ETF-Portfolio-Construction: The Camel-Strategy

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"A camel is a horse designed by committee"
(popular quote, see http://en.wikipedia.org/wiki/Design_by_committee)

Trading in the Sibyl-Fond is separated in 3 independent strategies. 40-60% of the money is invested in an ETF-Portfolio. This portfolio is a trend-follower. It should basically follow the market in a damped and hence risk-reduced fashion. Zero-15% of the fund is devoted to discretionary trading. The remaining money is invested in alternative strategies. These investments – like the Johnny Walker, Daiquiry, Mojito or Glen Strategy - are based on models of the Sibyl quant (see [1], [2], [3],[14]). They should exploit special market conditions and market-inefficiencies. This paper describes the ETF-Portfolio-construction.

Changes in Revision-2:
In Revision-2 a new block-sample method is used. This method is fully explained in [15].
In addition the previous version was implemented in C++. This version was rewritten from scratch in the new programming language Go [16]. Some experiences with this new language are presented.

Basic assumptions:

The portfolio should follow the market trend. Just a little bit better (aka positive Alpha) and with less risk/volatility. Otherwise one could simply buy once the SPY (S&P-500), go on holidays (or retire) and cash in the monthly money and the bonus. In fact, this simple and comfortable strategy would improve the performance of most hedge-funds.
The portfolio-weights of the ETF's should be reallocated every month. Shorter re-allocations increase the trading costs. Additionally one just adds the noise of the daily ups- and downs to the portfolio. It is well known that too frequent trading is one of the reasons for the disappointing performance of many funds. But one has to calculate forecasts for the covariance and the trend of the portfolio assets. It's possible to forecast the covariance. It's almost impossible to predict in a reliable way the return. But even the covariance does not form a stable time-series. I know from previous models, that the forecast-horizon of the volatility and hence also the covariance is limited to about 1 month. For longer horizons the long term value is the best guess. The 1-month horizon seems to be a good compromise.

The Covariance-Measure:

The covariance calculation follows the RiskMetrics-Standard (see [4]). The calculation uses the returns of the last 2 years. But the values are exponentially-smoothed with an alpha of 0.97. Recent returns get more weight. An alpha value of 0.97 means, that most of the information/weight is from the last 60 trading days (the last quarter). The value of 0.97 is the usual standard setting. Another popular value is 0.94. This places more weight on recent data. But the efficient time-window of 30 trading days seems to be too small.
The quarterly time-window is also in agreement with the results in [5]. I have analyzed the

periodogram of returns and volatility. There is in most equities a clear identifiable yearly and quarterly cycle present.
The RiskMetrics Covariance-Matrix calculation has the important practical advantage, that the Cholesky-Matrix-Decompostion always exists (at least theoretically, practically one can run into numerical problems if 2 or more ETF's are highly correlated). The Cholesky-Decomposition is the square-root of a matrix (see [6]). The square-root is needed to generate common return-scenarios which reflect the covariance/correlation between the ETF's.
For the second block-sample method of Rev.-2 no direct covariance matrix is used. The correlation of the assets is implicitly taken into account by the block-sample.

The Camel Trend Calculations:

For generating future scenarios one needs the covariance between the ETF's and the trend of the individual assets. The Covariance-calculation is a de-facto standard and relative reliable. This can't be said for the trend. According the standard model markets form a martingale. The best prediction of the future is the current price. For a portfolio-construction this would boil down to the simple rule: Select the asset(s) with the lowest volatility. Invest all your money in SHY (Short-Term US-Treasuries). SHY is a low risk but also low fun investment. Practically the situation is not so bad. It is well known, that asset prices have momentum (a detailed historic analysis can be found in the book by A.Ilmanen [7]). But the detailed nature of the momentum is less clear. The trend calculation addresses this problem with the Camel-approach. Although real-life committees have a bad reputation, properly designed decision-theoretic committees have attractive statistical properties. The decision error is under relative mild assumption reduced. The two main requirements are: Each committee-member must have a positive decision power (it must not be systematically wrong). The decisions should be as uncorrelated as possible.
It is also well known, that portfolio-models have the tendency for overconcentration. They tend to pick a few favorite assets (with high trend). Several methods have been proposed to circumvent this problem (see [9]). To my surprise I have not found any references to a committee approach. A committee improves in a natural way diversification (in standardization-committees this is a bad effect). In the Black/Litterman approach the human sets prior values. A high weight of the priors ensures also a proper diversification. In the camel approach the burden is taken from the shoulders of the human. It's the trend-committee which should diversify.

The trend-committee consists of 4 methods/members.

1) Local Linear Regression:

The trend is forecasted with a local-linear regression. The regression takes the last 200 trading-days into account. But more recent values get a higher weight. Like for the covariance-calculation the information is basically restricted to the last quarter. Local-Linear Regression is a well known semi-parametric regression method. One can model relations which show a modest non-linear behavior by a linear-relation. The method uses quite effectively the local-information.

2) Double Exponential Smoothed Forecast:

This method is also known as the Holt-Winters-method. It is one of the oldest and also one of the most popular forecasting methods. The method is rather robust and was the winner in several forecasting competitions (see [8]). The overall idea is similar to the Local-Linear-Regression. The method takes also the last quarter into account. But the mathematical details and behavior are somewhat different.

The two methods have a significant correlation (which is not optimal for a decision committee). But the combination of the 2 forecasts adds nevertheless some additional value.

3) The Independent Block-Sampling-Method with Daily Data.

Block-Sampling is a forecast-method which was developed by this author (see [10]). One samples returns from the past year (or any other reasonable time period). This is done also in usual Risk-Calculations (VaR). But the sampling is not done randomly. One calculates the current regime.
The first sample along a Monte-Carlo path is taken from the same regime in the past. In the next step one uses the last day of the block as the current state. One looks-up the regime of this day and selects again a block from the same regime. This process is repeated till the end of a simulated path is reached.
Since Rev-2 some details of this process have been (hopefully) improved (see [15]). The regime classification was before based on the realized volatility of each ETF. Now it is the Implied-Volatility-Term-Structure IVTS. The IVTS is the ratio between the VIX and its 3-month cousin the VXV. The IVTS has several advantages. The must notable is simplicity and speed. But it uses also the expectation of the market (for the details see [15]). In the previous version the block-size has been variable. The new one uses a fixed block-length of 5. I could not notice any relevant differences between the 2 methods. So I selected the simpler fixed-length approach. In the previous implementation the sampling was done from a window of 252 (1 year) trading days. Since Rev. 2 the window is extended to 378 (1.5 years). The longer window performed better in forecasting experiments.
The behavior of the first 2 methods and Block-Sampling is quite different (which is a desirable feature). The regression methods take mainly the last 3 months into account. Block-Sampling uses the information (the momentum) of the last 1.5 years. But it weights/discriminates according the current regime.
In 3) the scenario of each asset is calculated independently. One has therefore to multiply the scenarios with the Cholesky-Decomposition of the correlation matrix.

4) The Time-Synchronized Block-Sampling-Method with Daily Data.

In the previous implementation the second block-sample method was done with High-Frequency data. HF-Data improve the accuracy of the volatility calculation. But impose problems of their own.
The method was therefore replaced with the much simpler IVTS method of 3). But in 4) the scenario generation is separated in two steps. In the first step only the sample-dates along each path are calculated. In the second step the return-scenarios for all assets are generated from the same trading-days. Hence the correlation structure is preserved. There is no need to multiply with the Cholesky. The result is nevertheless not the same. The Risk-Metrics correlation-matrix reflects mainly the correlation of the last quarter. This approach uses in contrast the correlation of the full window-length of 1.5 years. The weight is not time but regime based. The first block is from the same regime than the current one. The regime can be different at the end of the block and hence the following blocks can be from different regimes. But especially for short paths historic periods with the same regime than the current one get a significant higher weight. This is after all the purpose of the regime-based block-sample. It is well known that the correlation depends on the regime. In times of trouble correlation increases. Method 4) models this behavior. The advantage of method 3) is to be more up-to-date. It reflects better the current correlation structure.
Methods 3) and 4) are relative similar. But the combination of the 2 block-sample methods adds nevertheless some additional value.
One could also vary the historic-window or the regime-thresholds. But calculating with a slightly different correlation structure seemed to be preferable.

Scenario-Generation:

For the first two methods one uses the trend as calculated by the regression model. For the variance the common covariance calculation with the RiskMetrics method is used. Both values are plugged in a method which generates random-values according a Student-t distribution with 5 degrees of freedom. The random values have the same mean (trend) and the same variance than the calculated values. The standard approach is to generate the scenarios with a normal distribution. But it is well known that returns have fat-tails. This approach underestimates the risk of large negative returns. The Student-t is a widely used distribution with fat-tails. One can easily tune the size of the tails by the degrees of freedom. I have found in previous studies that 5 degrees of freedom are a reasonable approximation for the tails of most asset-returns.
Scenario-Generation is especially easy for the Block-Sample methods. Only simply takes the returns of the full Monte-Carlo paths. It is a parameter-free method. The distribution of these returns matches automatically the empirical distribution of the historic values. The only assumption is that Block-Sampling is a reasonable model for the future behavior.

To generate for each of the first 3 models the final scenario, one has to multiply the individual asset-scenarios (which are independent from each other) with the Cholesky-Decomposition of the Covariance/Correlation matrix. This gives a matrix of scenarios with the correct correlation structure. Method 4) generates the correlation-structure already directly.

The Optimization-Criterion:

The mean-variance criterion of Markowitz is the usual optimization criterion. The implicit assumption of this criterion is: The asset-returns have a multidimensional Normal Distribution. This is – by construction – not the case for the 4 different scenarios. The scenarios of model 1 and 2 follow a Student-t distribution. The Block-Sample scenarios are in general skewed and fat-tailed. The optimizer uses therefore the Omega-criterion (see [12],[13]). Omega is a generalization of mean-variance. In case of a multinormal distribution it boils down to the Markowitz. The assumptions of the Markowitz criterion are not very realistic. But the calculation of the optimal solution is relative straightforward. This was in the 1950s an essential practical point. With modern computing power it’s less important. There exists no simple algorithm for an Omega-optimized portfolio. The optimizer uses the Differential Evolution heuristic. This heuristic is also used in the statistical R-package for general portfolio-optimization. The heuristic is simple to implement and efficient. It’s probably a better choice than the heuristic used in [13].
The optimizer calculates for each of the 4 models the optimal solution. To prevent the overconcentration to a few seemingly very attractive assets a maximum weight can be set. The default value is a maximum weight of 20%. The final weight of an asset is the mean of the 4 committee members. It can happen (and it happens) that one model gives an ETF a weight of 20%, whereas another model does not take the ETF at all into account. Only in exceptional cases is an ETF selected by all models. E.g. GLD (Gold) and TLT (20y treasuries) performed during the summer-2011 S&P crash quite strong and were selected unanimously. The general disagreement is on purpose. It creates a diversification effect among less clear assets.
The optimizer selects first from a list of currently 116 ETF’s (see the appendix for a full listing). Assets which have a weight less than a threshold (default 2%) are removed. The covariance matrix for the remaining ETF's is recalculated, the optimizer is run again. This process is repeated, till every ETF has a weight greater than the threshold.

These additional iterations take only a fraction of the time for the first round. Typically 20 out of the 116 ETF's remain after the first round. The method converges in 2 to 3 iterations. The running time of the optimizer is basically linear in the number of assets. The iteration stops also when a minimum number of assets is reached. This is currently set to 8. I can happen, that the final selection has therefore an asset with a rather low weight. These assets are for trading ignored and the minimal weights are distributed to other assets.
Removing ETF's with low weight and recalculating the Covariance matrix improves the final result considerable. It is a well known problem that the covariance matrix contains due to its shear size a lot of noise. One estimates with k*n data (n^2)/2 parameters. The number of data and hence information grows linearly, the number of parameters quadratic. Reducing n improves the data to parameter ratio.

Short-Selling:

The optimizer selects only non-negative weights. Hence no explicit short-selling is allowed. But this is practically no restriction. The ETF list contains short ETF's like RWM (Russel-2000), PSQ (Short-Nasdaq) and UDN (Short-$). Also the VIX based ETN's VXX and VXZ are effectively short the S&P-500. Including these inverse ETF's and restricting the weights to non-negative gave considerable better results than let the optimizer construct a general long-short portfolio. Programs are generally quite tricky to circumvent the meaning of constraints. The “cheating”-problem is worsened in a general long/short portfolio.

The Human Input:

Besides selecting some general parameters the method is so far fully automatic. There is no human intervention or human knowledge involved**.** Human intervention enters at the initial ETF list selection stage. A first selection filter was liquidity. Only liquid ETF's are considered. Each ETF must also have a history of at least 1 year. Otherwise the model has too less historic data for its calculations. Additionally there should be a broad diversification in the geographical but also asset-class domain: Equity-Indexes, Bonds, Treasuries, FX and Commodities. Additionally there are a few inverse ETF's (or ETN's) included, which allow the optimizer to go practically short. The number of inverse ETF's was on purpose restricted, to avoid the problem of excessive dummy-trades. Investing in the long and short ETF of the same index. The optimizer can reduce in this way quite effectively the variance.

It is not the task of the human to select ETF's with good momentum. This selection process is better handled by the optimizer. But to speed up calculations and the accuracy of the covariance matrix estimation, it is advisable to filter out by hand obviously very poor performing entries.
Human intervention takes also place at the output side. The final result is not automatically traded. The human has to check for program-”cheating”. E.g. if it likes Gold a lot, it can directly select the ETF GLD. If the optimizer wants to select more gold than the 20% maximal weight constraint, he can additionally select a similar ETF like JJP (Precious Metals). JJP has 80% gold in its portfolio. But the intention of the 20% limit is to restrict the exposure to gold (or any other asset). The optimizer is also quite tricky to find pseudo investments. A pseudo investment is the selection of the bullish- and bearish ETF of the same index. The positive effect from the point of view of the optimizer is: A pseudo-investment reduces the volatility of the portfolio. The effect is similar to keeping a part of the money in cash (besides the effect that one does not earn interest and has instead transaction costs). The Markowitz criterion and also Omega calculate a portfolio with lowest variance for a given excess-return. One can solve the pseudo-investment problem by selecting a higher minimum return level (and hence reducing the excess return). With a higher minimum-return one weights the return higher than the volatility. There is no reason for the optimizer to put some of the available money in a pseudo-

investment to reduce volatility. If one sees in the final result that the program starts to cheat with pseudo-investments, one sets the minimum-return parameter higher and reruns the optimization.
A value of 0.75%/month was in practice a good choice to prevent this problem at first hand.
The constraint-cheating problem can be solved in 2 ways. One can rerun the program without JJP in the initial list. But this can require several runs, as the program is quite tricky to find other ETF's with similar behavior. One can also distribute by hand the weight of JJP to other selected ETF's. Usually the effect is not very dramatic. E.g. if JJP has a weight of 10% and there are 12 ETF's in the final selection, each of the remaining ETF's gets an additional weight of 1%. As the input to the optimizer is rather noisy, these small adjustments do not really change the optimality of the portfolio in a fundamental way.

Trading-Results so far:

Note for Revision-2: There are at of this writing no trading results available. The following describes the implementation in Revision-1.

The ETF-Portfolio was traded the first time at 27.06.2011. 3.994.000$ were invested. 2 months later 26.08.2011 the trader Mats Persson and the Quant Chrilly Donninger decided to go out of the market, because the overall market conditions were not any more appropriate for a trend-following approach. The portfolio was at that date worth 4.169.000$. Or in other words the return in these 2 months was 4.28%. This return is insofar impressive, as the S&P went down from 1280 to 1176 or -8.47% in the same period. The portfolio outperformed the S&P by almost 13%. The volatility of the ETF-portfolio was typically only 20% of the S&P. On a return/variance basis the result was even more impressive. 2 months are of course too short for a final judgment.

The decision to go out of the market with the ETF-portfolio does not mean that the Sibyl-Fund stopped active trading in Aug. 2011. Instead other trading strategies which are more appropriate in a sideways moving market with high volatility - aka roller-coaster - were selected. The investments were concentrated to discretionary trading, the Johnny Walker (see [1]) and the Glenlivet (see [14]) strategy. The Johnny Walker was especially developed for the roller-coaster. The Glenlivet performs best in a medium to high-volatility market. But it assumes in contrast to the Johnny Walker no roller-coaster. There was a strong market recovery in the first month's of 2012. It would have been a very fine market-environment for the Portfolio. But the Sibyl-Fond was hit like many other funds by the MFGlobal default in Nov. 2011. This caused a severe interruption of the fund activities and so this this excellent chance of making high profits was missed.

Portfolio Example:
The following charts show the portfolio-selection at Friday, 2012.07.13. The data till Thursday 2012.07.12 are used for the calculation. One would enter the trade after the open on Friday.
For the meaning of the symbols see table-1 or search them on yahoo!-finance.

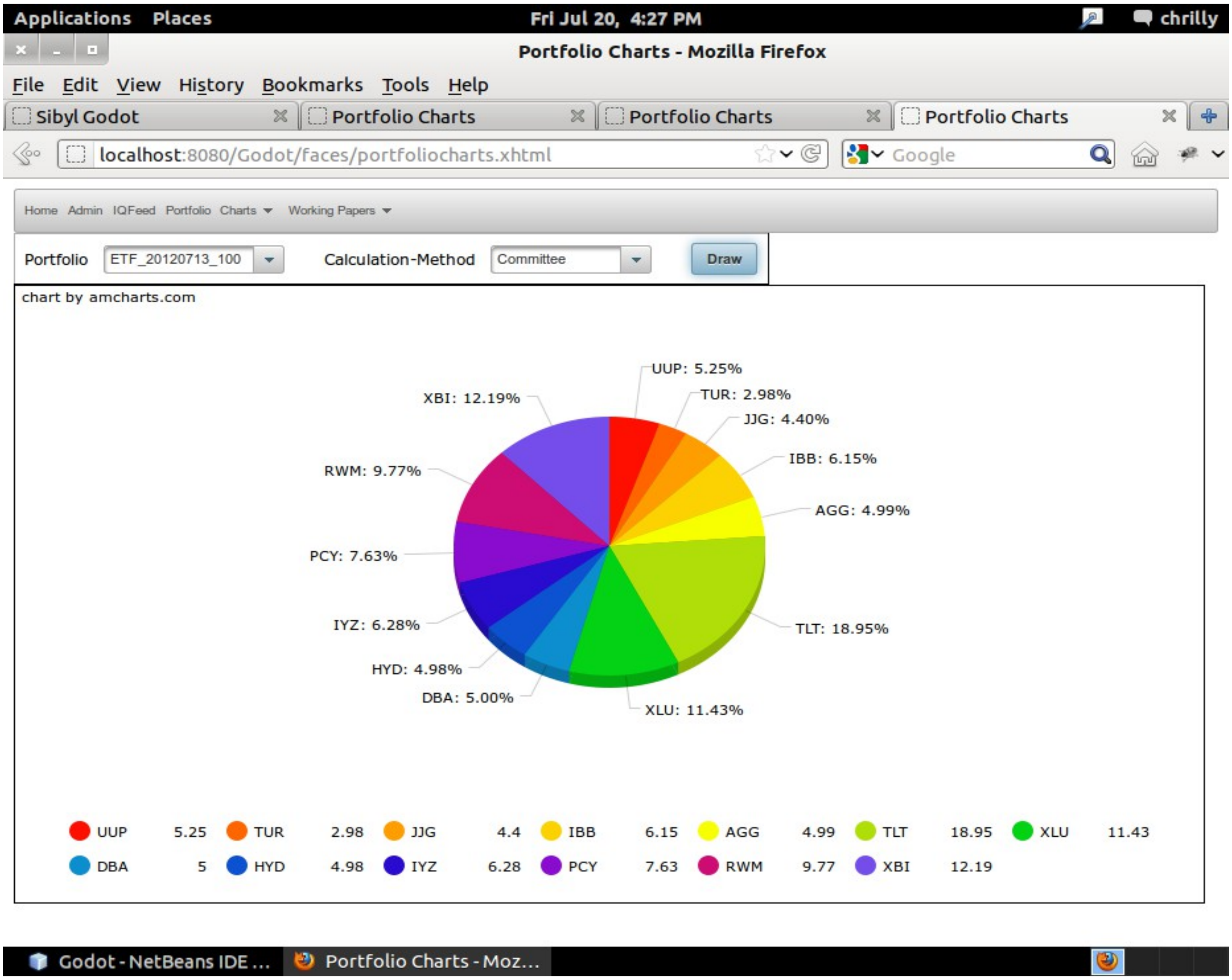

Chart-1: Committee Portfolio with monthly minR. of 1%

Chart-1 shows the overall committee portfolio. The expected minimum monthly return for Omega calculation was set to 1%. There are 5 stocks related assets. XBI (US-Biotechnology), IBB (US-Biotechnology) TUR (Turkey), XLU (US-Utilities) and IYZ (US-Telecom). UUP (Dollar-long) represents the FX-sector. TLT (20 year treasuries) and PCY (Emerging Markets Sovereign Debts) are Treasuries. AGG and HYD are Bonds. JJG, DBA are from the Commodities/Agricultural sector. The short part is 9.77% RWM (short-Russel 2000). RWM reduces the variance. If one sets minR to 0.75% (see Chart 8), the weight of RWM is increased.

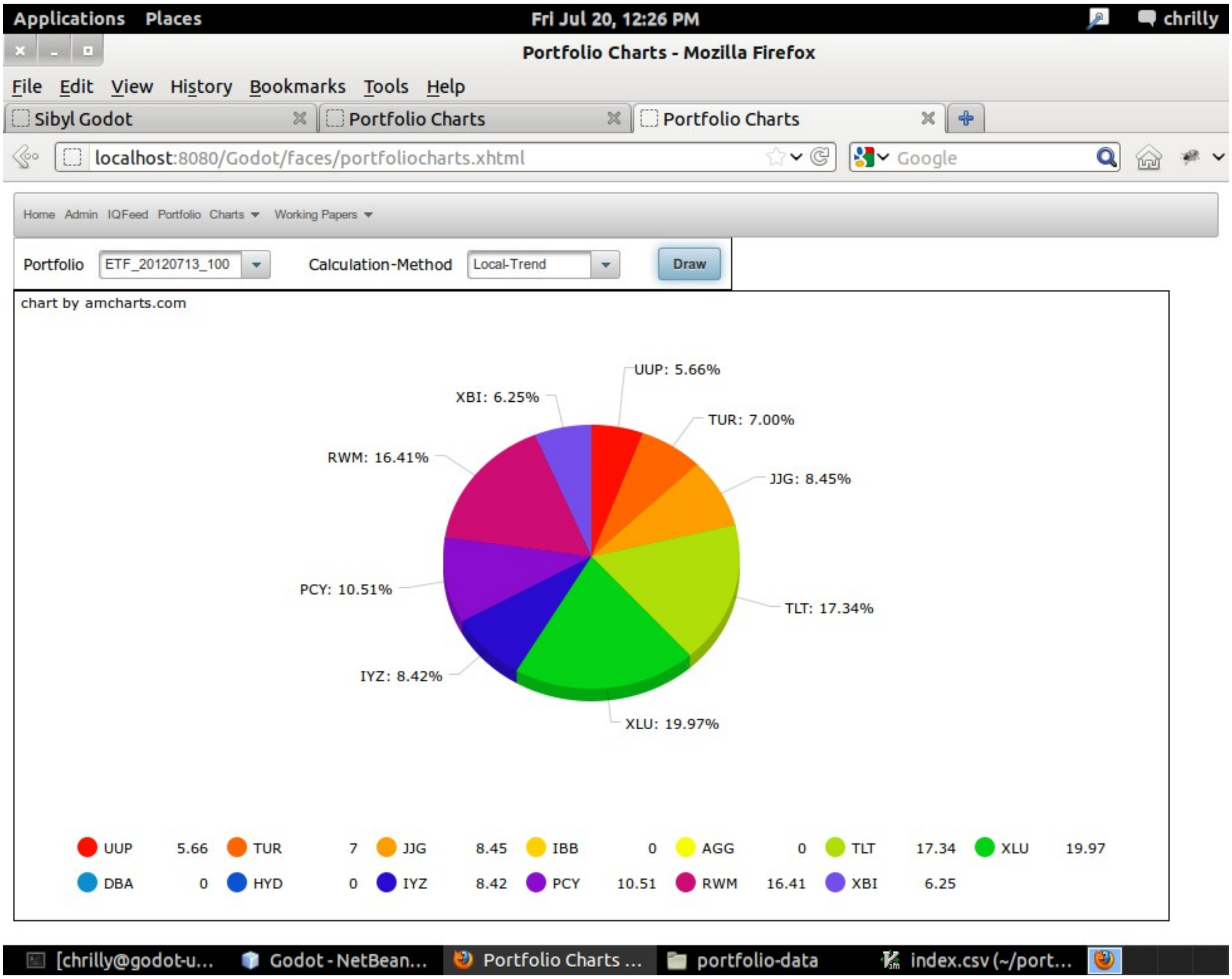

Chart-2: Local-Trend portfolio with minR 1%.

The local trend portfolio gives a greater weight to the stocks. But it increases also RWM. RWM is strongly negatively correlated with XLU, IYZ and XBI. The Bonds AGG and HYD are not selected at all by this method. The reason can be seen in Chart-3. The local trend weights the last quarter higher. In this time-period XLU (and other stocks) has clearly outperformed AGG. XLU has also over the whole year a higher return. But the variance of AGG is much lower.

The main-difference between the Local-Trend and the Double-Exponent-Trend Portfolio (Chart-4) is the reduced weight of RWM. UUP is increased. But the overall pattern is similar.

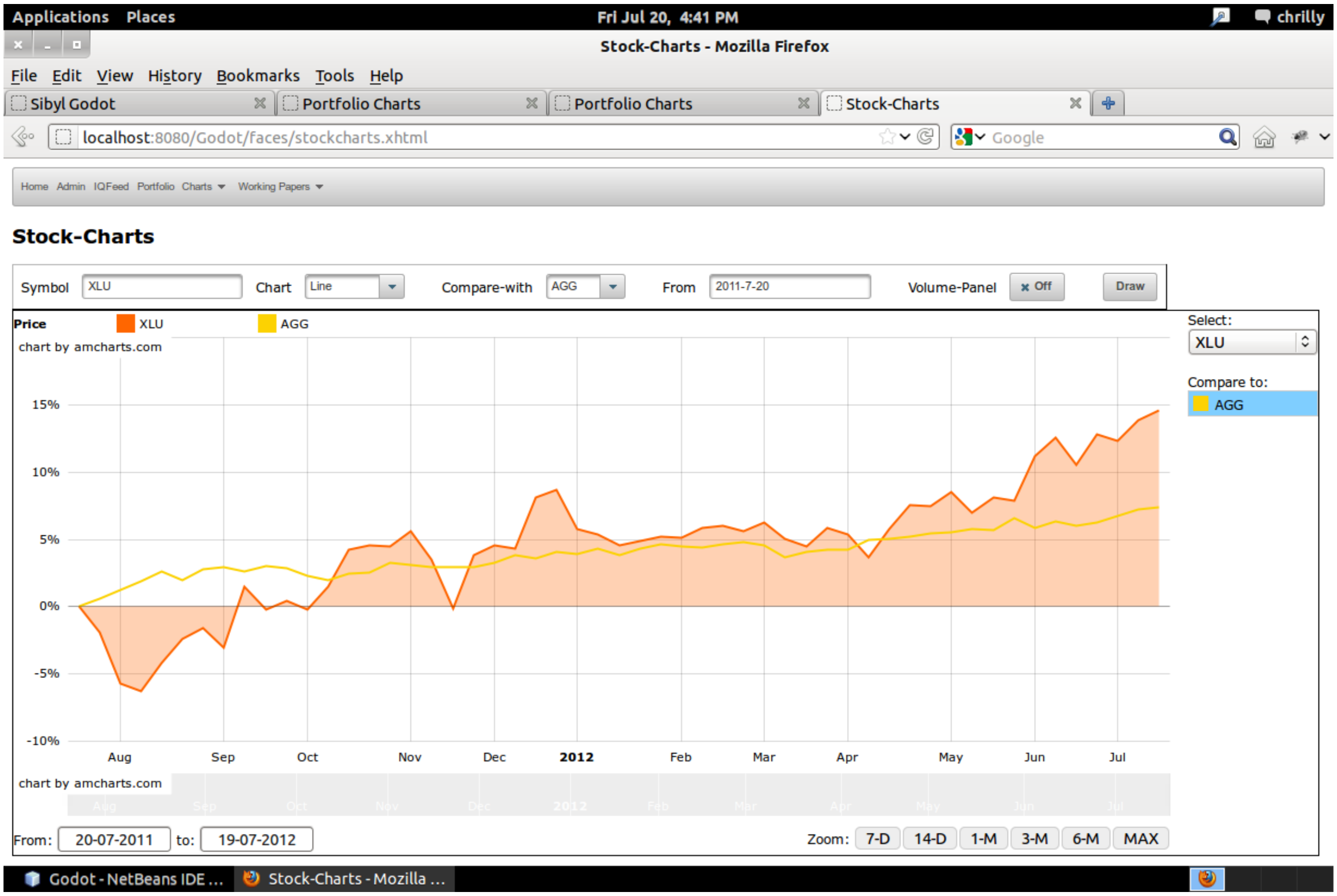

Chart-3: Performance of XLU (orange) and AGG (yellow) from 2011-07-20 to 2012-07-20

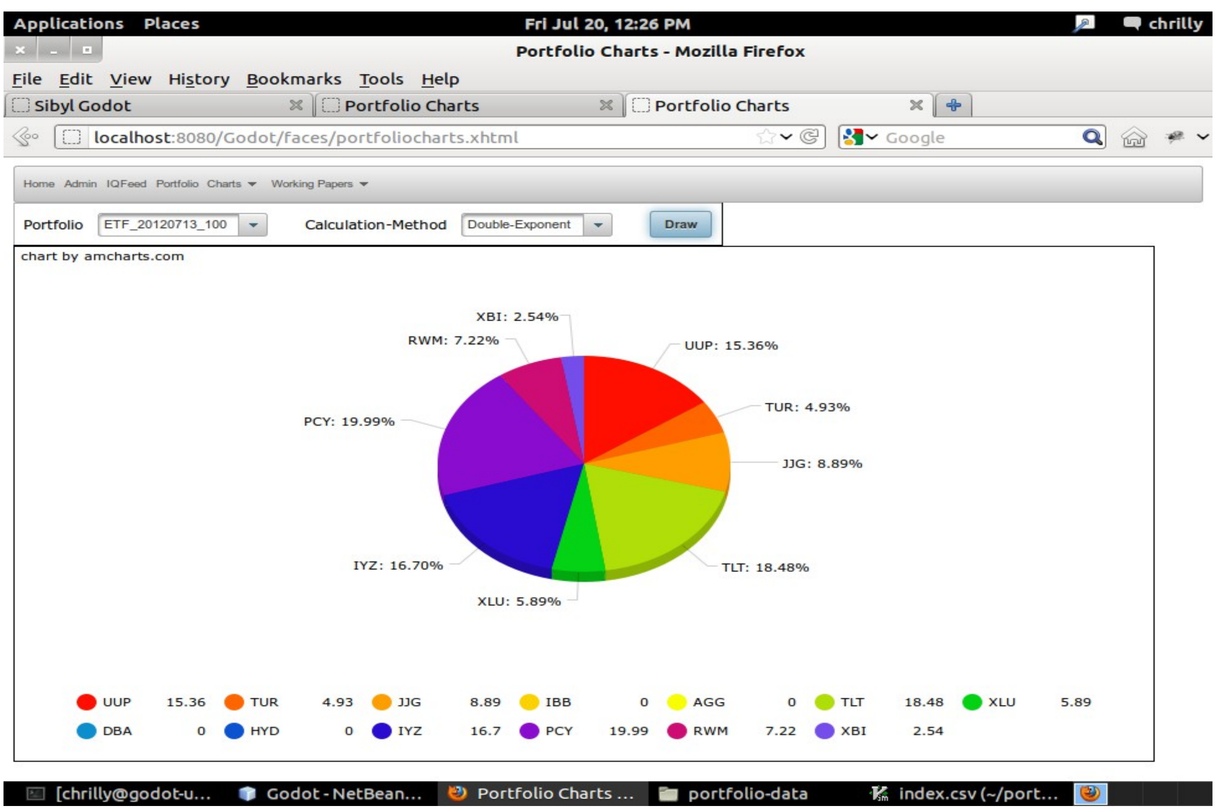

Chart-4: Double-Exponential-Trend with minR 1%.

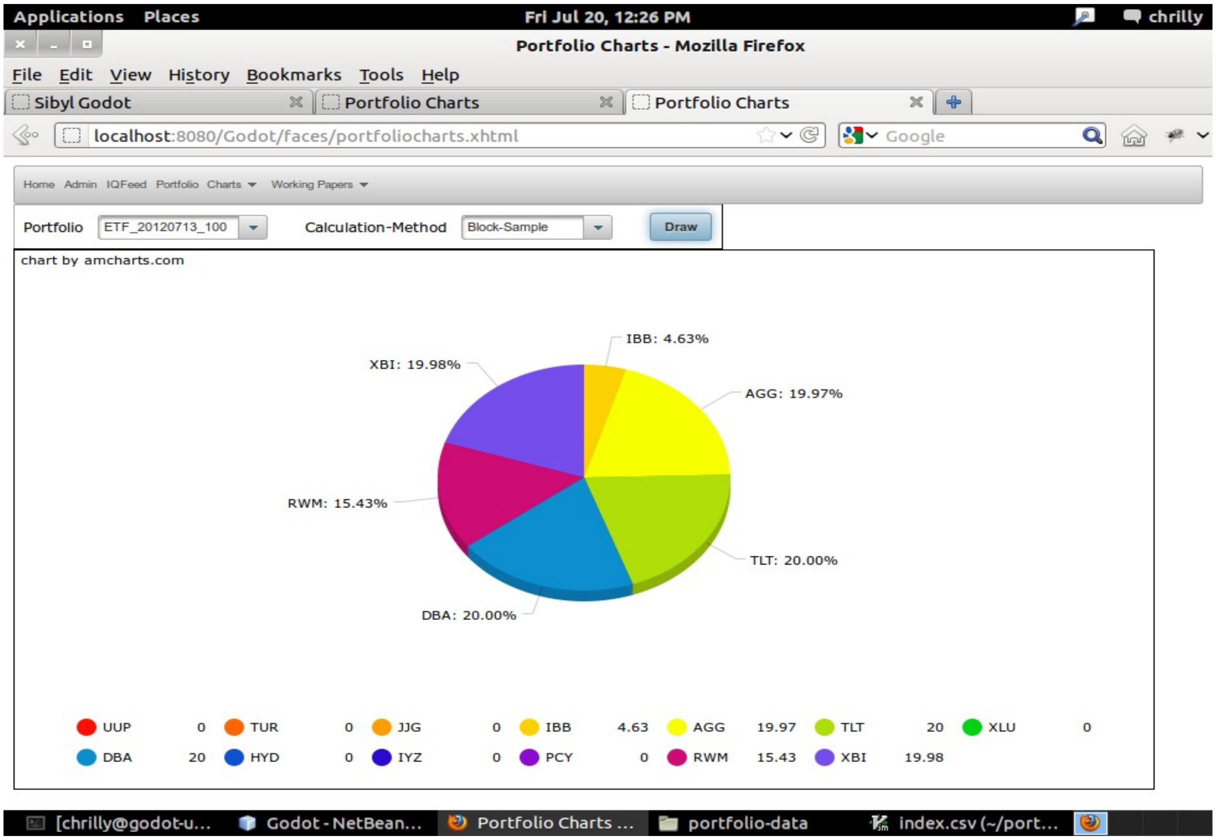

Chart-5: Block-Sample with minR 1%.

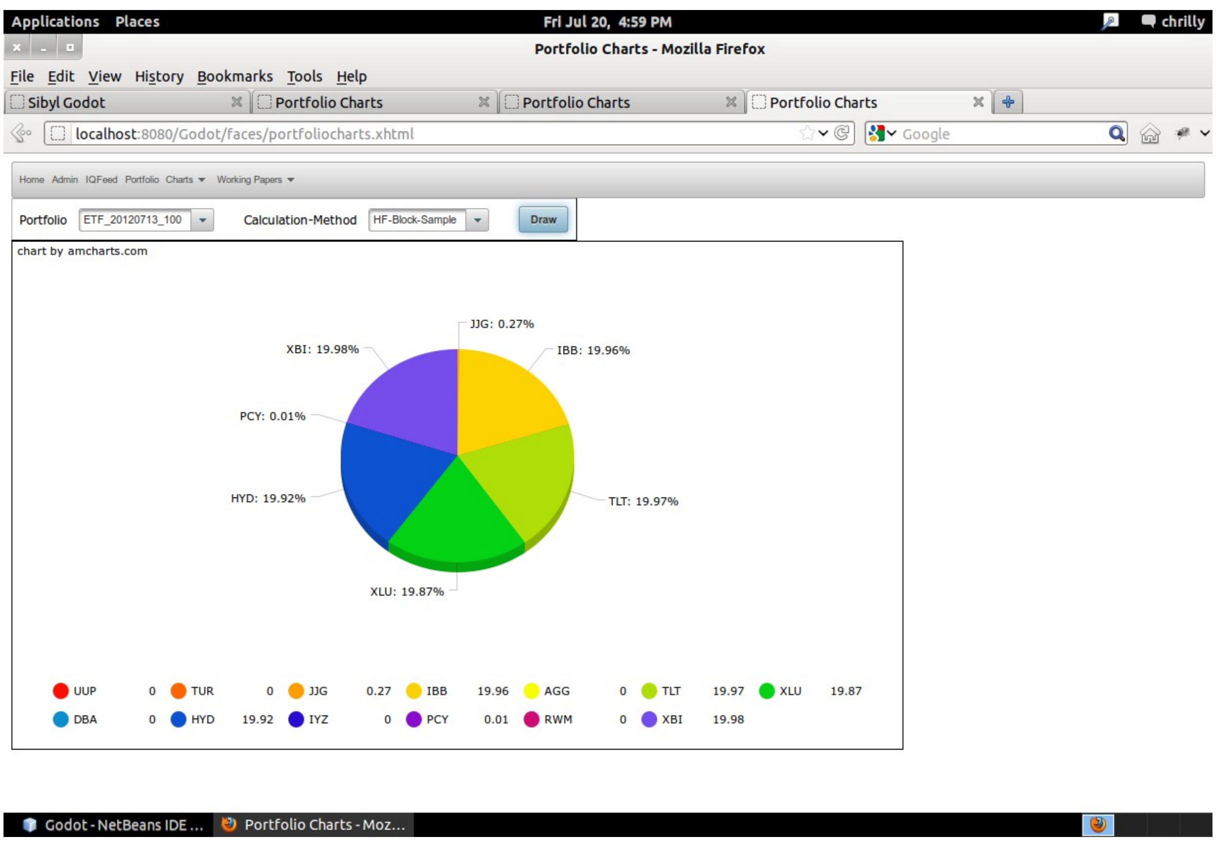

Chart-6: HF-Block-Sample with minR 1%.

The Block-Sampe and HF-Block-Sample method show a distinct pattern. Especially the HF-Block-Sample “likes” the Biotechnology sector. It cheats the 20% bound by selecting the highly correlated ETF's XBI and IBB. The Block-Sample methods consider the momentum in the last year. The high weight of Biotechnology is from this perspecitive not unreasonable. Biotechnology advanced in the last year by more than 20% (chart-7).

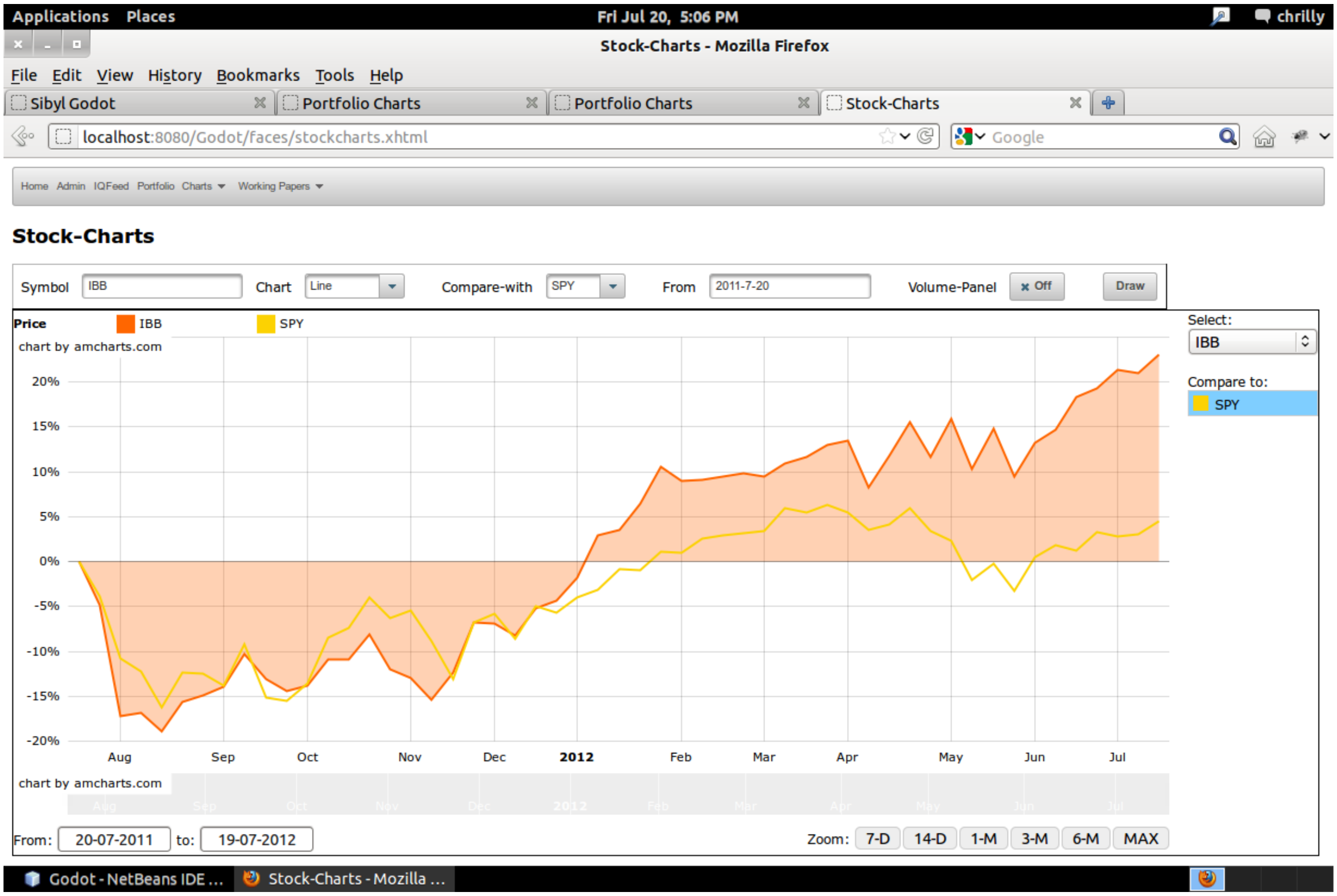

Chart-7: Performance of IBB (orange) to SPY (yellow) form 2011-7-20 to 2012-07-20.

Chart-8 shows the Portfolio where the monthly minimum expected return is set to 0.75. This portfolio weights the variance higher and the return lower. The overall structure is similar to the portfolio with minR. 1% in Chart-1. But the short hedge with RWM is increased.

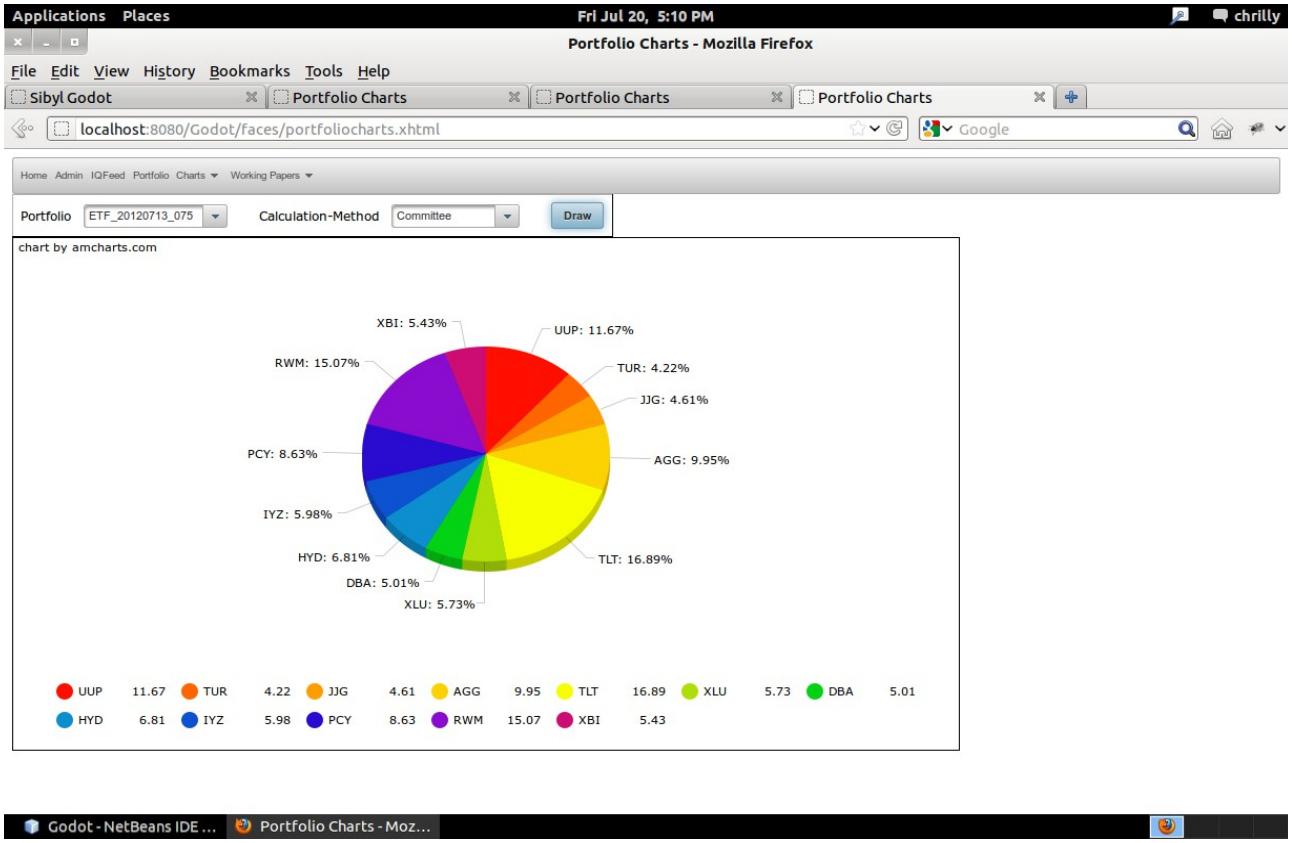

Chart-8: Committee Portfolio for minR 0.75%

Experiences with the Go-Programming language:

The previous versions of the optimizer were implemented in C++. They were running under Windows-XP (or higher). Revision-2 was implemented with the new programming language Go. Go was developed by the UNIX-heroes Ken Thompson and Rob Pike. For a detailed description of Go see [16]. Revision-2 runs currently on the Linux-server of **www.godotfinance.com**. A port to Windows-XP was done by a trivial recompile of the code.
A very attractive feature of Go is the concept of GoRoutines. A GoRoutine is the implementation of a CoRoutine in Go. After the scenarios have been generated (which takes only a few seconds) the Differential-Evolution Optimizer works for each scenario independently. The work load of each optimization is almost identical. This step is therefore a natural candidate for a parallelization via GoRoutines. One could also parallelize the scenerio-generation. But this would be already more difficult, because the methods differ and the speed is mainly bound by IO (reading the assets-data from disk). As this step takes only a minor fraction of the overall time, one would not even notice the speedup.
The parallelization with GoRoutines is trivial and takes about 5 minutes. This is the good news. The bad news is: Although the Linux-Server has 4 cores, there is almost no speedup. The current implementation of GoRoutines is obviously rather suboptimal. But this is a technical detail which will be probably improved in a further version. The language is generally very elegant and one can write a relative sophisticated program like the optimizer in a rather compact and clean way. Go has become my favorite programming language.

References:

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The Go homepage is golang.org

Appendix: ETF-List:

Ticker	Description	USA	Sector
AGG	US graded bonds	Yes	Bond
BKF	iShares MSCI BRIC Index	No	Stock-Index
BRF	Market Vectors Brazil Small-Cap ETF	No	Stock-Index
BWX	SPDR Barclays Capital Intl. Treasury Bond	No	Treasury
CEW	Wisdom Tree Dreyfus Emerging Currency	No	FX
CYB	Wisdom Tree Dreyfus Yuan	No	FX
DBA	PowerShares DB Agriculture	No	Commodity
DBB	PowerShares DB Base Metals	No	Commodity
DBC	Power Shares DB Commodity Index Tracking	No	Commodity
DBV	PowerShares DB G10 Currency Harvest	No	FX
DEM	WisdomTree Emerging Markets Equity	No	Stock-Index
DGS	WisdomTree Emerging Markets SmallCap Div	No	Stock-Index
DIA	Dow-Jones	Yes	Stock-Index
DJP	iPath DJ-UBS Commodity Index TR ETN	No	Commodity
ECH	iShares MSCI Chile Investable Market Index	No	Stock-Index
EEB	Guggenheim BRIC	No	Stock-Index

EEM	MSCI Emerging Markets Index	No	Stock-Index
EFA	MSCI EAFE stock index	No	Stock-Index
EMB	iShares JPMorgan USD Emerging Markets Bond	No	Bond
EPP	iShares MSCI Pacific ex-Japan Market Index	No	Stock-Index
EPU	iShares MSCI All Peru Capped Index	No	Stock-Index
EWC	iShares MSCI Canada Index	No	Stock-Index
EWG	iShares MSCI Germany Index	No	Stock-Index
EWH	iShares MSCI Hong Kong Index	No	Stock-Index
EWJ	iShares MSCI Japan Index	No	Stock-Index
EWL	iShares MSCI Switzerland Index	No	Stock-Index
EWM	iShares MSCI Malaysia Index	No	Stock-Index
EWS	IShares MSCI Singapore Index	No	Stock-Index
EWT	iShares MSCI Taiwan Index	No	Stock-Index
EWW	iShares MSCI Mexico Index	no	Stock-Index
EWY	iShares MSCI South-Korea Index	No	Stock-Index
EWZ	iShares MSCI Brazil Index	No	Stock-Index
EZA	iShares MSCI South Africa Index	No	Stock-Index
FCG	First Trust ISE-Revere Natural Gas Index	No	Stock-Index
FXA	Currency Shares Australian Dollar Trust	No	FX
FXE	Currency Shares Euro Trust	No	FX
FXF	Currency Shares Swiss Franc Trust	No	FX
FXI	iShares FTSE China 25 Index Fund	No	Stock-Index
FXY	Currency Shares Japanese Yen Trust	No	FX
GCC	GreenHaven Continuous Commodity Index	No	Commodity
GLD	SPDR Gold Shares	Yes	Commodity
GSG	S&P GSCI Global Commodity Index	No	Commodity
HYD	Market Vectors High-Yield Muni ETF	Yes	Bond
HYG	iShares iBoxx $ High Yield Corporate Bond	Yes	Bond
IBB	iShares Nasdaq Biotechnology	Yes	Industry-Sector
ICF	iShares Cohen&Steers Realty Majors	Yes	REIT
IDX	Market Vectors Indonesia Index ETF	No	Stock-Index
IEF	iShares Barclays 7-10years Treasuries	Yes	Treasury
IEI	iShares Barclays 3-7 Year Treasury Bond	Yes	Treasury
IEZ	iShares Dow Jones US Oil Equipment Index	Yes	Industry-Sector
ILF	S&P-Latin-America 40 index	No	Stock-Index
INP	iPath MSCI India Index ETN	No	Stock-Index
IWB	iShares Russel-1000	Yes	Stock-Index
IWM	iShares Russel-2000	Yes	Stock-Index
IWO	iShares Russel-2000 Growth	Yes	Stock-Index
IWS	iShares Russel Midcap Value Index	Yes	Stock-Index
IWV	iShares Russel 3000 Index	Yes	Stock-Index
IXC	iShares S&P Global Energy	No	Industry-Sector
IYT	iShares Dow Jones Transportation Average	Yes	Industry-Sector
IYZ	iShares Dow Jones US Telecom	Yes	Industry-Sector
JJC	iPath DJ-UBS Copper TR	Yes	Commodity
JJG	iPath Dow Jones UBS Grains	Yes	Commodity
JNK	SPDR Barclays High Yield Bond	Yes	Bond
KBE	SPDR S&P Bank ETF	Yes	Industry-Sector

KOL	Market Vectors Coal ETF	Yes	Commodity
KRE	SPDR S&P Regional Banking ETF	Yes	Industry-Sector
LQD	iShares Graded Corporate Bonds	Yes	Bond
MOO	Market Vectors Agribusiness ETF	Yes	Industry-Sector
MUB	iShares S&P National AMT-Free Muni Bond	Yes	Bond
OEF	iShares S&P 100 Index	Yes	Stock-Index
PBP	PowerShares S&P 500 BuyWrite	Yes	Stock-Index
PCY	PowerShares Emerging Marktet Sovereign Debt	No	Treasury
PFF	iShares S&P US Preferred Stock Index	Yes	Stock-Index
PGF	PowerShares Financial Preferred	Yes	Bond
PGX	PowerShares Preferred	Yes	Bond
PHB	Powershares High Yield Corp. Bond	Yes	Bond
PPH	Market Vectors Pharmaceutical ETF	Yes	Industry-Sector
PSQ	ProShares Short QQQ	Yes	Short-Index
QQQ	PowerShares Nasdaq-100	Yes	Stock-Index
RWM	ProShares Short Russel 2000	Yes	Shord-Index
RSX	Market Vectors Russia Index	No	Stock-Index
RTH	Market Vectors Retail	Yes	Industry-Sector
SDY	SPDR S&P Dividend	Yes	Stock-Index
SHY	iShares Barclays 1-3 Treasury Bond	Yes	Treasury
SLV	iShares Silver Trust	Yes	Commodity
SMH	Market Vectors Semiconductor	Yes	Industry-Sector
SPY	SPDR S&P-500	Yes	Stock-Index
TFI	SPDR Nuveen Barclays Capital Muni Bond	Yes	Bond
THD	iShares MSCI Thailand Invest Mkt Index	no	Country-Index
TIP	iShares Inflation Protected Securities	Yes	Treasury
TLT	iShares Barclays 20+ Treasuries Bond	Yes	Treasury
TUR	iShares MSCI Turkey Invest Mkt Index	No	Stock-Index
UDN	Short US-$ against FX-Basket	No	FX
UUP	Power Shares DB US Dollar Index Bullish	Yes	FX
USO	United States Oil	Yes	Commodity
UNG	United States Natural Gas Fund	Yes	Commodity
VEA	Vanguard MSCI EAFE stock index	No	Stock-Index
VGK	Vanguard MSCI Europe ETF	No	Stock-Index
VTI	MSCI US-Broad Market	Yes	Country-Index
VXX	iPath VIX Short Term Futures	Yes	Volatility
VXZ	iPath VIX Mid Term Futures	Yes	Volatility
WIP	SPDR Intl. Govt Infl-Protected Bond	No	Bond
XBI	SPDR S&P Biotech	Yes	Industry-Sector
XHB	SPDR S&P Homebuilders	Yes	Industry-Sector
XLB	Materials Select Sector SPDR	Yes	Volatility
XLE	Energy Select Sector SPDR	Yes	Volatility
XLF	Financial Select Sector SPDR	No	Industry-Sector
XLI	Industrial Select Sector SPDR	Yes	Industry-Sector
XLK	Technology Select Sector SPDR	Yes	Industry-Sector
XLP	Consumer Staples Select Sector SPDR	Yes	Industry-Sector
XLU	Utilities Select Sector SPDR	Yes	Industry-Sector
XLV	Health Care Select Sector SPDR	Yes	Industry-Sector

XLY	Consumer Discret Select Sector SPDR	Yes	Industry-Sector
XME	SPDR S&P Metal&Mining	Yes	Industry-Sector
XOP	SPDR S&P Oil&Gas Exploration&Prod	Yes	Industry-Sector
XRT	SPDR S&P Retail	Yes	Industry-Sector