Designing a System to Analyze Portfolio Risks and to Determine Optimum Margin Requirements

Serkan Kaba
Backbase R&D B.V.
INIT Building - Het Ei Jacob Bontiusplaats 9
1018 LL Amsterdam - NL

Murat ACAR
ISE Settlement & Custody Bank Inc.
Sisli Merkez Mahallesi, Merkez Caddesi, No: 6
Sisli/Istanbul TURKEY

ABSTRACT
In this paper, we focus on designing a real-time risk management system. The system will be using CME SPAN and will consist of a multithreaded daemon process to evaluate portfolios using SPAN calculation engines and programs to determine parameters fed to SPAN. SPAN parameters can be estimated by several methods using historical data. One of the goals is to determine the best method for each parameter for every asset class. The other goal is to develop a responsive system to analyze portfolios and orders in real-time and to update the portfolio risks accordingly. Ultimately when these two parts are combined, we'll be constructing a real-time system to evaluate portfolio risks and to determine optimum margin requirements.

General Terms
Finance, exchanges, computer aided decision making

Keywords
Financial risk management; Derivatives; Portfolio analysis; Estimation methods; SPAN

1. INTRODUCTION
Uncertainties and risk are often encountered in finance. Risk is a result of unfavorable effects of events and outcomes that were not foreseen which affects individuals, commercial firms, financial markets and society at large scale. As a result, a definition of risk involves

- consequences,
- their probabilities and their distribution,
- individual preferences and
- collective, market and sharing effects.

These elements of risk apply to other fields as well, not only finance. Each field provides its own approach to measurement, valuation and minimization of risk which is motivated by psychological needs and the need to handle problems that result from uncertainty and the unfavorable consequences they may occur [1].

Financial risk management is a process to deal with the uncertainties resulting from financial markets. Practical measurements of risk are extremely important for financial risk management. VaR or 'value at risk', is a widely applied measure of risk. VaR is a technique for determining the value loss that the derivatives portfolio could hypothetically suffer with some given probability and assumptions about the statistical properties of the underlying price processes. The wide usage of the VaR-based risk management (VaR-RM) by financial as well as nonfinancial firms stems from the fact that VaR is an easily interpretable summary measure of risk and also has an appealing rationale, as it allows its users to focus attention on "normal market conditions" in their routine operations. However, VaR estimates not only serve as summary statistics for decision makers but are also used as a tool to manage and control risk [2,3].

Margins are security deposits required by brokers from their customers for certain kinds of transactions. These margins serve to cover losses that may result from adverse price movements affecting the customer's net balance. The amount of margin requirement depends on the broker's estimate of his probable loss and market exposure of the customer portfolio if he must close out his customer's position owing to the unwillingness or inability of the customer to increase the size of the security deposit [4].

Along with price limits and capital requirements, the margin mechanism ensures the integrity of derivatives markets. The existence of margins decreases the likelihood of customers' default, brokers' bankruptcy and systemic instability of derivatives markets. Initial deposits and subsequent variation margin payments are designed to guarantee that investors will perform according to the terms of the contract. Setting a high margin level thus reduces default risk. The risk of default, however, cannot be completely eliminated, because margin deposits cannot fully cover all adverse price changes. On the other hand, if the margin level is set too high, then the futures market will be less attractive for investors. Because maintaining funds on margin deposits amounts to a transaction cost on traders, an increase in margin requirements can be expected to decrease trading activity and thus brokers' commissions. More research should be done to assess the costs and benefits of margins [5]. The margin starts at an initial level in, generally, the form of Treasury bills. It is adjusted every day to reflect the day's gains or losses. Should the margin fall below a maintenance level, the trader will ask the investor to add funds to meet margin requirements. If the investor fails to meet such requirements, the trader cuts his losses by reversing the position.

Central counterparty clearing houses (CCPs) were established originally to protect market participants from counter-party risk in derivatives markets. The CCP interposes itself in transactions by becoming the buyer to every seller and the seller to every buyer. The original bilateral contracts between market participants are extinguished and replaced by new contracts with the CCP. As a result, bilateral counterparty risks are replaced with a counterparty risk against the CCP [6].

The Istanbul Stock Exchange (ISE) was established in late 1985 for the purpose of ensuring that securities are traded in a secure and stable environment, and commenced to operate in 1986. The derivatives market began operation in 2001. In 2005, Turkish Derivatives Exchange (TURKDEX) started its operation as a successor. ISE will reinitiate its derivatives market including options. As being the CCP in Turkey, ISE Settlement & Custody Bank will handle risks and margins of ISE Derivatives Market [7].

The Standard Portfolio Analysis of Risk (SPAN) system is a sophisticated methodology that calculates margin requirements by analyzing the what-if's of virtually any market scenario. Developed and implemented in 1988 by Chicago Mercantile Exchange (CME), SPAN was the first system ever to calculate margin requirements exclusively on the basis of overall portfolio risk at both clearing and customer level. In the years since its inception, SPAN has become de-facto standard for portfolio risk assessment. SPAN evaluates overall portfolio risk by calculating the worst possible loss that a portfolio of derivative and physical instruments might face over a specified time period (typically one trading day). This is done by computing the gains and losses that the portfolio would incur under various market conditions. At the core of the methodology is the SPAN risk array, a set of numeric values that indicate how a particular contract will gain or lose value under various conditions. Each condition is called a risk scenario. The numeric value for each risk scenario represents the gain or loss that that particular contract will experience for a particular combination of price (or underlying price) change, volatility change, and decrease in time to expiration [8]. Table 1 shows 16 scenarios of price and volatility movement by PSR and VSR values accordingly.

Fig. 1 shows the architecture of the real-time risk management system using SPAN done in following steps.

- Trades are fed to clearing system as soon as they're matched in exchange.
- Trades are processed in clearing system and new positions are calculated.
- New positions are polled by SPAN daemon for margin calculations. For efficiency multiple SPAN calculation engines are used.
- Margin requirements are sent back to clearing system and ac-count risk is updated accordingly.
- Notification is sent to exchange if the account becomes risky.

Table 1. 16 scenarios of SPAN.

Scenario No.	Price change (in terms of PSR)	Volatility change (in terms of VSR)	Scenario Weight
1	0	1	1
2	0	-1	1
3	1/3	1	1
4	1/3	-1	1
5	-1/3	1	1
6	-1/3	-1	1
7	2/3	1	1
8	2/3	-1	1
9	-2/3	1	1
10	-2/3	-1	1
11	1	1	1
12	1	-1	1
13	-1	1	1
14	-1	-1	1
15	3	0	0,32
16	3	0	0,32

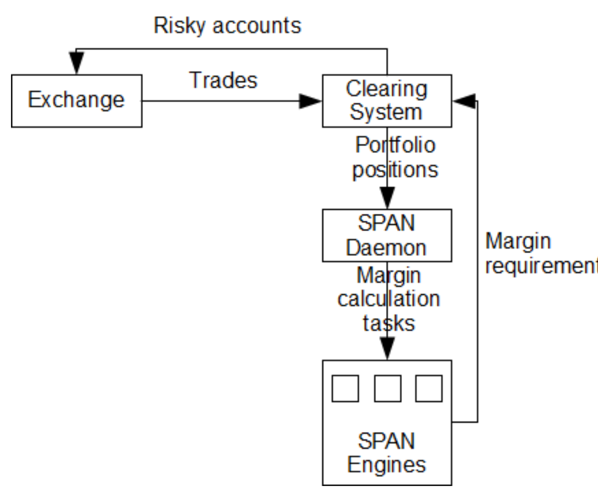

Fig 1: Architecture of real-time risk management system.

Zooming to SPAN details the flow of SPAN processes is as follows (Fig. 2)

- Requestor polls clearing system for new requests and puts the requests into MQ.
- Dispatcher gets messages from MQ sequentially and dispatches the message to an available SPAN engine.
- Each SPAN engine calculates the margin requirement for the messages assigned to it and puts the result message into MQ.
- Responder gets result messages from MQ sequentially and posts them to clearing database.

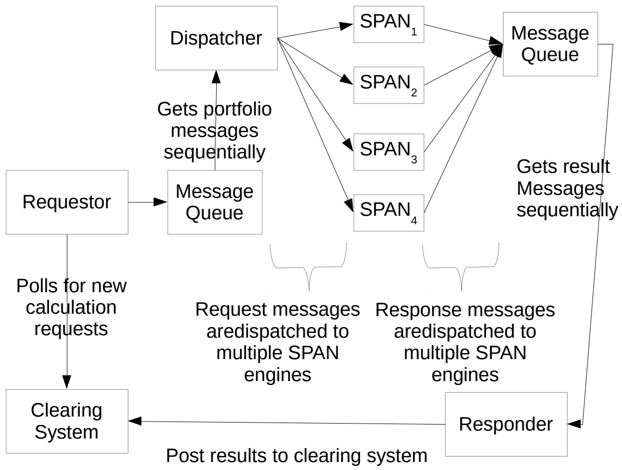

Fig. 2: Architecture of real-time risk management system.

This system designed for post-trade risk management can also be used in pre-trade risk management by feeding hypothetical positions calculated by applying orders onto existing positions.

SPAN parameters such as price scan range (PSR), volatility scan range (VSR), intercommodity spread credit, intra-commodity spreading (intermonth) risk charge, short option minimum (SOM) , delivery (spot) risk can be estimated by several methods using historical data. To determine the best method for each parameter, the efficiency of the methods is tested against extreme conditions. We study PSR estimation methods in this paper.

2. LITERATURE OVERVIEW

Bear examines different margin levels are associated with the price behavior differences of certain commodity futures. He uses margin levels as a basis for rational subgrouping of selected commodity futures. His results of observed dependency and distribution properties verify the hypothesis that setting margin levels too high at certain times to attract speculators is sufficient randomize price behavior [9].

Telser finds that an extreme increase of the margin requirement can reduce market liquidity. This happens because the higher margin raises the cost of trading in the market so there is less trade. A reduction of trade increases the dispersion of the distribution of market clearing prices thus raising the cost of using the futures market which reduces use of the market. On the other hand, margins do react to natural market forces and can change. Such changes are consistent with a competitive equilibrium that determines the terms of trade in a futures market which include the commission and the margin [4].

Fishe constructs a model of futures market trading where margins act as security deposits against default. The primary prediction of the model is that the open interest of futures contracts is inversely proportional to margin requirements [10].

Furbush and Poulsen do not support a policy decision of higher margins in futures markets. Though margins do impose costs on traders, the effect of margin changes on volume is difficult to evaluate and there is no evidence of a systematic relation between different margin levels and the trading volume. Even if low margins encourage speculative trading, there is no empirical support for the view that speculators raise price volatility and theoretical reasoning supports the view that speculators provide liquidity to markets. Recent evidence, although limited, suggests that higher margins for stock index futures are not associated with lower price volatility in futures markets [11].

Dutt and Wein's study deals with the empirical estimation of the effect of margin requirements on trading volume. Although theory supports the idea that margin requirements impose a cost and will likely reduce trading volume, their empirical examinations generally failed to find this relationship [12].

Figlewski describes the current structure of margin requirements on stocks and equity-based derivative securities and the principles used in setting these requirements. He discusses alternative procedures which may be easier, more equitable to apply, and more effective in meeting the most important objectives of margin setting [13].

Gay et. al explore the margin setting behavior on futures exchanges. The essential argument of the article led to the observation that exchanges should set margins on their different commodities contracts at levels such that the probability of the price movement exceeding the margin during a given time interval was constant across contracts [14].

Tomek's study provides a detailed description of the institutional framework of self-regulation, appraises the role of margins in protecting against contract defaults, and analyzes other consequences of changes in margins [15].

Edwards and Neftci's paper leads to two major conclusions: There exist statistically significant relationships among extreme price changes in different commodities and the existence of interdependence (or jointness) among the probability distributions of extreme price changes may result in inappropriate margin levels being imposed on customers who simultaneously trades a variety of commodities (or futures contracts) [16].

Harmantzis tests the performance of different models for value at risk (VaR) and expected shortfall (ES) estimation [17].

3. MATERIALS AND METHODS

We use ISE 100 Index data from 1990 to 2010 in Fig. 3 and determine the best method to estimate PSR parameter for ISE100 futures contracts. We use Formula 1 to obtain the daily return series in Fig. 4 for ISE 100 Index.

$$r_t = \frac{x_t}{x_{t-1}} - 1 \qquad (1)$$

For each of the methods except historical simulation, a 500 day window of daily returns is used to estimate the PSR for the next day. A confidence level of 99.5% is used, which corresponds to 1 or 2 exceedances per year, an acceptable rate for a clearinghouse. We used CAViaR variations, EGARCH(1,1), extreme value, historical simulation, risk metrics, hybrid of historical simulation and risk metrics models, variance-covariance methods to estimate PSR values. We compare each day's margin value with the actual return and count exceedances and calculate exceedance rates for each method by using Formulae 2,3 and 4.

$$e_t = \begin{cases} 1, |r_t| > |VaR_t| \\ 0, |r_t| \le |VaR_t| \end{cases} \qquad (2)$$

$$\text{Total exceedance} = \sum_{t=1}^{T} e_t \qquad (3)$$

$$\text{Exceedance rate} = \frac{\sum_{t=1}^{T} e_t}{T} \qquad (4)$$

To judge the methods, we compare the exceedance rates and average margins obtained from the methods. Among these methods, we will further discuss EGARCH, extreme value, historical simulation and asymmetric CaViaR which outperformed in terms of exceedance rates.

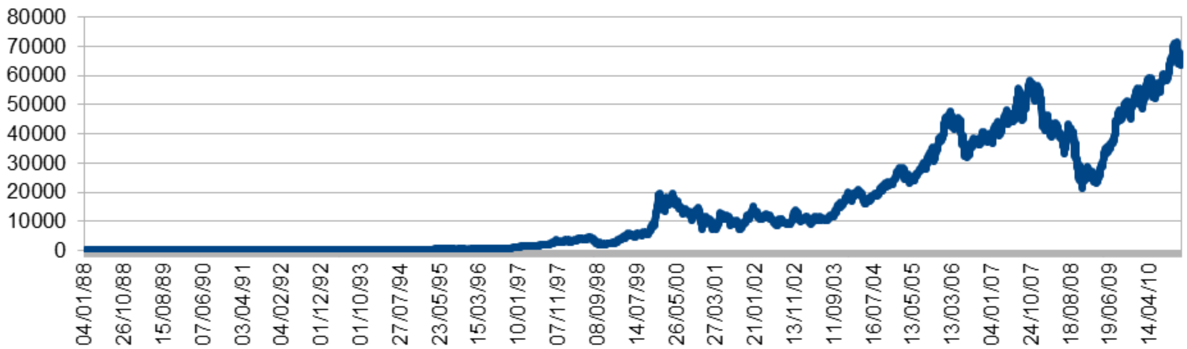

Fig. 3: ISE 100 Index series

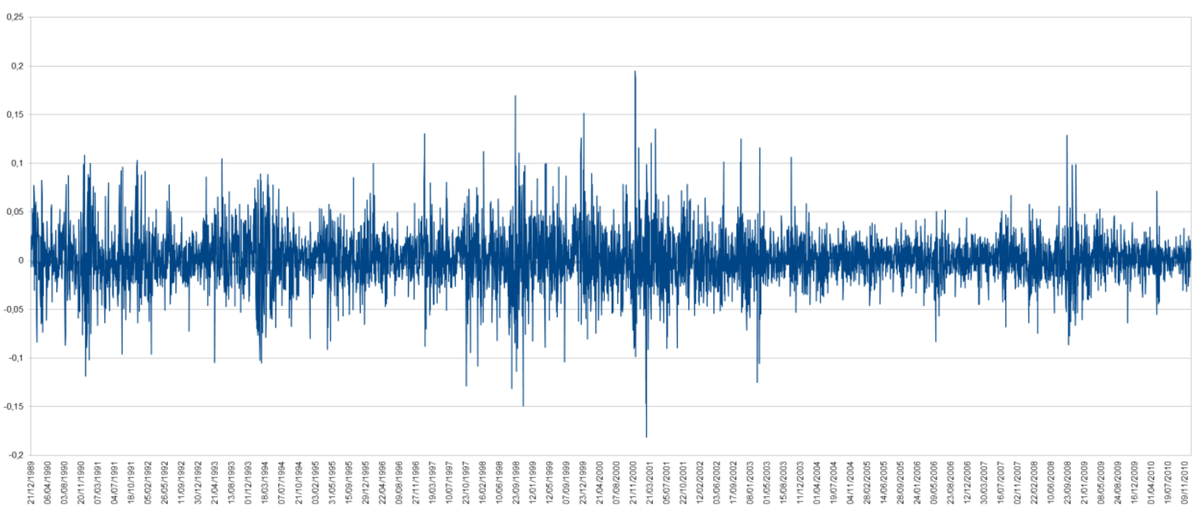

Fig. 4: ISE 100 daily return series

3.1 Extreme Value

Extreme value based methods try to model the fat tails in returns, in other words high possibility of bigger losses. Extreme value based methods determine characteristics of the tail instead of the entire distribution. Our approach uses Peaks Over Threshold method which uses values above a high threshold and Generalized Pareto Distribution (GPD) as limiting distribution of these values.

3.2 Historical Simulation

Historical simulation is a nonparametric VaR estimation method, which directly uses historical data to estimate the current market conditions. A confidence level of 1% estimated using a 500 day window returns 5th worst return in that period as VaR [18]. As an exception to using 500 day windows in other methods, we use 750 day window which is recommended by Basel II guidelines.

3.3 GARCH

GARCH model established by Bollerslev estimates the current volatility by using recent volatility values and returns by using Formula 5 [19].

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (5)$$

The error term in the model can be estimated as

$$\varepsilon_{t-i} = r_{t-i} - \mu_{t-i} \quad (6)$$

$$\mu_{t-i} = \frac{1}{t-i} \sum_{m=1}^{t-i} x_m \quad (7)$$

In our tests we use GARCH(1,1) since using higher lags do not improve the results. Using the volatility obtained, with the assumption that returns are distributed conditionally normal, we calculate the PSR as follows:

$$VaR_t = 2.576\sigma^2 \quad (8)$$

3.4 EGARCH

GARCH model considers positive and negative returns equally; in other words, positive and negative returns have symmetric effect on volatility. In practice, positive and negative returns have asymmetric effect on volatility. For equities, volatility increases more with a negative return shock where as foreign exchange volatilities exhibit an opposite relationship.

EGARCH model established by Nelson is a form of GARCH which considers these asymmetries. EGARCH(1,1) is specified as follows where ε_{t-1} is the error term [20].text. For two addresses, use two centered tabs, and so on. For three authors, you may have to improvise.

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_{1a} \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha_{1b}\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \mathrm{E}\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} \right] \right) + \beta_1 \ln(\sigma_{t-1}^2) \quad (9)$$

Using Student's t as return distribution gives better results in our tests.

3.5 Asymmetric CAViaR

Conditional autoregressive value at risk (CAViaR) methods introduced by Engle and Manganelli focus on behavior of a quantile. They model quantiles autoregressively [21]. The one which outperforms in our tests is the asymmetric variation which takes into account asymmetric effect of returns on volatility is as follows:

$$VaR_t = \beta_1 + \beta_2 VaR_{t-1} + \beta_3 (x_{t-1})^+ + \beta_4 (x_{t-1})^- \quad (10)$$

where $(y)^+ = \max(y,0)$

and $(y)^- = -\min(y,0)$

The unknown parameters are estimated using regression quantile framework.

4. FINDINGS

As shown in Table 2, when these methods tested against near term data (2004-2010), none of the methods is able to meet the 5‰ exceedance level. Extreme value and EGARCH, come close to this performing below 1% exceedance rate. Next best performers are CAViaR asymmetric and historical simulation performing below 1.5% exceedance rate.

Table 2: Performances of the methods for near term data

Method	Exceedence Count	Exceedence Rate	Average Margin	Max. Margin	Min. Margin
CaViaR Adaptive	40	2.30%	5.32%	19.30%	0.01%
CaViaR Assymetric	24	1.38%	5.20%	16.76%	2.07%
CaViaR IGarch	41	2.36%	5.30%	19.35%	0.00%
CaViaR Symmetric	33	1.90%	5.57%	25.67%	2.41%
Egarch Tdist	16	0.92%	5.94%	16.80%	3.07%
EGarch	35	2.01%	4.75%	13.35%	2.14%
Garch	30	1.73%	4.84%	14.57%	2.66%
Extreme Value	10	0.58%	8.84%	11.90%	4.11%
Historical Simulation	26	1.50%	6.87%	11.60%	4.26%
Hybrid Model	162	9.32%	3.12%	5.27%	2.21%
RiskMetrics	30	1.73%	5.22%	9.53%	3.92%
Variance Covariance	33	1.90%	5.25%	6.82%	4.04%

Examining results obtained from long term data (1990-2010) in Table 3, we see that exceedance rates for extreme value, EGARCH and historical simulation decreased slightly, whereas that of CAViaR asymmetric decreased drastically. We can conclude that CAViaR asymmetric could have performed better for earlier years of ISE and other 3 slightly underperformed in the near term.

Table 3: Performances of the methods for long term data

Method	Exceedence Count	Exceedence Rate	Average Margin	Max. Margin	Min. Margin
CaViaR Adaptive	129	2.60%	7.65%	28.06%	0.01%
CaViaR Assymetric	105	2.12%	7.56%	32.17%	1.74%
CaViaR IGarch	131	2.64%	7.54%	27.93%	0.00%
CaViaR Symmetric	98	1.98%	7.65%	32.77%	2.32%
Egarch Tdist	44	0.89%	8.92%	36.63%	3.07%
EGarch	108	2.18%	6.77%	25.20%	2.14%
Garch	101	2.04%	6.82%	28.77%	2.66%
Extreme Value	25	0.50%	11.07%	17.40%	4.11%
Historical Simulation	59	1.19%	9.24%	14.75%	4.26%
Hybrid Model	537	10.84%	4.17%	7.55%	2.21%
RiskMetrics	109	2.20%	7.18%	15.01%	3.92%
Variance Covariance	122	2.46%	7.20%	10.30%	4.04%

When we take into account average margins, we see that extreme value comes with a price, higher margin rates. Long term margin averages of the best perfoming models, extreme value and EGARCH, are 11% and 8.9% respectively, way above the 7.5% maintenance margin rate currently used. Near term averages are more acceptable 8.8% and 5.6% respectively. Analyzing average margins, since both methods cause exceedances below 1%, approximately 2 exceedances per year, we can say that EGARCH can be more usable since it produces much lower margin rates. Fig. 5 shows the margin rates produced by best performing methods against the current margin rate and the return series.

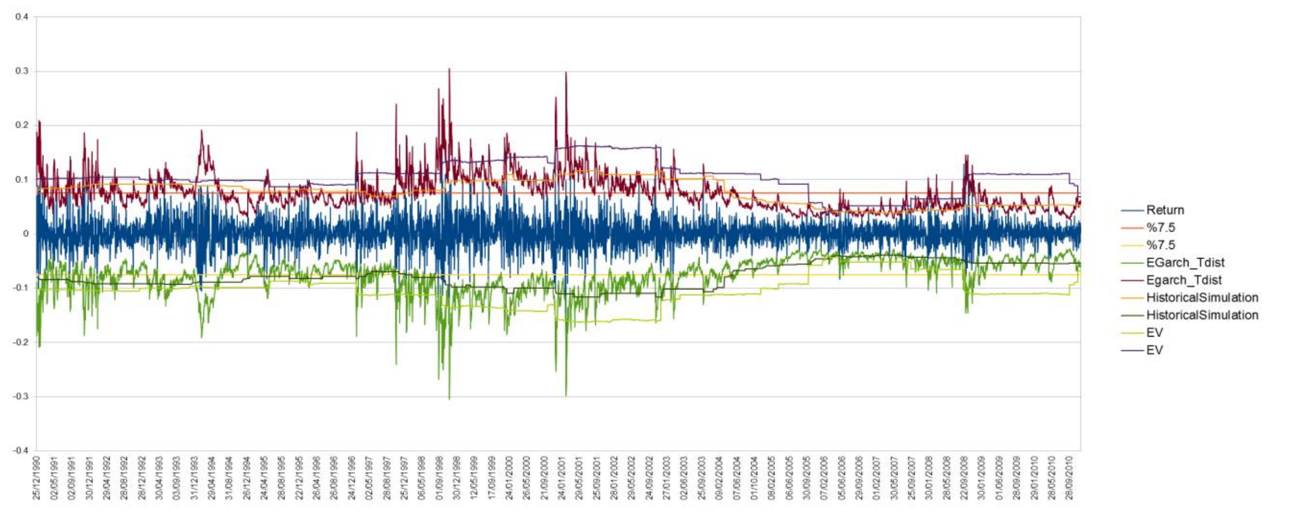

Fig. 5: Daily return series and margin rates

5. CONCLUSIONS

In this paper, we presented a methodology for estimating PSR parameter for SPAN because it's important for a risk management system to calculate optimum margin rates. PSR estimation methods can be further compared by analyzing other characteristics such as margin variance. Margins changes can be decreased by smoothing, in other words discarding tolerable changes in margin levels. The other parameters of SPAN that we mentioned can be estimated using similar methods. Also to check the validity of the chosen method these tests should be run periodically. Improvement in IT, especially in hardware power will allow to do so.

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