Kampas) Distributed by Pintér Consulting Services, Inc., Canada. Available from Internet: <http://www.pinterconsulting.com>.

Sharpe, W. F. 1966. Mutual Fund Performance, *Journal of Business*, January 1966, p. 119–138. doi:10.1086/294846

Sharpe, W. F. 1975. Adjusting for Risk in Portfolio Performance Measurement, *Journal of Portfolio Management*, Winter 1975, pp. 29–34.

Sharpe, W. F. 1992. Asset Allocation: Management Style and Performance Measurement, *Journal of Portfolio Management*, Winter 7–19. doi:10.3905/jpm.1992.409394

Treynor, J. L. and Black, F. 1973. How to Use Security Analysis to Improve Portfolio Selection, *Journal of Business*, January 66–85. doi:10.1086/295508