University of Piraeus
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"Value at Risk for Greek Mutual Funds"

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Abstract

In this paper we apply several non-parametric, parametric and semi-parametric methods in order to determine the market risk of Greek mutual funds, according to the Value at Risk measure. More specifically, the methods used are Historical Simulation for two sample sizes, Simple Moving Average and Exponentially Weighted Moving Average (RiskMetrics model), GARCH (1,1) and EGARCH (1,1) with normally and Student's t distributed innovations, unconditional and GARCH (1,1) filtered Extreme Value Theory for different thresholds and Filtered Historical Simulation for two sample sizes. All calculations were made in a rolling basis and our sample consists of the logarithmic returns of nine mutual funds over the period 22/3/1993 to 21/11/2008 (3954 observations). The evaluation framework focuses on three tests proposed by Christoffersen (2003), namely unconditional coverage, independence and conditional coverage tests. Our results suggest that for the 95% VaR forecasts almost all methods do not perform well, while this is not the case for 99% confidence level. For the latter, some methods exhibit remarkably good performance, depending on the type of fund. Finally, we compute simple HS based Expected Shortfall just to give the reader an intuition of this alternative to VaR measure.

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Introduction

Over the last years risk management has evolved to a very important part of the financial and other industries. Although a lot of firms adopt risk management techniques, there is much debate over their effectiveness. A series of financial disasters has led to this discussion and has triggered the adoption of a series of regulations, especially with regard to the trading activities of financial institutions. As an illustration of the aforementioned disasters, in 1993 MG Refining and Marketing, a US subsidiary of Metallgesellschaft AG, reported losses in the amount of $1.3 billion dollars from positions in oil. Similarly, Gibson Greetings, Mead, P&G and Air Products and Chemicals reported losses from positions in differential swaps, the Japanese firm Kashima Oil lost $1.5 billion dollars on currency positions and the Orange County Investment Pool lost $1.7 billion dollar. The most remarkable failure, however, came in 1995, when Bearings, with over 230 years of history, went bankrupt after the realization of $1.4 billion dollar losses in Nikkei futures and option positions.

The constant growth of the financial transactions between institutions globally, the use of derivatives and highly leveraged products, securitization, the steadily increasing accounts of portfolio investments in banks' balance sheets and the fragility of the whole system due to uncontrolled market risks led to the imposition of legislative frameworks, such as the Capital Adequacy Directive by the Bank of International Settlements in Basle (1996).

In general terms, risk is defined as a situation that if materialized, could give rise to problems concerning the achievement of certain business goals or, in a more probabilistic expression according to McNeil (1999), “Risks are random variables, mapping unforeseen future states of the world into values representing profits and losses”. There are many types of risks, such as market risk, operational risk, credit risk, liquidity risk, business risk, sovereign risk and off-balance sheet risk. The focus of this paper is on market risk as measured by means of the Value at Risk standard, applied for Greek mutual funds. Market risk can be defined as the loss that could be experienced by a portfolio investor, due to adverse moves in the market factors which affect the value of the given portfolio. In these terms, market risk includes interest rate, currency, equity and commodities risk.

In this dissertation, we examine the performance of several parametric, non-parametric and semi-parametric methods in order to compute the downside risk of Greek mutual funds. A lot of academic research has been carried out, mainly focused on stock portfolios and indices, bonds and exchange rates but little is done in the mutual funds field. Since this form of institutional investing is primarily index linked though, our results are comparable to the existing literature. From our analysis, for 95% VaR estimations the results are not satisfactory, while at 99% confidence level we conclude that the performance of the models depends on the type of mutual funds, with some methods exhibiting good overall performance.

The rest of the paper is organized as follows: in Chapter 1 we present briefly the historical evolution of Value at Risk, while in Chapter 2 we define it. In Chapter 3 we define Expected Shortfall; in Chapter 4 the main approaches to determine VaR are presented with Extreme Value Theory discussed in Chapter 5. Afterwards, we discuss the most important criticism points of VaR, in Chapter 7 we analyze some well documented facts about returns series, in Chapter 8 we describe explicitly the methods applied to estimate volatility and in Chapter 9 we present the evaluation framework. In Chapter 10 we discuss the most recent and, to the best of our knowledge, most similar past papers, while in Chapter 11 we introduce some facts about the Greek mutual funds market. Finally, in Section 2 (chapters 12 to 15) we discuss the empirical investigation and the results.

1. History of Value at Risk

The first and most inspiring ideas concerning risk and finance generally were expressed by Markowitz (1952), in a mean-variance framework. Markowitz's work constituted the base for later innovations by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966), who independently introduced the Capital Asset Pricing Model. According to Holton (2002) these and some other theories are the predecessors of the Value at Risk measures (“VaR”), in the sense that VaR is a category of probabilistic measures of market risk. Later Ross (1976) subsequently introduced the Arbitrage Pricing Theory, which is based on somehow more realistic assumptions than CAPM.

As we shall see later in this section, capital requirements were legislated since the 20's in the US and later in all over the world. According to Holton (2002), working towards these legislations, Garbade (1986, 1987) introduced a VaR measure for bond portfolios and Wilson (1993) made a breakthrough by replacing the normal distribution with the t-distribution, in order to capture the fatter tails of financial time series. Finally, in 1994 JP Morgan introduced Riskmetrics Technical Document and increased the popularity of VaR measures. Also, it widened the use of the term "Value at Risk".

Prior to VaR measures: Regulatory Capital Requirements

The regulations concerning capital requirements date back to 1922 in the New York Stock Exchange. By 1929 they became more formal, and as Holton (2002) states "the NYSE capital requirement had developed into a requirement that firms hold capital equal to:

- 5% of customer debits;
- a minimum 10% on proprietary holdings;
- 30% on proprietary holdings in other liquid securities and
- 100% on proprietary holdings in all other securities"

This formulation constituted the basis that developed into the capital requirements concerning securities firms, including Mutual Fund Management Companies as well. In the following years further developments took place, including the establishment of the US Securities and Exchange Commission (SEC).

In 1975 the original capital requirement framework was developed by SEC in order to apply to securities firms, resulting in the Uniform Net Capital Rule (UNCR) introduction. This rule posed a number of "haircuts", i.e. a number of ratios that ensured that firms would continue to function and meet their obligations, even if markets plunged. These ratios determined the capital requirement depending on the asset class (equity, treasury, illiquid assets etc).

In 1980, nevertheless, these “haircuts” were modified. They were updated in order to capture losses with 95% confidence and with liquidation period of 30 days. In other words, it resembles the 95% 30 - day ahead VaR and it is very close to the form known today. Later on, legislation frameworks were developed worldwide, in order to sustain stability of the financial system. Towards this direction, the 1988 Basle Accord sets minimum capital requirements for banks, which were adopted by the G-10 countries. In Britain, the Securities and Futures Authority also set capital requirement measures for credit and market risk, followed by the 1993 Capital Adequacy Directive (CAD) by the European Union which introduced minimal capital requirements for banks' trading books based on a 95% 10 - day VaR measure. The latter measure, according to RiskMetrics Technical Document (1996) did not count for diversification effects and led to unreasonably high capital requirements. Finally, the 1996 Basle Accord laid the foundations of the current market-based capital requirements, allowing institutions to choose between Basle VaR measures or their own, if acceptable, in order to define the capital requirements.

2. Definition of Value at Risk

Value at Risk is a measure that captures the potential loss of an asset or a portfolio of assets over a certain period of time for a given confidence interval. In other words, as Cristoffersen (2003) states: "*Value at risk is a simple risk measure that answers the following question: What dollar (euro in our case) loss is such that it will be exceeded p x 100% of the time in the next K trading days?*" Mathematically expressed, VaR is:[1]

$$\Pr(\text{€Loss} > \text{€VaR}) = p, \qquad (1)$$

which stands for the probability of getting an even larger loss than VaR, or expressed in form of returns:

$$\Pr(R_{MF} < -VaR) = p \qquad (2)$$

where R_{MF} stands for mutual fund returns.

Assuming that the returns of a portfolio are normally distributed, with zero mean and standard deviation $\sigma_{MF,t+1}$, the p% one day ahead VaR will be:

$$\begin{aligned} &\Pr(\mathrm{R}_{\mathrm{MF,t+1}} < -VaR_{t+1}^{p}) = p \Leftrightarrow \Pr(\mathrm{R}_{\mathrm{MF,t+1}} / \sigma_{MF,t+1} < -VaR_{t+1}^{p} / \sigma_{MF,t+1}) = p \Leftrightarrow \\ &\Leftrightarrow \Phi(-VaR_{t+1}^{p} / \sigma_{MF,t+1}) = p \Leftrightarrow VaR_{t+1}^{p} = -\sigma_{MF,t+1} * \Phi_{p}^{-1} \end{aligned} \qquad (3)$$

[1] as derived from Christoffersen P, 2003, Elements of Financial Risk Management, Academic Press

where $\Phi(*)$ denotes the cumulative density function of the standard normal distribution and Φ_{p}^{-1} the inverse cumulative density function for the Pth quantile.

In the case where student's t distributional assumptions are utilized (GARCH (t) and EGARCH (t) models), VaR takes the form:

$$\mathrm{VaR}_{t+1}^{p} = -\sigma_{MF,t+1}\sqrt{\frac{d-2}{d}}\, t_{p}^{-1}(d) \tag{4}$$

where d denotes the degrees of freedom of the student's t distribution and $t_{p}^{-1}(d)$ the inverse cumulative density function[2] of the distribution, whose density is described by the formula:

$$f_{\tilde{t}(d)}(z;d) = \frac{\Gamma((d+1)/2)}{\Gamma(d/2)\sqrt{\pi(d-2)}}(1+z^{2}/(d-2))^{-(1+d)/2}, \ d>2$$

where z denotes a random variable with mean zero and standard deviation one and $\Gamma(*)$ denotes the gamma function.

3. Expected Shortfall

Artzner et al. (1999) introduced "coherent measures of risk", after finding evidence that VaR exhibits some flows (non subaddtitive) as explained in detail in chapter six later on in this paper. The alternative measure they proposed is the so called Expected Shortfall (ES or Conditional VaR or Tail VaR) that answers the question: "*If things do get bad, how large are the losses expected to be*"? In other words, while VaR tells us the number of losses that exceed it, ES tells us about the magnitude of the losses if VaR is exceeded. ES remains as simple as VaR, but conveys information about the shape of the tail and not just a point of it.

$$\mathrm{ES}_{t+1}^{p} = -\mathrm{E}_{t}[R_{t+1} \mid R_{t+1} < -\mathrm{VaR}_{t+1}^{p}] \tag{5}$$

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[2] $z = F^{-1}(p;d) = \{z : F(z;d) = p\}$, where $p = F_{\tilde{t}}(z;d) = \int_{-\infty}^{z} \frac{\Gamma((d+1)/2)}{\Gamma(d/2)\sqrt{\pi(d-2)}}(1+z^{2}/(d-2))^{-(1+d)/2}\, dt$

In this paper we compute unconditional ES for 95% and 99% confidence intervals for sample of 100 and 252 observations, based on historical simulation method.

4. Methods for computing VaR

There are mainly three families of methods used to calculate VaR: Variance – Covariance methods (V-CV), Historical simulation methods (HS) and Monte – Carlo simulation (MS) methods. The first two methods are used and discussed in this paper.

4.1 Variance – Covariance methods

This family of methods lies upon certain distributional assumptions of the returns. The basic distribution attributed to the returns is the standard normal, which has very convenient properties and it is fully described by the first two moments, mean (which for daily data is usually set to zero) and variance. Assuming that the returns of each asset follow normal distribution, a portfolio with positions in these assets will follow normal distribution as well. Thus, after computing the covariance matrix of the assets and the historical volatility of the portfolio, VaR is computed as the product of a scaling factor (depending on the confidence level) and the volatility of the portfolio. Volatility can be estimated using a variety of models.

The main advantage of the V-CV methods is that they can be easily implemented. On the other hand, financial returns exhibit fatter tails and negative skewness, which are moments that do not count for the normal distribution. This causes underestimation of the VaR measure, especially with regard to portfolios containing non linear financial instruments like options.

In addition, financial time series are non stationary. We, therefore, use GARCH models to deal with the problem of heteroskedasticity and student's t distributional assumptions (which has fatter tails than the normal) to deal with the "fat tails" effect.

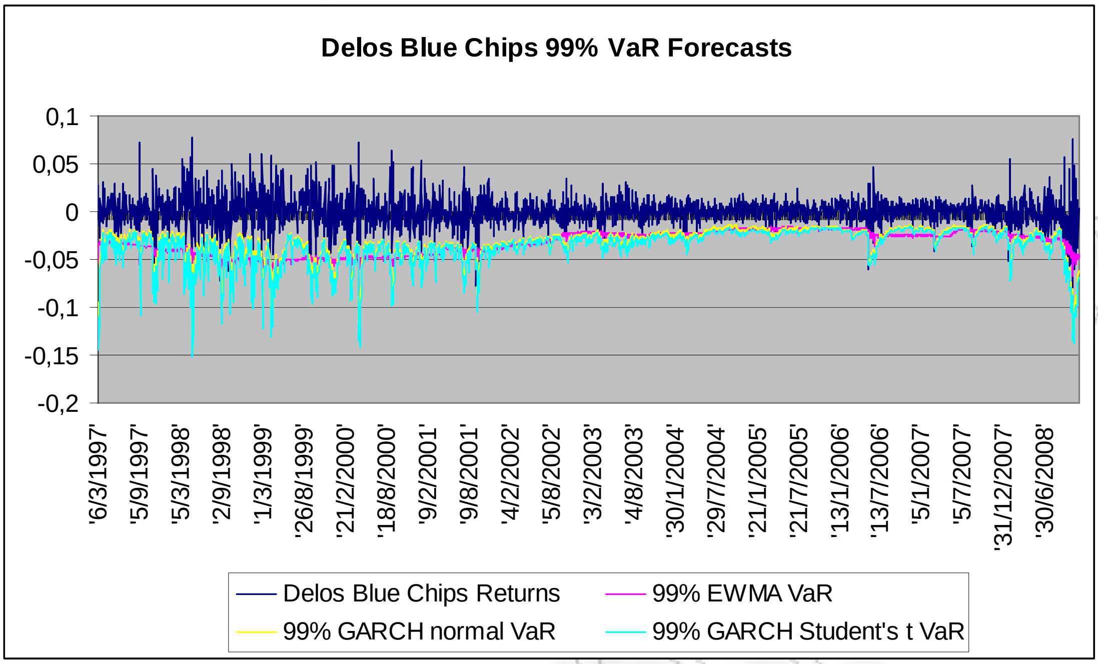


Figure 1: Delos Blue Chips logarithmic returns and 99% Exponentially Weighted Moving Average, GARCH (n) and GARCH (t) VaR forecasts from 6/3/97 to 21/11/08

4.2 Historical simulation methods (HS)

This method is, by intuition, the simplest one. It does not have a parametric nature but assumes that the distribution of future returns can be approximated from the empirical distribution of past returns. In other words, the historical returns are possible scenarios for the future returns. In this context, in order to compute the VaR measure at p confidence level, we sort the historical returns in ascending order and find the corresponding percentile for which the 100p% observations will be smaller, or:

$$\mathrm{VaR}_{t+1}^{p} = -Percentile\left\{\left\{\mathrm{R}_{\mathrm{MF},t+1-\tau}\right\}_{\tau=1}^{m}, 100p\right\} \tag{6}$$

where m is the sample size of past returns.

As with all methods, HS has certain advantages and drawbacks. Its main advantage is its simplicity, as no estimations have to be made. Additionally, its distribution-free nature implies that it counts for “fat-tails” and negative skewness.

On the negative side lies the cost of not counting for volatility clustering, since all sample observations have equal weights and volatility updating is slow. The equal weights scheme causes much dependence on the sample selection. If a very large sample is used, the latest observations that should count more to the result will actually have small weights and if we use a small sample we will have little extreme observations. Thus, a large unusual loss at t will lead to (overestimated) large VaR at t+1, which may not be the case. Vlaar (2000) states though, that the accuracy of HS VaR forecasts tends to increase, as sample size increases up to a point. Furthermore, HS lies upon the assumption that returns are i.i.d., which is not the case. It should be noted that Lambadiaris et al. (2003) has been used herein, who has used samples of 100 and 252 observations.

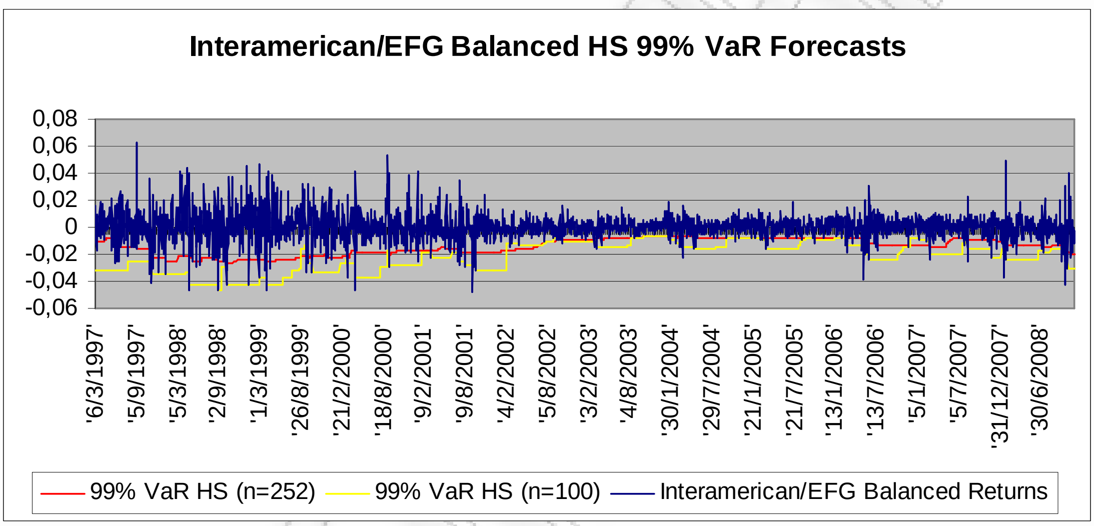


Figure 2: Interamerican/EFG Balanced logarithmic returns and 99% Historical Simulation (for rolling samples of 100 and 252 observations) from 6/3/1997 to 21/11/2008.

As seen in figure 2, VaR forecasts produced by Historical Simulation exhibit box-shaped patterns due to the slow volatility updating and the ignorance of volatility clustering.

4.3 Semi-Parametric methods: Filtered Historical Simulation

As previously discussed, Variance-Covariance and Historical simulation methods have certain advantages and drawbacks. Barone-Adesi, Giannopoulos and Vosper (1999) and Hull & White (1998) proposed a method that combines the volatility updating patterns of V-CV methods (GARCH or EWMA models), a drawback of HS method, and the non-parametric nature of the HS method to overcome the problem of attributing a non-realistic distribution to the returns series. Assuming a GARCH or an EWMA variance model, they state that "*the probability distribution of a market variable, when scaled by an estimate of its volatility, is often found to be approximately stationary*". Thus, let:

$R_{N,j}$: historical return of the mutual fund j on day N

$\sigma^2_{N+1,j}$: historical GARCH/EWMA estimate of the daily variance of the return of mutual fund j, made at day N for the next day N+1

$\sigma^2_{t+1,j}$:the most recent GARCH/EWMA variance estimation, made now (at t) for tomorrow (t+1).

Thus, we create a "new" stationary time series as:

$$R^*_{N,j} = \sigma_{t+1,j} \frac{R_{N,j}}{\sigma_{N+1,j}} \qquad (7)$$

Thus, they have achieved to create a stationary time series that incorporates a GARCH/EWMA volatility updating scheme. The historical simulation method is then applied to the new $R^*_{N,j}$ series and the one day ahead VaR is computed as:

$$VaR^p_{t+1} = -Percentile\left\{\left\{R^*_{MF,t+1}\right\}^m_{\tau=1}, 100p\right\} \qquad (8)$$

where m stands for the sample size.

In this paper, we will use GARCH volatility updating and rolling sample of 500 and 1000 observations for the calculation of the FHS VaR, due to the sensitivity of HS method to the sample selection.

The reader can notice that the FHS method incorporates the volatility dynamics, due to the GARCH volatility modeling, and does not exhibit the box-shaped patterns of simple HS. A comparison of figures 2 and 3, which are constructed for the same mutual fund, is obviously in favor of the FHS method.

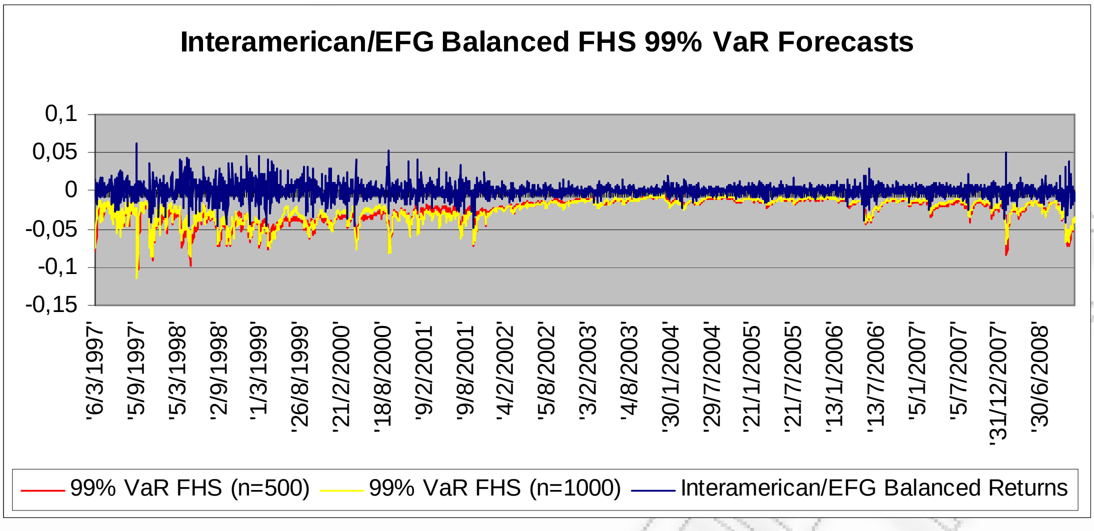


Figure 3: Interamerican/EFG Balanced logarithmic returns and 99% Filtered Historical Simulation (for rolling samples of 500 and 1000 observations) VaR forecasts from 6/3/1997 to 21/11/2008.

5. Extreme Value Theory

The need for distributions that capture the probabilities of downside returns (or extremes) has led to the development of Extreme Value Theory, which focuses on estimating the tails of financial time series. In this paper we apply the Peaks over Threshold method (POTS) for different thresholds. The returns time series should be i.i.d., otherwise as Angelidis et al. (2004) state the estimations could be biased. In this paper, we follow closely McNeil & Frey (2000), who apply the EVT method both at raw returns and at GARCH standardized ones (two stage model – G-EVT). As they state, the latter method gives “approximately i.i.d.” series and thus leads to better estimations. Assuming we have a series of i.i.d. returns $X_1, X_2, ..., X_n$ and a high threshold u, given that X>u for all X’s, the probability of the returns less the threshold u being bellow a value y is (y = X - u):

$$F_u(y) \equiv \Pr\{X - u \leq y | X > u\} \tag{9}$$

and $F_u(*)$ is the excess distribution function.

The excess distribution function can be written in terms of the actual returns function F (*):

$$F_u(y) = \frac{F(y+u) - F(u)}{1 - F(u)} \tag{10}$$

Extreme Value Theory lies upon the fact that as the threshold u gets large, the excess distribution $F_u(*)$ converges to a generalized Pareto distribution:

$$F_u(*) = G_{\xi,\beta}(y) = \begin{cases} 1-(1+\xi y/\beta)^{-1/\xi} & \xi \neq 0, \\ 1-\exp(-y/\beta x & \xi = 0, \end{cases} \tag{11}$$

with β>0, and

$$\begin{cases} y \geq u & \text{if } \xi \geq 0 \\ u \leq y \leq u - \beta/\xi & \text{if } \xi < 0 \end{cases}$$

ξ is the shape (or tail) parameter and β is a scale parameter.

The Generalized Pareto distribution covers a number of other distributions. A positive ξ means that the distribution is heavy tailed (like the student's t), which is the case of the mutual funds' returns and present the greatest interest for risk management. If the underlying distribution is the normal one then $\xi=0$.

Combining equations (10) and (11) the following transformation can be made:

$$F(X) = (1 - F(u))G_{\xi,\beta}(x - u) + F(u) \ , X>u \tag{12}$$

since X= y + u

F(u) can be estimated by $(n - N_u)/n$, where n is the size of the sample and N_u is the number of data points beyond the threshold u. Combining it with maximum likelihood estimates of the Generalized Pareto Distribution, we get that:

$$F(X) = 1 - \frac{N_u}{n}\left(1 + \xi\frac{X - u}{\beta}\right)^{-1/\xi} \ , X>u \tag{13}$$

If we invert the above function, we get to estimate the desired quantile of F(X) and thus compute VaR:

$$VaR_{t+1}^{p} = u_t + \frac{\beta_t}{\xi_t}\left(\left(\frac{n}{N_{u,t}}(1-p)\right)^{-\xi_t} - 1\right) \tag{14}$$

where p is the confidence level.

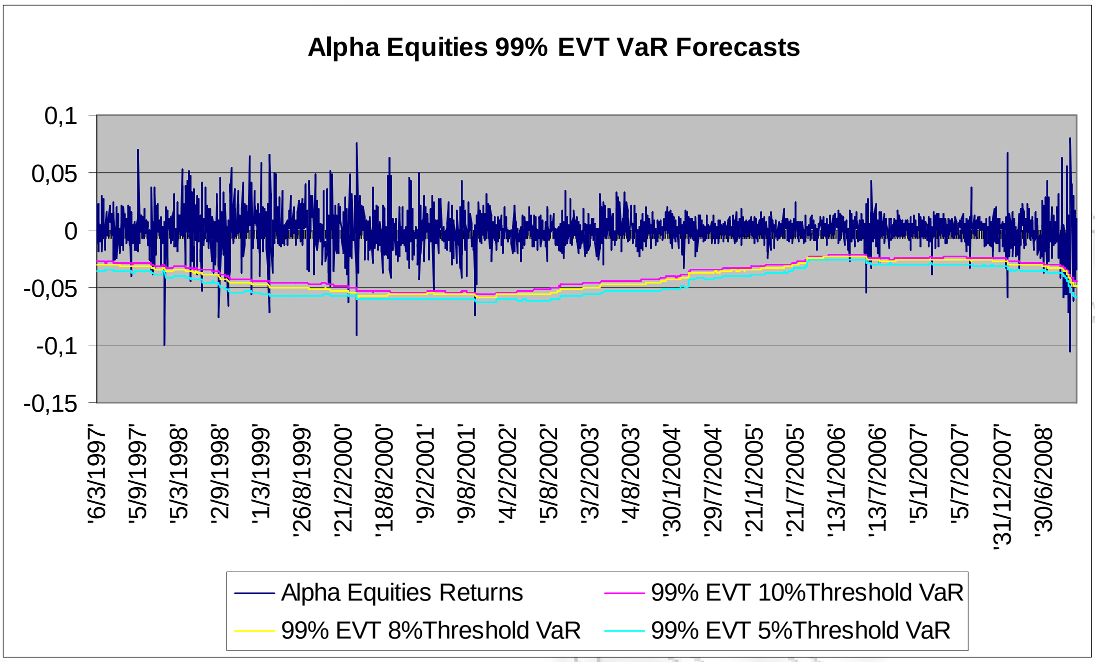


Figure 4: Alpha Equities logarithmic returns and 99% unconditional EVT (for 10%, 8% and 5% thresholds) VaR forecasts from 6/3/1997 to 21/11/2008.

As seen in the above figure, EVT VaR produces smooth patterns, ignoring the volatility dynamics. Furthermore, raw returns are non i.i.d., thus the estimations could be biased. As Seymour et al. (2003) state, Danielsson and De Vries (2000) argue that since extreme returns occur infrequently, and do not appear to be related to a particular level of volatility, an unconditional approach is better suited to VaR estimation than conditional volatility forecasts. But since McNeil and Frey (2000), there is much evidence in the literature that their method (G-EVT hereafter) gives more accurate VaR forecasts than unconditional EVT. Thus, we applied their method as well, which assumes that GARCH standardized returns can reasonably be assumed as i.i.d. series and computing VaR with EVT based on the standardized returns gives better results. Furthermore, as observed in the following figure, it incorporates the volatility dynamics, although it some times overestimates VaR, as discussed in the results section.

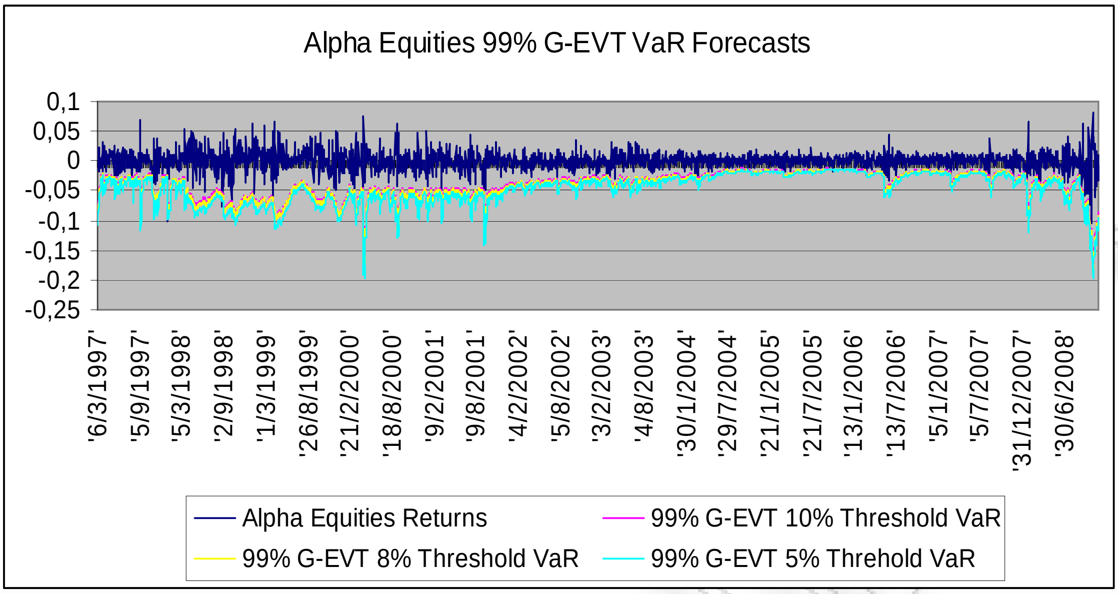


Figure 5: Alpha Equities logarithmic returns and 99% GARCH standardized Extreme Value Theory (for 10%, 8% and 5% thresholds) VaR forecasts from 6/3/97 to 21/11/08.

5.1 Advantages and Disadvantages of EVT

Main advantage of the EVT method is that it exclusively focuses on the tails of the distribution, ignoring the center which is out of interest for risk management. GPD utilization makes no specific assumption about the distribution, but covers many types of them depending on the tail parameter. Furthermore, it treats each tail differently, allowing for asymmetries.

According to Diebold, Schuermann and Stroughair (1999), EVT should be applied mostly for high quantiles ($p \geq 0.99$). This is in accordance with our results of the EVT method, as it performs best at the 99% confidence level. Furthermore, as they state, the most important debate on EVT is about the choice of the threshold since “there is an important bias - variance trade off when varying u for fixed sample size”. Indeed, as threshold u increases and we move towards the center of the distribution, more data are used for the estimation of ξ and thus variance decreases, but bias increases as the observations may not comply with GPD. On the other hand, high threshold means smaller sample for the estimation. In this paper, we use 10%, 8% and 5% thresholds to overcome this problem.

6. Advantages of VaR and criticism

Value at Risk provides the usefulness of aggregating the risk of a variety of instruments and portfolios in a single number, which can be easily understood by the stakeholders of an organization. Furthermore, a VaR breakdown per section/ market/department/trader etc could allow for more accurate risk-adjusted returns and lead to more efficient capital allocation and remuneration methods. Moreover, Culp, Miller and Neves (1998) state that, under certain circumstances, some of the financial mishaps mentioned in the introduction part could have been avoided if adequate VaR measures were implemented.

On the other hand, a highly aggregate figure as VaR may loose in accuracy. Moreover, Beder (1995) characterizes VaR as “seductive but dangerous”. Seductive because it is simply communicated, but dangerous because the VaR figures depend heavily on the methodology, the data set, the assumptions and the parameters used. Thus, according to the author, differences in these factors produce considerably large variations in VaR measures for the same portfolios, pointing out that, although VaR is a powerful measure, it should be correctly understood.

The main criticism point of VaR, though, came out by Artzner et al. (1999). In their study, they introduced the “coherence” framework for risk management measures. According to the authors, a risk measure can be seen as an amount of cash, that if added on a position, can make it accepted by the regulators. Furthermore, it is “coherent” when it fulfils the following axioms:

Let Ω a set of states of the world, X a random variable counting the final worth of positions of each element of Ω, G the set of all risks, p the risk measure, mapping from G to the set of real numbers and r the rate of return of a reference instrument:

1) Translation invariance: For all real numbers a, we have $p(X+ar)=p(X) - a$

That is, if we add cash equal to a to our position, the risk measure should decrease by the same amount.

2) Positive homogeneity: For all $\lambda \geq 0$ and all $X \in G$, $p(\lambda, X)=\lambda p(X)$, meaning that keeping the synthesis (weigths) of a portfolio constant but increasing its’ size by λ, will increase the risk measure by λ as well.

3) Monotonicity: For all X and Y∈G with X≤Y, we have p(Y)≤p(X), or a portfolio with lower returns (X) than an other portfolio (Y) should have bigger risk measures.

4) Subadditivity: For all X1 and X2∈G, p(X1+X2)≤p(X1) + P(X2) or if two portfolios are merged to one, the latter should have smaller risk measure or at least equal to the sum of the two risk measures individually.

They proved that VaR does not always conform to the last axiom, meaning that diversification could not lead to lower VaR measures and they proposed Expected Shortfall (or Conditional VaR or Tail VaR) instead.

7. Financial returns and Volatility

Financial time series exhibit a number of characteristics, the presentation of which is crucial in order to understand the methods developed for dealing with them.

7.1) Leptokurtosis ("fat tails")

The most common distribution used in order to describe returns is the standard normal, which is fully defined by its first two moments. But usually this is not the case, as the probability of extreme losses is greater than the one proposed by the normal, as witnessed by Mandelbrot (1963) and others. The empirical distribution usually has fatter tails and higher peak (i.e. kurtosis > 3) as can be concluded by the following histogram, with normal and empirical distributions superimposed:

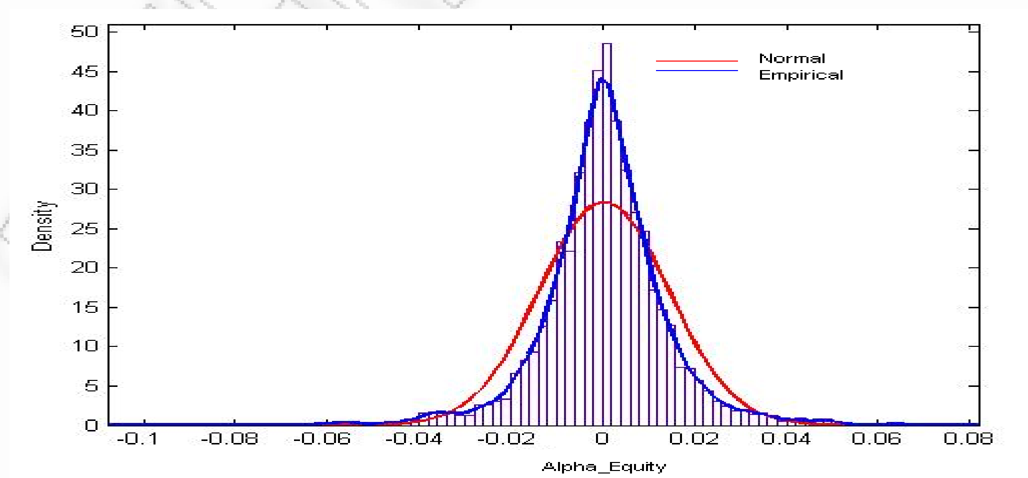


Figure 6: Alpha equities logarithmic returns empirical distribution with the normal distribution superimposed.

This holds for the whole sample of mutual funds and as illustrated in the Q-Q plots in the appendix, student's t distribution seems to capture this effect better.

Another fact against the normal distribution is that asset returns have larger probability of moving upwards than downwards, but when the latter comes into effect the drops are larger than the up movements. In other words, the unconditional distribution of returns is negatively skewed, a property not so obvious in the above histogram but discernible in the table of the descriptive statistics of our sample in the data set section.

7.2) Volatility clustering

Except for the fact that homoskedasticity does not hold for financial time series, volatility is clustered in time, i.e. we have periods of concentrated high volatility followed by periods of also concentrated lower volatility, as put by Mandelbrot (1963). Alternatively, variance exhibits significant autocorrelation, as witnessed in the following figure:

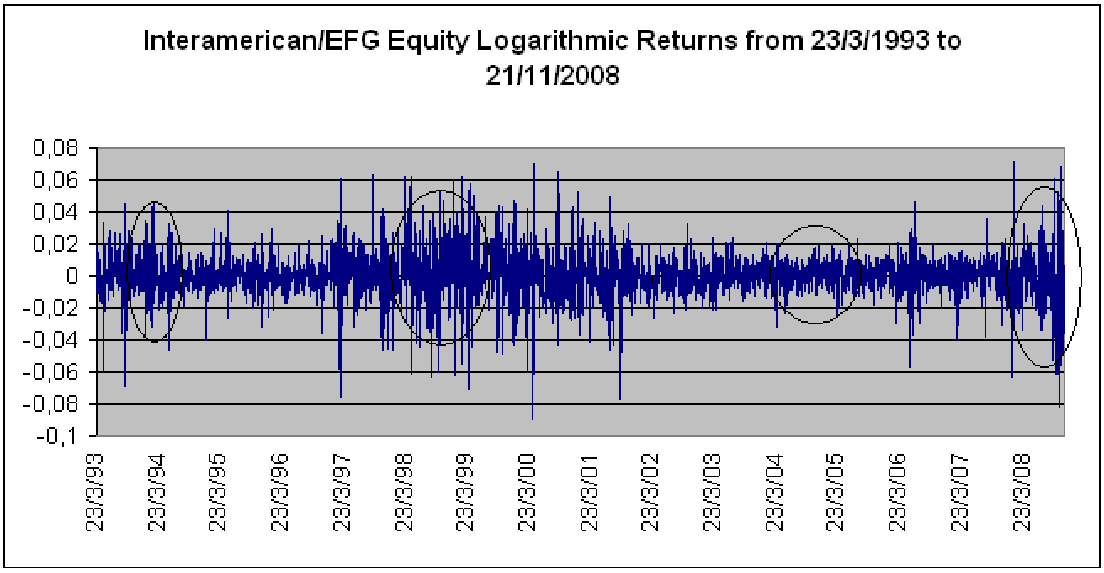


Figure 7: Interamerican/EFG Dynamic Equity logarithmic returns from 23/3/1993 to 21/11/2008

Consequently, in order to model volatility, we should apply methods that count for time varying variance and attribute more weight to the most recent returns. The latter will allow for volatility clustering, since if the most recent observations exhibit large/small volatility, so will our forecasts for the future. Towards this direction, models such as the Exponentially Weighted Moving Average (EWMA hereafter) by JP Morgan (RiskMetrics Technical Document, fourth edition, 1996) and the GARCH family models (Bollersev, 1986) have been developed, which will be presented later on in this section.

7.3) Leverage effect

The so-called leverage effect refers to the negative correlation between variance and returns, first observed by Black (1976). To put it more simply, when bad news "hit" the market and asset prices drop, they cause volatility to increase more than it would have as a result of good news and upward shifts. Using stocks as an example, this could be attributed to the fact that when prices drop, a firm's leverage becomes larger creating more doubts about its financial stability and thus increased volatility. To incorporate this fact in volatility modeling and forecasting, models like NGARCH and EGARCH have been proposed and will be presented bellow.

8. Volatility Estimation and Forecasting

In accordance with Figlewski (1994), we assume that the mean of the returns for our daily data is equal to zero. As he concluded, estimating the mean adds more bias in volatility estimation than considering it to be zero. This hypothesis is also statistically tested and proved to be correct for our sample, as we will see later on in the data set analysis. The methods used in this paper to estimate and forecast volatility are presented herein bellow.

8.1) Simple Moving Average (SMA)

The simplest way to estimate volatility (standard deviation) is:

$$\sigma_{t+1} = \sqrt{\sum_{\tau=1}^{n} \frac{1}{n-1} R_{t+1-\tau}^{2}} \qquad (15)$$

n: the sample size

τ: the lag of past observations

R: the past logarithmic returns

As noticed, this method puts equal weights 1/n-1 in all past squared returns, posing issues concerning the choice of n. A relatively high n will cause weights to be lower and thus produces smoother volatility estimations over time, while the opposite will give more jagged patterns. Furthermore, the equally weighting scheme does not allow for most recent returns to count more in tomorrow's volatility, a fact not in accordance with volatility clustering. To overcome these problems, JP Morgan proposed the following method;

8.2) Exponentially Weighted Moving Average (EWMA)

JP Morgan's method, as described in RiskMetrics Technical Document (1996), estimates volatility as:

$$\sigma_{t+1} = \sqrt{(1-\lambda)\sum_{\tau=1}^{\infty} \lambda^{\tau-1} R^2_{t+1-\tau} \quad \text{for } 0 < \lambda < 1} \qquad (16)$$

or

$$\sigma_{t+1} = \sqrt{\lambda\sigma_t^2 + (1-\lambda)R_t^2} \qquad (17)$$

λ is termed the decay factor and it determines the relative weights attributed to past observations and the length of the sample. The advantages of this method are two: Firstly, it gives more weight to the most recent observations in a declining scale as we move towards the oldest ones (as lag t gets bigger), which means that the most recent observations matter more. In this way, it incorporates volatility clustering better than SMA.

Secondly, the only estimation needed is the decay factor λ. It is estimated for many asset classes by RiskMetrics and found to be 0.94, a fact that automatically sets the length of the sample to 100 observations, since for the lags from 1 to 100 the vast majority of the weight has been used.

On the other hand, as simple as this model is, it does not count for leverage effect discussed earlier. Also, it does not incorporate the mean reverting patterns of volatility as will be shown later on.

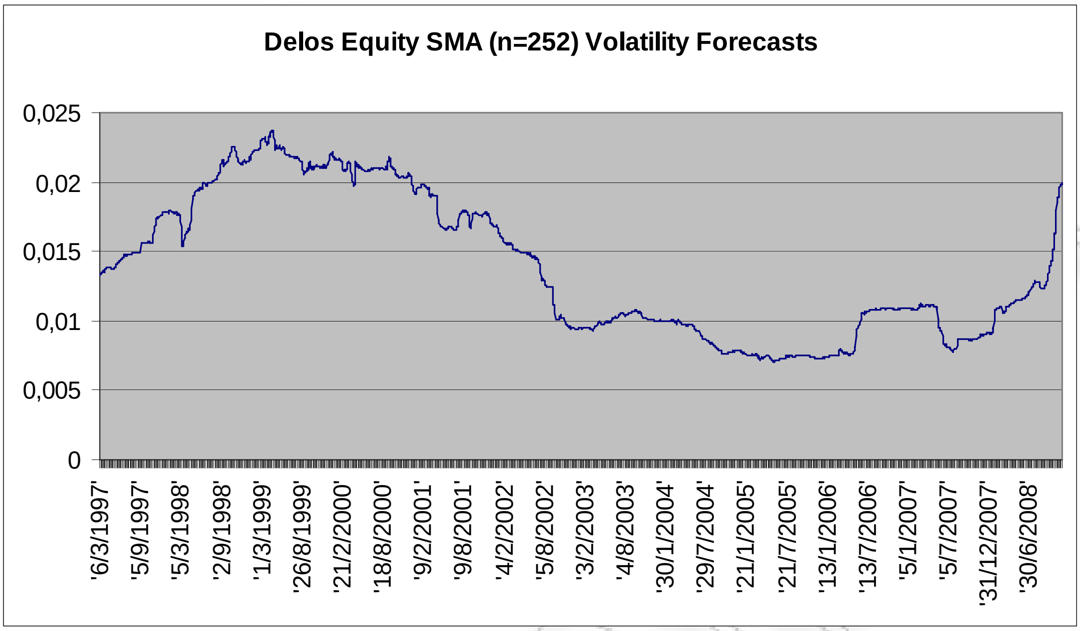


Figure 8: Delos Blue Chips Simple Moving Average (rolling sample of 252 observations) volatility forecasts from 6/3/1997 to 21/11/2008.

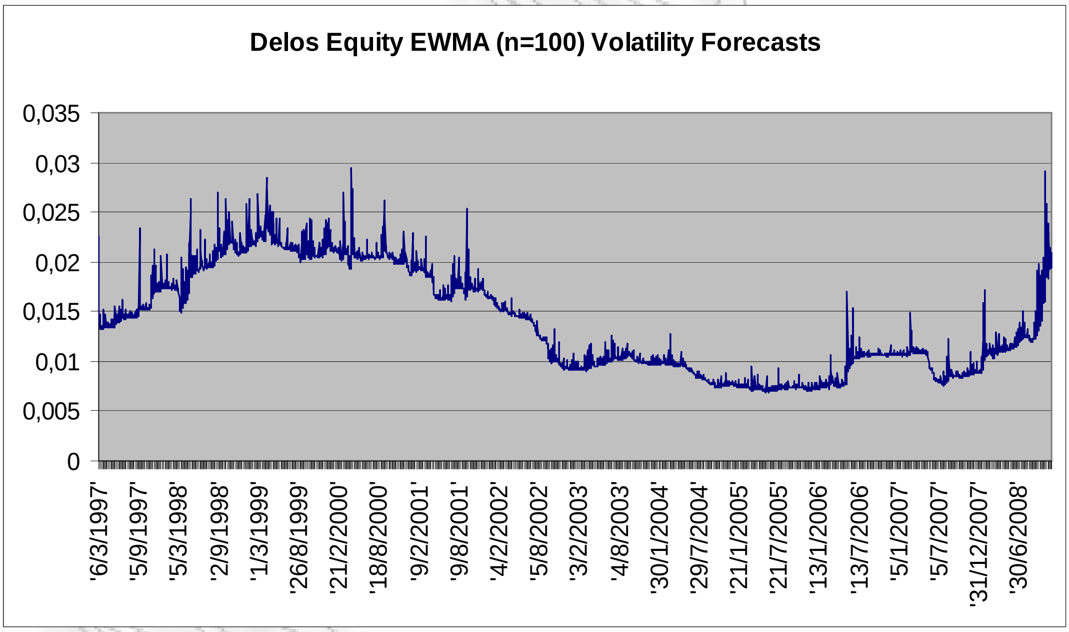


Figure 9: Delos Blue Chips Exponentially Weighted Moving Average (rolling sample of 100 observations) volatility forecasts from 6/3/1997 to 21/11/2008.

The above figures present the volatility forecasts for the same mutual fund over the same time period. We can see that SMA produces a smooth pattern, while EWMA a jagged one. This happens due to the fact that the second method reacts better to the "latest news", allowing for volatility clustering more efficiently.

8.3) GARCH(p,q)

The GARCH model was introduced by Bollersev (1986) in his paper "Generalized Autoregressive Conditional Heteroskedasticity". The GARCH (p, q) volatility process is:

$$u_t = \sigma_t z_t \, , z_t \sim i.i.d.\, N(0,1)$$

$$\sigma_{t+1}^2 = \omega + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \beta_j u_{t-j}^2 \qquad (18)$$

Where: ω>0, α_i >0, β_j >0 and $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j$ <1 and z_t is a random variable.

The idea is that the variance of returns depends both on past values of the shocks (the past squared error terms) and on past values of itself. Also, p refers to the length of GARCH (or variance) lags and q to the length of ARCH (squared error terms) lags. The latter captures volatility clustering.

The GARCH (1, 1) model is specified as:

$$u_t = \sigma_t z_t \, , z_t \sim i.i.d.\, N(0,1)$$

$$\sigma_{t+1}^2 = \omega + \alpha \sigma_t^2 + \beta u_t^2 \qquad (19)$$

Where: ω>0, α >0, β >0 and $\alpha + \beta < 1$

Intuitively, the GARCH (1, 1) specification estimates variance at t+1 as the long run variance ω plus/minus a value depending on the magnitude of squared residuals and variance at t. This is a key difference with the EWMA model, which is actually a special case GARCH model with α=λ and β=1-λ. We can, therefore, infer that GARCH specification incorporates mean reverting patterns for variance (and volatility), as it fluctuates around ω, while EWMA does not.

Another perspective can be gained by examining this via the persistence of the model, i.e. the value α+β. Persistence expresses for how long the shocks that move variance away from the long run variance will persist. For the EWMA model, where α+β=1 means that shocks will persist forever or that there is not long run variance. High variance at t means that in the future there will always be high variance, which may not actually be the case.

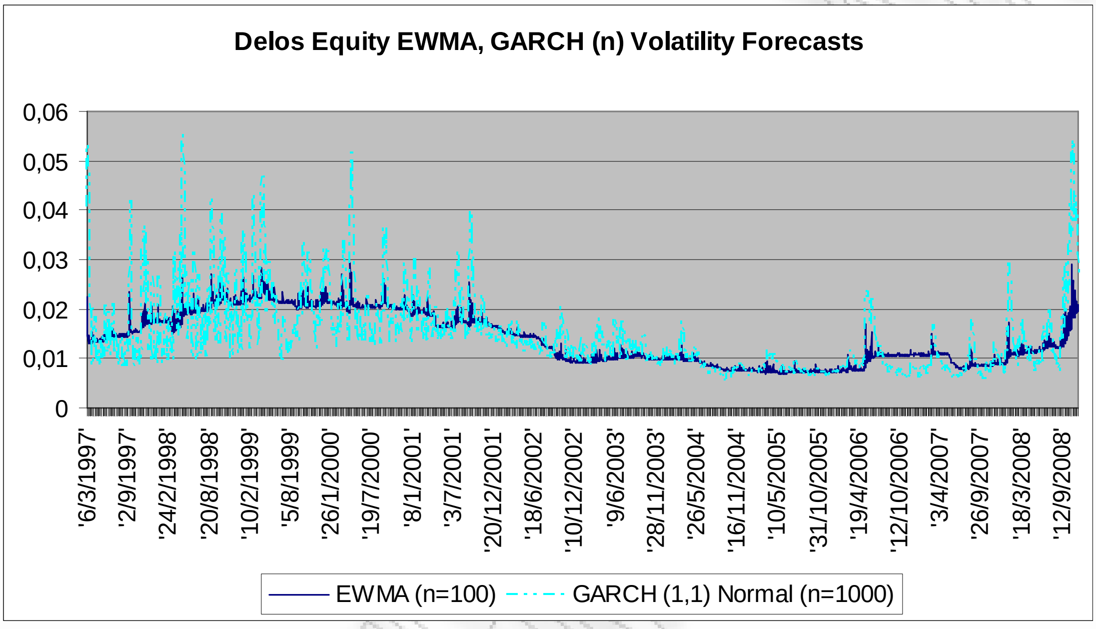


Figure 10: Delos Blue Chips Exponentially Weighted Moving Average (rolling sample of 100 observations) and GARCH (n) (rolling sample of 1000 obsevations) volatility forecasts from 6/3/1997 to 21/11/2008.

The above mentioned arguments are obvious in the figure 10. As can be noticed, the GARCH (1,1) volatility forecasts seem to vary around a long run average, while the EWMA forecasts do not. Also, GARCH (1, 1) seems to update volatility forecasts faster and with greater magnitude than EWMA.

Except for normal, innovations can follow student's t distribution that has fatter tails and seems to fit better to extremes than the normal. Thus, in figure 11 GARCH (1, 1) with student's t innovations seems to produce higher volatility forecasts than GARCH (1, 1) with normal innovations.

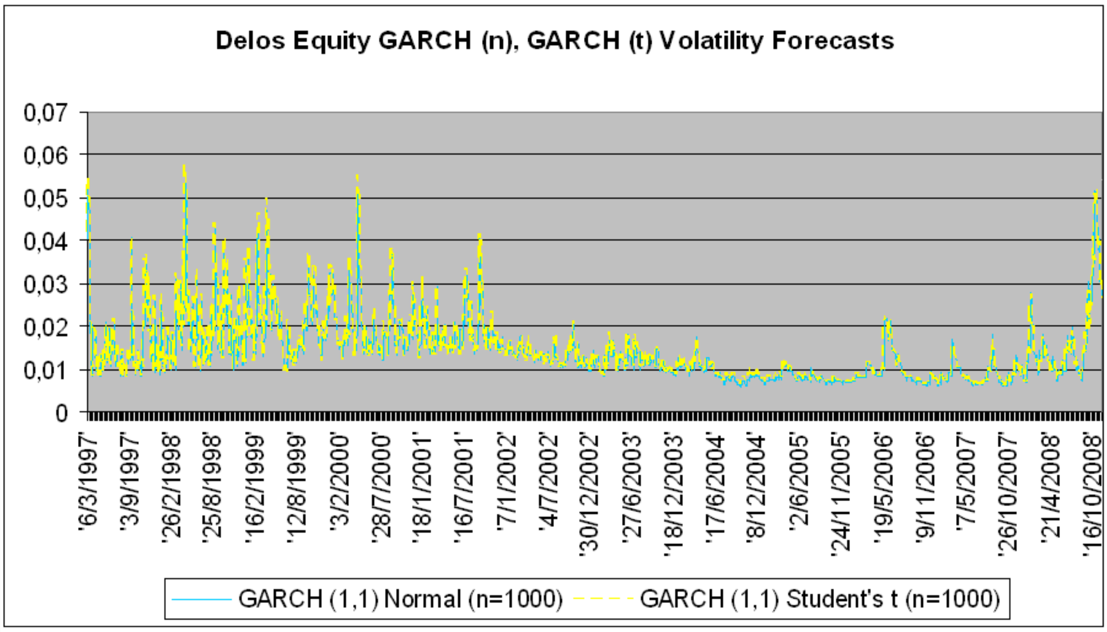


Figure 11: Delos Blue Chips GARCH (t) (rolling sample of 1000 observations) and GARCH (n) (rolling sample of 1000 observations) volatility forecasts from 6/3/1997 to 21/11/2008.

8.4) EGARCH (p, q)

As discussed earlier, financial return series exhibit the leverage effect, i.e. negative correlation between variance and returns. The GARCH (p, q) models presented previously do not count for this fact, as they weight equally (and positively) both positive and negative returns (the innovations are squared) and do not count for asymmetries. To this end, a number of alterations have been proposed in order to capture it, namely, NGARCH (Non Linear GARCH), GJR-GARCH by Zakonian (1990) and Glosten, Jaganathan, Runkle (1993) and EGARCH (Exponential GARCH) by Nelson (1991), which is utilized in this paper.

Nelson (1991), after posing some limitations of GARCH models, introduced Exponential GARCH:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \ln(\sigma_{t-i}^2) + \sum_{j=1}^{q} \beta_j g(u_{t-j}), \quad \beta_1 \equiv 1 \qquad (20)$$

In order to incorporate asymmetry, $g(u_t)$ must be a function of both the magnitude and the sign of u_t. Thus:

$$g(u_t) = \theta u_t + \gamma\left[|u_t| - E|u_t|\right] \qquad (21)$$

with θ, γ constants.

As Nelson states, $g(u_t)$ is by construction a zero-mean i.i.d. sequence and in the spirit of GARCH models, it represents a magnitude effect according to the sign of the last return, relatively to the expected one ("bad or good news"). Finally, in the EGARCH model there are no inequality constraints as in the GARCH model. Volatility forecasts are assured to be positive due to the logarithmic expression.

In comparing the two methods in the following plot, can conclude that GARCH model gives higher volatility forecasts than EGARCH, due to the difference in the magnitude of each innovation in estimating volatility.

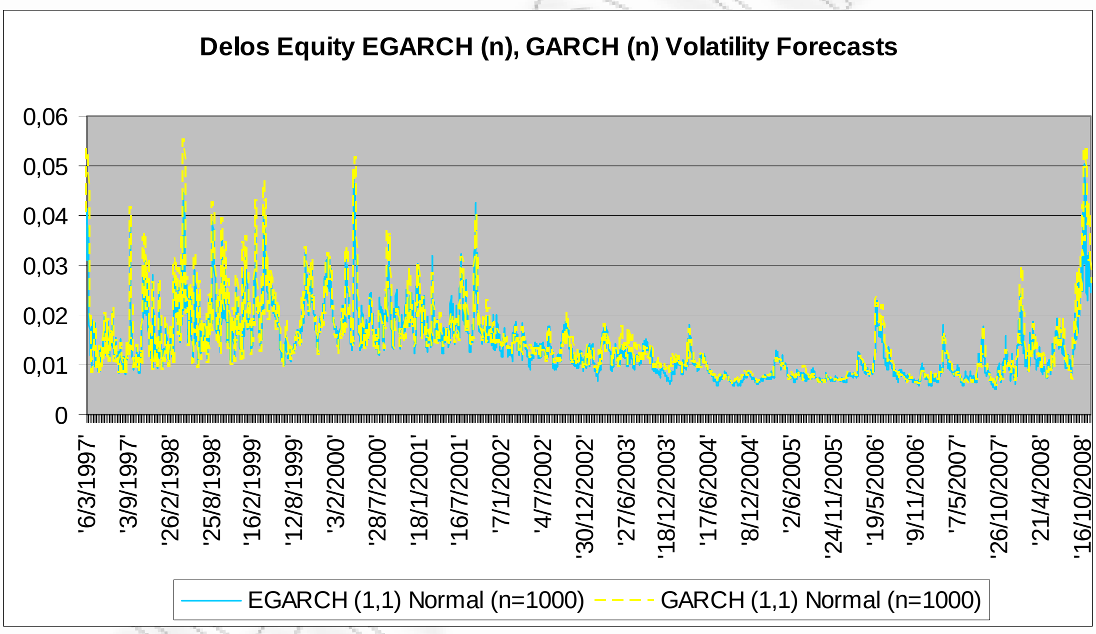


Figure 12: Delos Blue Chips EGARCH (n) (rolling sample of 1000 observations) and GARCH (n) (rolling sample of 1000 obsevations) volatility forecasts from 6/3/1997 to 21/11/2008.

9. Backtesting[3]

In order to find out if a VaR model has adequate predictive power we should compare the series of p*100% VaRs to the series of the corresponding realized returns of the mutual funds and construct the "hit sequence" of VaR violations, as:

[3] based on Christoffersen, P., 2003. "Elements of Financial Risk Management, Academic Press

$$I_{t+1} = \begin{cases} 1, \text{if } R_{pf,t+1} < -VaR^{p}_{t+1} \\ 0, \text{if } R_{pf,t+1} > -VaR^{p}_{t+1} \end{cases} \quad (22)$$

Thus, the hit sequence returns 1 on day t+1 if the loss is greater than the forecasted VaR, which means we have a violation. Otherwise, if the projected VaR is not violated, the hit sequence returns 0.

Assuming that we are using a perfect VaR model, then we should not be able to predict whether the VaR will be violated. This means that our forecast of a violation should be 100*p% every day, so that the above described hit sequence of violations should be completely unpredictable and thus independently distributed over time:

$$Ho : I_{t+1} \sim \text{i.i.d. Bernoulli}(p)$$

The Bernoulli distribution function is:

$$f(I_{t+1}; p) = (1-p)^{1-I_{t+1}} p^{I_{t+1}}$$

In the classic coin tossing example with p=0.5 the Bernoulli distribution describes the distribution of getting a head. In our case, p will equal the coverage rate of the forecasted VaR, that is 1% and 5%, and the hit sequence will return 1 (meaning violation) 1% or 5% of the time assuming that the VaR model used is perfect. In these terms, there are three types of hypotheses to be tested:

1) The number of VaR violations is as promised by the coverage rate (Unconditional Coverage Testing),
2) The violations are independent throughout the backtesting period (Independence Testing) and
3) The hypotheses 1 and 2 are jointly valid (Conditional Coverage Testing).

9.1 Unconditional Coverage Testing

In order to find out if the actual fraction of violations π is as promised, we should test whether it is significantly different from the coverage rate (or significance level) p. This is the unconditional coverage hypothesis that π=p. The likelihood of an i.i.d. Bernoulli (π) hit sequence is:

$$L(\pi) = \prod_{t=1}^{T} (1-\pi)^{1-I_{t+1}} \pi^{I_{t+1}} = (1-\pi)^{T_0} \pi^{T_1} \quad (23)$$

where t=1,2,…T are the days for which we have VaR predictions and realized returns with T the number of observations, T_0 and T_1 are the number of 0s and 1s in the sample (i.e. the hit sequence). π can be estimated by the fraction $\hat{\pi}$=T1/T that stands for the observed fraction of violations in the hit sequence and the likelihood. Thus the likelihood function becomes:

$$L(\hat{\pi}) = (1 - T_1 / T)^{T_0} (T_1 / T)^{T_1} \quad (24)$$

As we stated earlier, under the unconditional coverage null hypothesis π=p and thus the likelihood becomes:

$$L(p) = \prod_{t=1}^{T} (1-p)^{1-I_{t+1}} p^{I_{t+1}} = (1-p)^{T_0} p^{T_1} \quad (25)$$

The unconditional coverage hypothesis can be tested using a likelihood ratio test:

$$LR_{uc} = -2\ln[L(p)/L(\hat{\pi})] \quad (26)$$

Asymptotically, as the number of observations T goes to infinity the test will be distributed as x^2 with one degree of freedom and inserting the likelihood functions we finally get:

$$LR_{uc} = -2\ln\left[(1-p)^{T_0} p^{T_1} / \{(1-T_1/T)^{T_0} (T_1/T)^{T_1}\}\right] \sim x_1^2 \quad (27)$$

After choosing a significance level we compare the LRuc and the critical value of the x_1^2 distribution. If LRuc> critical value, we reject the VaR model at the specified significance level, otherwise it is not rejected. Choosing the significance level depends on making two types of errors:

- Type I error: reject a correct model
- Type II error: accept an incorrect model

If we increase the significance level, we will probably face larger Type I errors but smaller Type II errors and the opposite. Typically, in academic work 1%, 5% or 10% significance levels are used but in practice Type II errors are more costly and thus 10% significance level should be preferred.

9.2 Independence Testing

With the previous test we can assure that the number of violations is as promised. But that is not enough. These violations should be scattered in time. If many violations happen in a small time period, we have violations clustering and this raises serious doubts about the viability of the organization. If we have violations clustering, then if today is a violation, tomorrow it is more than p*100% likely to be a violation as well. Thus we need a test that will reject such models.

We assume that the hit sequence is dependent over time and it can be described by as a first order Markov sequence with transition probability matrix:

$$\Pi_1 = \begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix}$$

This means that, conditional that today we have non-violation ($I_t = 0$), then the probability that tomorrow we will have violation ($I_{t+1} = 1$) is π_{01}. If today we have a violation, then the probability that tomorrow we will have also a violation is $\pi_{11} = \Pr(I_t = 1 \text{ and } I_{t+1} = 1)$. The first-order Markov property means that only today matters for what happens tomorrow, i.e. the 1 or 0 of the hit sequence today matters for tomorrow's 1 or 0 and not any past outcomes. Since the possible outcomes are two (0 or 1) the whole process is described by the two probabilities π_{01} and π_{11}. The probability of a non-violation following a non-violation π_{00} is $1-\pi_{01}$ and the probability of a non-violation following a violation π_{10} is $1-\pi_{11}$. The likelihood function of this first-order Markov process is:

$$L(\Pi_1) = (1-\pi_{01})^{T_{00}} \pi_{01}^{T_{01}} (1-\pi_{11})^{T_{10}} \pi_{11}^{T11} \quad (28)$$

with $T_{i,j}$, i, j=0, 1 being the number of observations with an i followed by j. For the maximum likelihood estimates we get:

$$\hat{\pi}_{01} = \frac{T_{01}}{T_{00}+T_{01}}, \hat{\pi}_{11} = \frac{T_{11}}{T_{10}+T_{11}}, \hat{\pi}_{00} = 1 - \hat{\pi}_{01} \text{ and } \hat{\pi}_{10} = 1-\hat{\pi}_{11} \quad (29)$$

since probabilities sum to one.

Substituting these estimations to the transition probability matrix we get:

$$\hat{\Pi}_1 = \begin{bmatrix} \hat{\pi}_{00} & \hat{\pi}_{01} \\ \hat{\pi}_{10} & \hat{\pi}_{11} \end{bmatrix} = \begin{bmatrix} 1-\hat{\pi}_{01} & \hat{\pi}_{01} \\ 1-\hat{\pi}_{11} & \hat{\pi}_{11} \end{bmatrix} = \begin{bmatrix} \frac{T_{00}}{T_{00}+T_{01}} & \frac{T_{01}}{T_{00}+T_{01}} \\ \frac{T_{10}}{T_{10}+T_{11}} & \frac{T_{11}}{T_{10}+T_{11}} \end{bmatrix}$$

If the hit sequence has dependence (and our model gives violations clustering) then $\pi_{01} \neq \pi_{11}$ but if we have independence (no violations clustering - good model) then $\pi_{01} = \pi_{11} = \pi$, which is the independence hypothesis that we will test. Under independence, all probabilities are the same and the transition probability matrix will be:

$$\hat{\Pi} = \begin{bmatrix} 1-\hat{\pi} & \hat{\pi} \\ 1-\hat{\pi} & \hat{\pi} \end{bmatrix}$$

We use a likelihood ratio test to test the independence hypothesis $\pi_{01} = \pi_{11}$:

$$LR_{ind} = -2\ln\left[L(\hat{\pi}) / L(\hat{\Pi}_1)\right] \sim \chi_1^2 \quad (30)$$

where $L(\hat{\pi}) = (1 - T_1 / T)^{T_0} (T_1 / T)^{T_1}$, the likelihood under the alternative hypothesis from the previous test. As the number of observations becomes large, the LR_{ind} statistic is also distributed as χ^2 with one degree of freedom.

9.3 Conditional Coverage Testing

Conditional coverage testing provides a way to test jointly for independence and correct coverage and thus consists a strong indication whether to accept or not a model. In this case the hypothesis tested is $\pi_{01} = \pi_{11} = p$.

$$LR_{cc} = -2\ln[L(p) / L(\hat{\Pi}_1)] \sim \chi_2^2 \tag{31}$$

or, since it combines the previous two tests:

$$LR_{cc} = LR_{uc} + LR_{ind} \sim \chi_2^2 \tag{32}$$

with two degrees of freedom.

10. Past papers review

McNeil & Frey (2000) compute VaR end Expected Shortfall with a variety of methods for five series of financial logarithmic returns: S&P 500 (1/1960 – 6/1993), DAX and BMW share price (1/1973 – 6/1996), US dollar/British pound exchange rate (1/1980 – 5/1996) and the price of gold (1/1980 – 12/1997). They use a rolling sample of 1000 observations for each method: Conditional EVT (POTS with AR(1)-GARCH(1,1) process), Unconditional EVT (POTS) each with threshold set at 10%, Conditional Normal (GARCH(1,1) with normal innovations) and Conditional student's t (GARCH(1,1) with t distributed innovations) for 95%, 99% and 99,5% confidence levels. They conclude that conditional EVT performs best, with GARCH (t) following, emphasizing that it works well for symmetric tails but not otherwise. GARCH (n) looses accuracy for confidence levels grater than 95%. For ES, their EVT approach proved to perform better than GARCH (n).

Vlaar (2000) focuses on VaR for the banking sector. He calculates the performance of several historical simulation, variance – covariance and Monte Carlo simulation methods at predicting 99% 10-day VaR for 25 portfolios consisting of Dutch fixed interest securities. The data set covers 17 years of historical returns with daily frequency. The historical simulation method was applied for sample of 250, 550, 750, 1250 and 2550 observations. For the Monte Carlo simulation, there was a variety of methods concerning the calculation of the expected price change of the process used including random walk and positive autocorrelation and the variance – covariance matrix was construed either with naive variance, EWMA or GARCH specification assuming normal or student-t distributions. For the VC method, also naïve variance, EWMA and GARCH methods were used and finally there was a combination of Monte Carlo Simulation and VC methods. The best results were obtained by the combined Monte Carlo - VC methods, especially the GARCH specified ones. Good performance was also achieved by the VC naive variance method. In all cases, the worst results came from student's-t distributional assumptions. From a supervisory point of view, it was proved that accurate VaR calculation methods could lead to higher capital requirements than simpler but inaccurate measures, under the k-multiplier BIS framework.

Barone – Adesi & Gianopoulos (2001) carry out a comparative study of Historical Simulation and Filtered Historical Simulation methods. After a brief description of the two methods and their pros and cons respectively, they apply them on three hypothetical portfolios: One that consists of a long position on S&P 100 and the other two consist of a short position on a European call option on the same basis. The data set covers the period from 1/1/1997 to 26/11/1999 and the VaR computed is at 99% confidence level for 1, 5, 10 and 20 days ahead. They conclude that there are discrepancies between the results of the two methods, with FHS being better due to its ability to produce VaR figures consistent with the current state of markets.

Lambadiaris, Papadopoulou, Skiadopoulos and Zoulis (2003) apply historical and Monte Carlo simulation methods in order to calculate one day ahead 95% and 99% VaR for linear and non-linear portfolios, using data from the Greek stock and bond market. More specifically, the historical simulation methods applied are one day rolling window with sample of 100 and 252 observations. For the linear portfolio, the Monte Carlo simulation methods used were Moving Average, Exponentially Weighted Moving Average and diagonal BEKK volatility estimators, using a geometric Brownian motion. For the non-linear bond portfolio Monte Carlo simulation, they used a process analogous to the one used in the Libor market models and its volatility was estimated by principal component analysis. The results are mixed, depending on the portfolio size, the criterion and confidence level. For the linear portfolio, the historical simulation method leads to more capital commitment than needed, but for the non-linear one there is no clear superiority and the number of the PCA factors does not affect the performance of the VaR model.

Sarma, Thomas and Shah (2003) examine several methods in estimating 95% and 99% 1 day ahead VaR for the S&P 500 and India's NSE - 50 indexes. The methods applied are HS for windows of 50, 125, 250, 500 and 1250 observations, due to its sensitivity in the sample size, Equally Weighted Moving Average (or Simple Moving Average in the present paper) and the RiskMetrics model (or EWMA in the present paper) also for windows of 50, 125, 250, 500 and 1250 observations for different lamdas (0.9, 0.94, 0.96, 0.99) and AR(1) – GARCH (1,1) models for window of 1250 observations. Their sample covers the period from July 1990 to July 2000 (approximately 2500 observations). Their backtesting procedure is based on two aspects, the conditional coverage rate (as in the present paper) for the statistical accuracy and loss functions in order to conclude to the model that yields the least loss. For the 95% VaRs on S&P 500, EWMA (500) and all HS methods are rejected, except from HS (125), while for the NSE – 50 EWMA (50), EWMA (500), all RiskMetrics models except from RiskMetrics (0.90) and all HS models except from HS (1250) are rejected. For the 99% VaR on S&P 500, all models are rejected, while for the NSE – 50 EWMA (50), EWMA (1250) and all HS methods except from HS (500) are rejected. The loss functions determine that the AR(1) – GARCH (1,1) model produces the lower economic losses, while the differences from the RiskMetrics (0.90) model are not statistically significant.

Seymour and Polakow (2003) examine the performance of Historical Simulation, EWMA and Extreme Value Theory based methods in the emerging South African market. More specifically, they apply HS, EWMA and EVT (HS based as in Danielsson and DeVries (2000) and based on a two stage model as in McNeil and Frey (2000) for portfolios consisting of nine stocks, with at least ten years of historical data with windows of 1500 observations. The predicted VaR covers confidence levels from 95% to 99,95%. HS is found to perform poorly in all cases, as the HS based EVT, which gave superior results though for confidence intervals larger that 99% as expected. The EWMA model performed well for low confidence levels and the two-stage EVT model had the superior performance due the GARCH type volatility incorporation. The backtesting procedure was performed in a percentage of violations framework.

Angelidis and Benos (2004) compute 97.5% and 99% 1 day ahead VaR for long and short positions on the Greek stock market. The models they use are GARCH, TARCH and EGARCH with normal, student’s t and skewed student’s t distributed innovations, simple Variance – Covariance, EWMA, Historical Simulation, Filtered Historical Simulation and EVT with GARCH filtered returns series (as in McNeil and Frey, 2000) for 5% threshold. Their dataset covers four stocks (Alpha Bank, Commercial Bank, National Bank, Titan), two equally weighted portfolios with positions on this stocks and ASE index for the period of January 2nd, 1991 to December 18th, 2003. The VaR estimation for each position (long – short) is made with a rolling window of 1000 observations. In order to decide for the best models, they apply two tests: 1)

Unconditional and Conditional Coverage, to test the percentage of violations with respect to the confidence level and 2) Loss functions in order to see whether the differences between the VaR forecasts are statistically significant. V-CV and EWMA methods often fail to match the backtesting criteria, normal GARCH (1,1), EGARCH (1,1) and TARCH (1,1) perform better for 97.5% VaR for the long positions, while fail for the short ones. The parametric models under student's t and skewed student's t overestimate VaR, HS presents violations clustering and FHS and EVT methods perform best for both long and short positions. According to the loss function, there is no unanimous decision on the best model, as it varies across different assets and positions.

Gencay and Selcuk (2004) focus on VaR for emerging markets. They use data for stock indices of nine countries, namely Argentina, Brazil, Hong Kong, Indonesia, Korea, Mexico, Philippines, Singapore, Taiwan and Turkey. The sample size varies from 1076 to 7305 observations and one-day ahead VaR is computed with rolling window of 500, 1000 and 1500 observations for 95%, 97.5%, 99%, 99.5% and 99.9% confidence levels. The models applied are Variance - Covariance with normal and student's t distributional assumptions, Historical Simulation and Generalized Pareto Distribution (GPD – POTS) with threshold set to 2.5%. The decision over the best performing model comes in the sense of having the right percentage of violations depending on the confidence level, or as much closer to it, as fewer violations would mean overestimation of VaR and consequently high market capital requirements. They conclude that GPD (POTS) performs best, with ascending success as we move towards to the highest confidence level.

Papadamou and Stephanides (2004) apply four models in order to estimate one month ahead 95% VaR and Expected Tail Loss (Expected Shortfall herein) for US mutual funds investing in Europe. The models used are Conditional Normal, Bootstrapping, Historical Simulation and an alternative Style Based Method. This method comes as a consequence of Sharpe's (1998) style analysis framework and it is a two-step procedure: The first step is to find the factors (or indices) that contribute to the MF's performance, compute the market risk VaR for each factor and then the overall impact on the fund. The second step is to compute the VaR of the fund manager specific characteristics ("Value at Selection Risk") and add it to the total VaR. Their sample covers 19 US mutual funds over the period from 31/06/97 to 31/01/2002 which leaves the authors with a rather small sample of 56 monthly observations and 20 observations for backtesting, using a rolling window of 36 observations. The backtesting was carried out in an unconditional coverage and magnitude of violations framework. Style based VaR was found to perform well, while Style Based ES leads to overestimations in comparison with the other models. The MF's VaR major source is the market VaR, while "Value at Selection Risk" does not count much. Finally, the authors conclude that the selection of VaR methods should be made according to the style followed by each fund.

Kuester, Mitnik and Paolella (2005) examine the performance of a variety of models, classified as Historical Simulation Methods (and filtered ones), fully parametric models, Extreme Value Theory models and quantile regression models. Their analysis is applied on a long position in the NASDAQ Composite Index, with more than 5000 stocks, for 30 years of data (8/9/1971 – 22/6/2001) or 7681 observations and the estimation of one day ahead 95%, 97,5% and 99% VaR is performed with moving windows of 1000, 500 and 250 observations. The backtesting methods are the ones used in the present paper and the results are also evaluated under the Basle Committee thre-zone framework. The unconditional models, HS, Normal, student's t, skewed student's t and EVT do not give good results, with skewed student's t being superior from others. Although they perform badly, some of them could enter the "yellow zone" of the BIS framework. GARCH filtering methods (for a variety of innovations' distributions) improve significantly the results, giving GARCH with skewed t distributed errors, FHS and EVT with filtered innovations (normal, skewed t or GED) the best overall performance. CAViaR models achieved a rather poor performance. Finally, they conclude that the validity of the aforementioned best methods is not affected by the window size, except from the reversion of EVT normal and EVT skewed t performance.

So and Yu (2005) use seven models for twelve market indices and four exchange rates, in order to compute 1 day ahead 95%, 97.5% and 99% VaR for both long and short positions. More specifically, the models used are GARCH (1,1), IGARCH (1,1), FIGARCH(1,d,0) with normal and student's t innovations and EWMA. Their data set covers equity indices from Australia (AOI), United Kingdom (FTSE100), Indonesia

(JSX), Hong Kong (HIS), Malaysia (KLSE), South Korea (KOSPI), United States (NASDAQ and S&P500), Japan (NIKKEI), Thailand (SET), Singapore (STII) and Taiwan (WEIGHT) and varies from 1975 to 1998. The exchange rates under consideration are GPB/USD, YEN/USD, AUD/USD and CAD/USD from 1980 to 1998. In all cases, the backtesting period covers 1995 to 1998 and it is carried out in a percentage of violations to VaR confidence level framework. For the long equity positions, IGARCH(t), GARCH(t) and FIGARCH(t) perform best at 99% confidence level, IGARCH and IGARCH(t) perform best at 97,5% and EWMA performs best at 95% predictions. For the short positions, at 99% GARCH(n) and FIGARCH(n) perform well, at 97,5% GARCH (n) and GARCH(t) and at 95% EWMA and GARCH (t). For the exchange rate positions, results are similar for both long and short positions, as at 99% confidence level the student's t distributed error models perform well, IGARCH(n) and GARCH(t) at 97.5% and EWMA at 95%. Finally, the authors conclude that although there is presence of long memory in variance, FIGARCH models do not produce more accurate VaR predictions than GARCH models.

Bali and Theodossiou (2006) illustrate that the skewed generalized t (SGT) distribution matches better the returns than other distributions. Thus, they calculate 95%, 97,5%, 98%, 98.5%, 99% and 99.5% 1 day ahead VaR and Expected Shortfall for the S&P 500 index, using data from 1950 to 2000. The models used are GARCH, AGARCH, EGARCH, GJR-GARCH, IGARCH, NGARCH, QGARCH, SQR-GARCH, TGARCH, TS-GARCH and VGARCH with SGT and normally distributed innovations with a rolling sample of ten years of observations. From the unconditional coverage tests, the TS-GARCH performs well, followed very closely by the EGARCH and NGARCH models all with SGT innovations, while the results for the normal ones are disappointing for 99.5%, 99% and 98.5% confidence levels and exhibit some predictive power only for 95% VaRs. The conditional coverage test accepts all SGT models but rejects almost all normal ones, except for the 2.5% VaRs. For the Expected Shortfall measure, the SGT ES predictions perform better for levels larger than 98%, in the sense that actual violations of ES are closer to the ones obtained by the empirical distribution. The same results apply for ES calculated from standardized returns, with normal models giving accurate predictions for confidence levels up to 97.5%.

Angelidis, Benos & Degiannakis (2007) apply several parametric, non – parametric and semi – parametric models in order to compute 97.5% and 99% VaR for long and short positions on small and big capitalization stocks of the DJ Euro Stoxx index. More specifically, they apply Variance – Covariance, GARCH, EGARCH, TARCH and APARCH with normal, student's t and skewed student's t distributional assumptions, Filtered Historical Simulation and Extreme Value Theory with GARCH and APARCH specifications and finally Historical Simulation. Their sample covers the period from January 2, 1987 to July 29, 2005 and it is split into two subgroups of 2399 observations to test the results more efficiently and the window used is 1750 observations. They test if the forecasted VaRs are as promised by the confidence level and if they produce statistically significant deviations from each other. FHS with GARCH specification was found to perform well in all cases, while ARCH models with normally distributed innovations and FHS with ARCH updating technique seem to describe the tails more efficiently.

Füss et al. (2007) determine VaR for hedge funds. After a brief explanation of hedge fund strategies and styles (based on S&P categorization, i.e. Arbitrage, Event - driven and Directional – Tactical) they move on to calculating the 95% daily VaR for totally one month ahead in order to check the out of sample performance for three methods: conventional, Cornish Fischer, GARCH and EGARCH VaR with normally distributed residuals. The dataset covers the period from September 2002 to May 2006 (926 observations, 904 for estimation and the rest for out of sample testing) and consists of S&P hedge fund index series, with the authors admitting the possible presence of selection and survivorship bias. Due to the small sample for out of sample testing, they construct hit ratios with weights depending on how big each violation is. The results show better performance of the GARCH VaRs - mainly due to the incorporation of time varying volatility and thus risk - although skewness and kurtosis are not completely removed from the standardized errors.

Giamouridis & Ntoula (2009) study the downside risk of hedge funds by means of VaR and ES. They perform their analysis in a univariate framework rather than disaggregating risk exposures, by applying several methods in a series of HFR (Hedge Fund Research Inc) investable strategy indices: Equity Hedge, Macro, Relative Value Arbitrage, Event – Driven, Convertible Arbitrage, Distressed Securities, Equity

Market Neutral and Merger Arbitrage. Their sample covers the period from March 3 2003 to May 25 2006, limiting the window choice to 500 observations and 295 observations for backtesting, which may allow for some caution in the results. The methods applied are Historical Simulation for 125 and 250 observations, Filtered Historical Simulation (FHS), Generalized Pareto Distribution (GPD), Cornish – Fisher (CF) and Gaussian (G) model. In all cases except from the HS method, an ARMA – GARCH specification is used (as in McNeil & Frey, 2000) to filter the residuals. Their results suggest that FHS, G, CF and GPD perform equally for 95% VaR predictions, outperforming HS methods on the basis of lower average size of violations and number of threshold violations, while for 99% VaR FHS, CF and GPD perform best with G being the worst method. Backtesting shows evidence in favor of the conditional models at 95% VaR and for CF and GPD at 99% VaR. For the ES measures, they conclude that HS250, FHS, CF and GPD perform better than HS125 and G, in the sense that they are not often violated. The backtesting suggests that HS250, FHS and CF have the best overall performance.

11. The Greek Mutual Funds Market

According to Karathanasis and Limperopoulos (2002), the idea of pooling holdings in a mutually managed scheme dates back to ancient Greece and more specifically in the fifth century B.C. These entities where not managed in order to achieve certain performance goals as known today, but rather for military purposes. The first form of mutual funds was created in the US in 1924, due to the need for new investing vehicles in a steadily developing economy and the positive returns of the stock market. After the 1929 crisis, mutual funds faced many difficulties, but in the 40's the American Congress approved a new legislative framework ("Investment Company Act") on their operations, establishing this form of institutional investing in the financial industry. Since then, total assets of mutual funds globally steadily increased, except from periods of crises as 2008. By the end of 2008 13.6 trillion euros were invested in mutual funds.

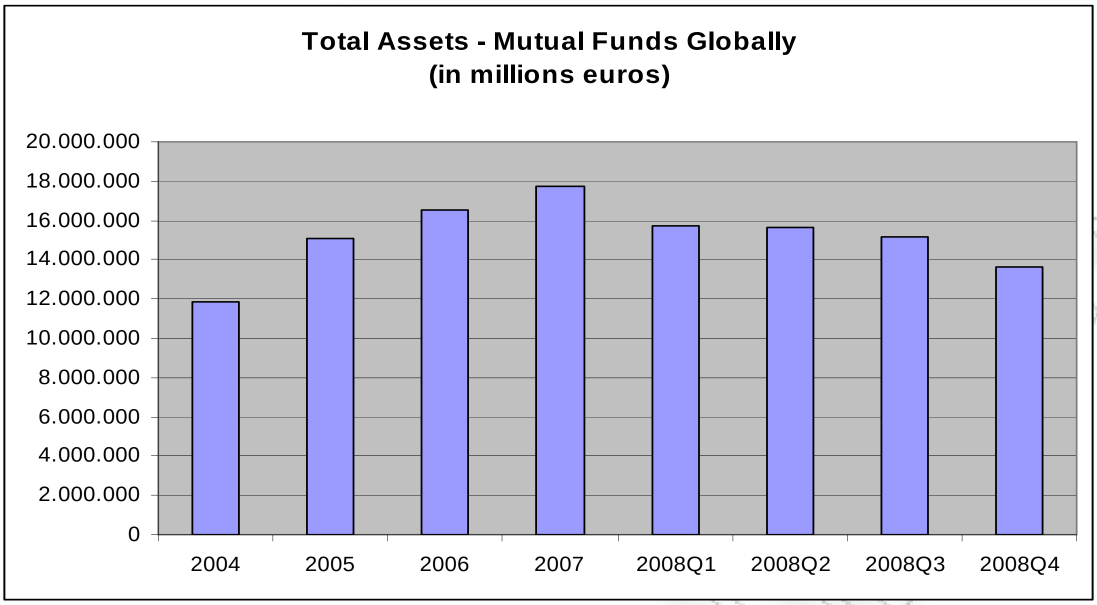


Figure 13: Total assets value of mutual funds globally
Source: EFAMA, International Statistical Release Q4 2008

In Greece, mutual funds began to operate in the 70's. The first two mutual funds where "Delos Balanced" (included in our sample) by the National Bank of Greece and "Ermis Dynamic" by Emporiki Bank. Until the late 80's the mutual fund industry did not achieve significant developments, but in the early 90's, as new management companies joined the market, it began to expand. Currently, 22 management companies operate, managing 322 mutual funds with total assets of 8.7 billion euros by 31/12/2008.

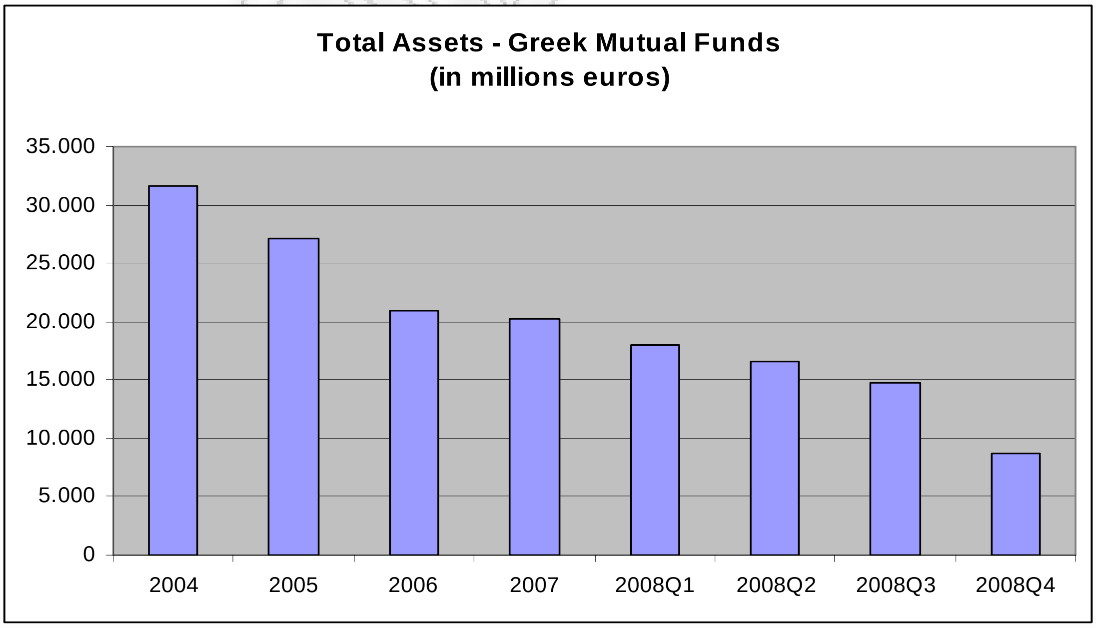


Figure 14: Total assets value of Greek mutual funds
Source: EFAMA, International Statistical Release Q4 2008

There are five types of mutual funds in the Greek market:

1) Equity: Invest mainly in equity markets (at least 65% of total assets) and secondarily in bonds and money market instruments.
2) Bond: Invest mainly in bonds (at least 65% of total assets), in money market instruments and up to 10% in equity markets.
3) Balanced: Invest in all three asset classes mentioned, with an upper limit of 65% in each one.
4) Money market: Invest mainly in short term money market instruments (at least 65% of total assets), in bonds and up to 10% in equity markets.
5) Fund of funds: Invest in other funds. Depending on the type of funds they invest, they are characterized as equity, bond or balanced and they where established in 2005.

All types above can be domestic, i.e. invest mainly in Greece, foreign, i.e. invest abroad or international, i.e. invest both domestically and abroad.

11.1 Sample Selection

The selection of mutual funds included in our sample was made according to the following criteria:

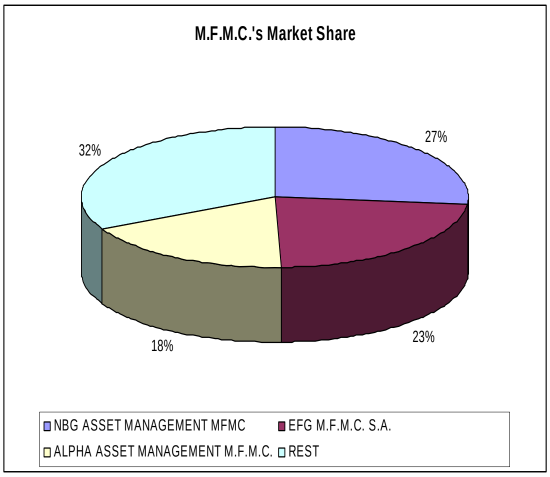
1) Include the management companies (and mutual funds) with the greatest market share, in order for the results to be as much as possible indicative for the whole market, and
2) Include mutual funds that provide large number of past data in order to have adequate sample size for the backtesting procedure.

In these terms, we use historical returns for nine funds, (three of each category: equity, balanced and bond) of the three major management companies.

The three management companies included are:

1) NBG ASSET MANAGEMENT M.F.M.C.
2) EFG M.F.M.C. S.A.
3) ALPHA ASSET MANAGEMENT M.F.M.C.

Cumulatively, they serve the 67.54% of the market at 31/12/2008 and manage 177 out of the total 322 funds (55%), as illustrated by the following figures.



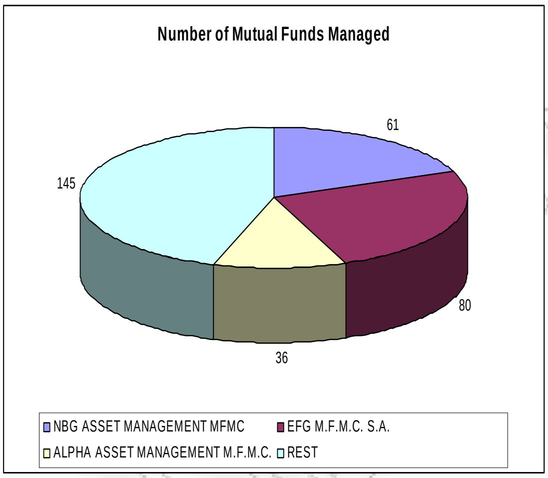


Figure 15: Total market share and number of funds managed by the MFMC's included in our sample

Source: Association of Greek Institutional Investors

The funds of our sample are:

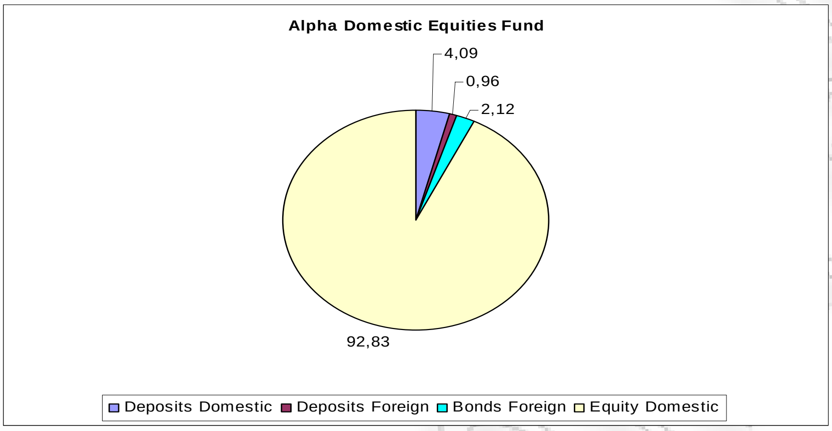
Equity	Balanced	Bond
Alpha Domestic Equities Fund	Alpha Domestic Balanced	Alpha Domestic Bonds Fund
Delos Blue Chips Domestic	Delos Balanced Domestic	Delos Income Bonds Domestic
Interamerican Dynamic Domestic Equity	Interamerican Hellenic Domestic Balanced	Interamerican Fixed Income Domestic Bond Fund

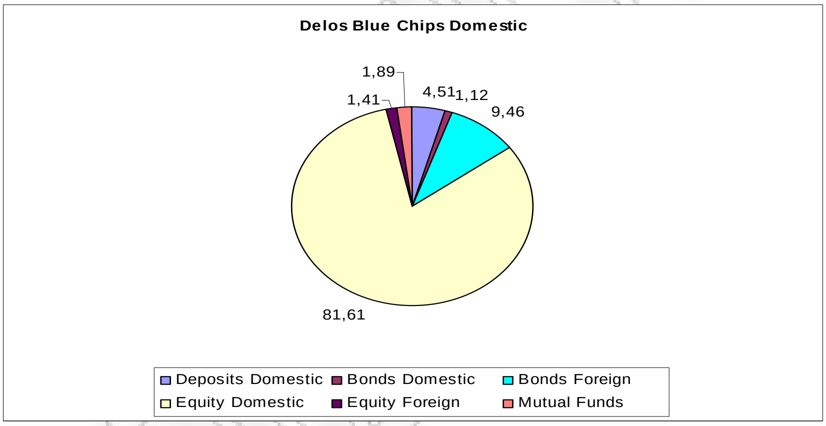
Table 1: Mutual funds included in our sample.

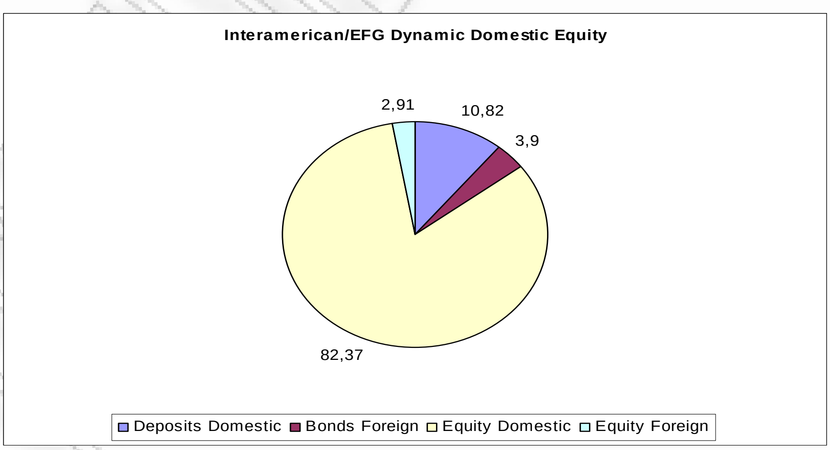
In order to include in our sample EFG, one of the three biggest M.F.M.C.'s, we included "Interamerican" funds, which are managed by EFG since 2004. Afterwards we present the figures that depict the average portfolio synthesis for the first quarter of 2009, except for Delos funds for which the data found cover the last month of 2008.

Figures presenting the historical evolution of the Net Asset Value[4] of each fund can be found in the appendix.

Equity Funds

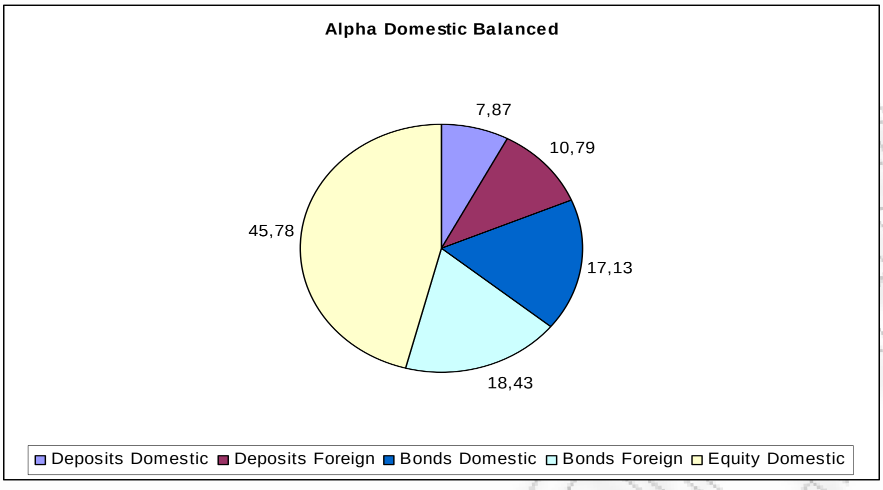


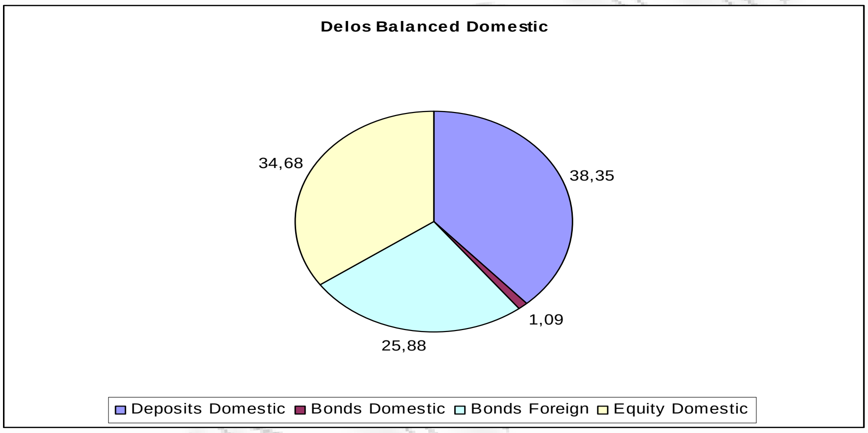


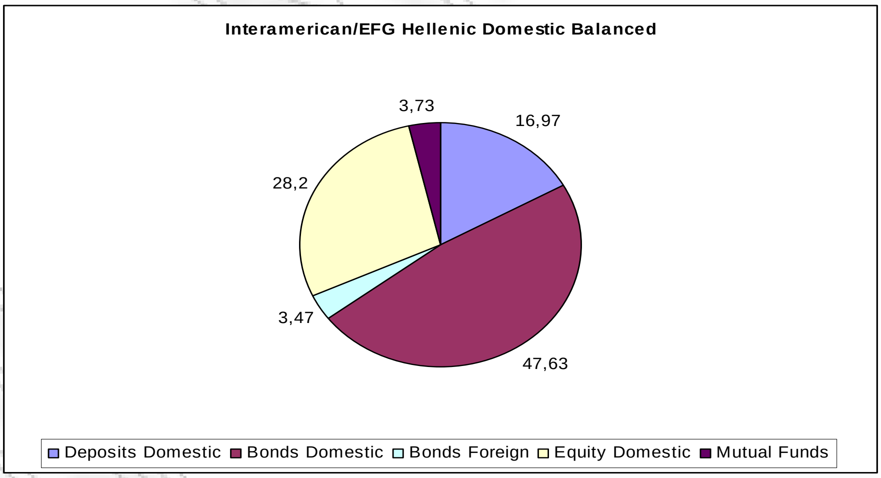


Balanced Funds

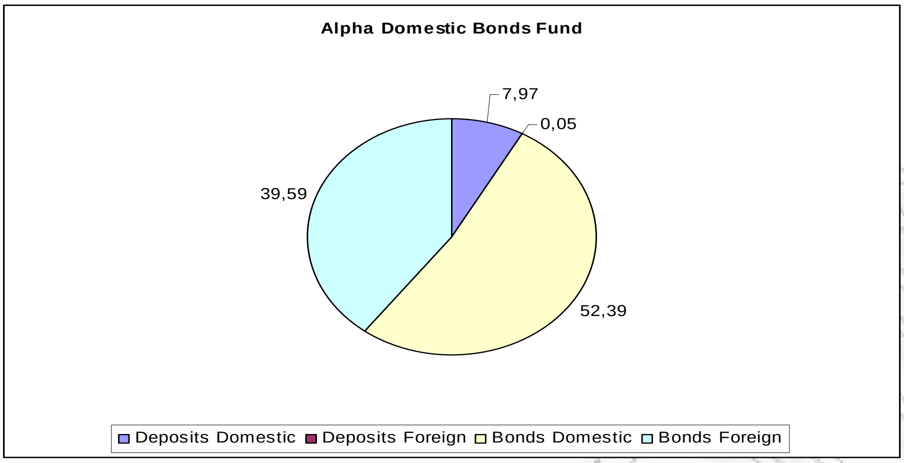
[4] The NAV of each MF is defined as:
NAV = (Market Value of Assets – Liabilities)/ Number of Shares Outstanding

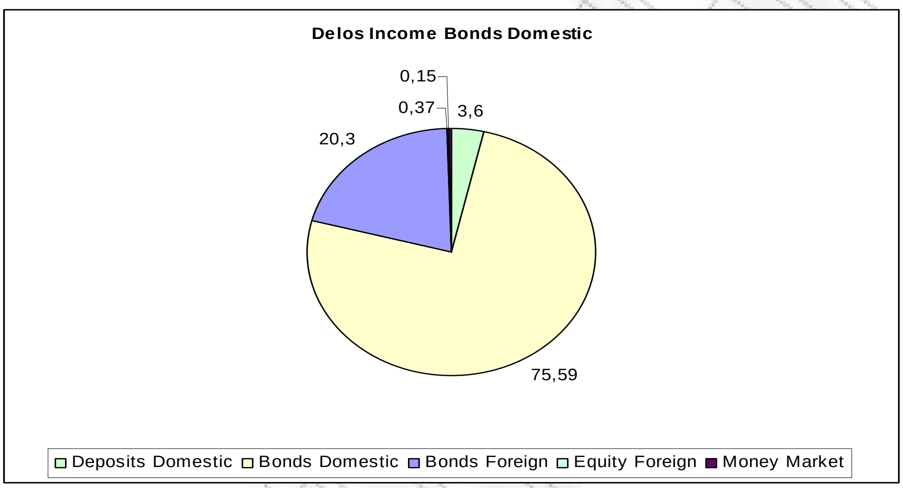

Alpha Domestic Balanced
7,87
10,79
17,13
18,43
45,78
Deposits Domestic
Deposits Foreign
Bonds Domestic
Bonds Foreign
Equity Domestic


Delos Balanced Domestic
34,68
38,35
1,09
25,88
Deposits Domestic
Bonds Domestic
Bonds Foreign
Equity Domestic


Interamerican/EFG Hellenic Domestic Balanced
3,73
16,97
28,2
3,47
47,63
Deposits Domestic
Bonds Domestic
Bonds Foreign
Equity Domestic
Mutual Funds

Bond Funds





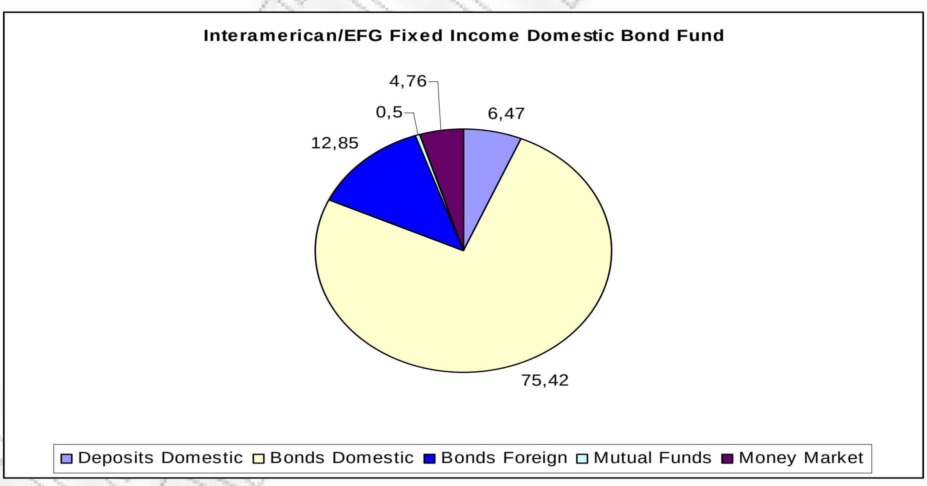


Figure 16: Portfolio breakdown for the mutual funds included in our sample.
Source: Association of Greek Institutional Investors

It is interesting to see which models can capture best the extremes of the bond funds, which exhibit the greatest kurtosis.

SECTION 2 - Empirical Investigation

12. Methods

In this part of the paper, we present the implementation of the methods used. In all cases, rolling windows of different sizes have been used in the estimation procedure.

1) Variance – Covariance Methods (V-CV)

Several models where used within this family of methods. Standard deviation is estimated with various methods, applied on the logarithmic returns time series. Simple Moving Average (SMA) is applied with eqn. (15) and a rolling sample of 252 observations (or one year of historical data as regulators usually state). Exponentially Weighted Moving Average (EWMA or RiskMetrics model) is applied as in eqn. (17), with λ set at 0.94, as estimated by RiskMetrics. The rolling sample in this case contains 100 observations, as the weights are almost completely used until lag 100. Also, GARCH (1,1) and EGARCH (1,1) with normal innovations are applied, using eqns. (19) and (20) respectively for a rolling sample of 1000 observations (approximately four years of data). In all cases, the estimation restrictions where fulfilled. All aforementioned methods where applied assuming normality. Consequently, VaR was computed through eqn. (3) for confidence levels (p) of 95% and 99%.

Since normality is usually a very unrealistic hypothesis, and as can be seen from the descriptive statistics and the Q-Q plots in the appendix, cannot describe the tails of the distributions, we applied GARCH (1,1) and EGARCH (1,1) specifications with student's t distributed innovations for rolling samples of 1000 observations. In these cases, VaR was computed from eqn. (4). The crucial point in using student's t distribution, is the degrees of freedom (d), that must be larger than two in order to be well defined. In most of the literature we are aware of in our effort to write this paper, d was assumed to be constant (usually set to 5, as in Vlaar (2000)) in order to avoid values below two. In this paper, however, d was calculated[5] in a rolling basis (as volatility estimates) and in all cases was found to be larger than two.

2) Historical Simulation (HS) and Filtered Historical Simulation Methods (FHS)

HS is the simplest method, as the only (unrealistic) assumption is that the returns are i.i.d series. Here, we apply HS for rolling samples of 100 and 252 observations (as in Lambadiaris et al. (2003)), to eliminate any bias that could be attributed to the sensitivity of these methods to the sample election. In order to compute VaR, returns are sorted in groups of the size of the rolling window and then VaR is computed as in eqn. (6). Despite its' assumption – free nature, it has certain drawbacks, as mentioned earlier. Thus we also apply FHS (Hull and White (1998)) for sample of 500 and 1000 observations. The greater sample size is due to the fact that the raw returns are standardized via a GARCH (1,1) specification, creating new "stationary" series, as in eqn. (7). Then, VaR is computed as in simple HS to the new returns series (eqn. (8)).

3) Extreme Value Theory (EVT) and GARCH specified EVT (G-EVT)

EVT is also applied with a rolling window of 1000 observations, both at raw returns (EVT) and GARCH standardized ones (G-EVT), as in McNeil and Frey (2000). VaR from EVT based methods is computed with eqn. (14). The tail parameter ξ is also estimated in a rolling basis, and in the vast majority of the cases it has a positive value, meaning that the distribution of the returns has fatter tails than the normal distribution. As explained previously, there is a bias – variance trade off when choosing the threshold u. To overcome this problem, we compute VaR for 10%, 8% and 5% thresholds for both methods.

4) Expected Shortfall (ES)

Artzner et al. (1999) proposed ES as an alternative, "coherent" measure of risk that is mathematically expressed in eqn. (5). Herein, we compute unconditional ES for 95% and 99% confidence levels for samples of 100 and 252 observations. Since the

[5] d was calculated from the formula d=(6/excess kurtosis) + 4 , as derived from Christoffersen P, 2003, Elements of Financial Risk Management, Academic Press, p.77

primary purpose of this paper is to examine market risk in means of the VaR measure, ES is computed with only one method, in order to allow the reader to get the intuition. The results are presented in unconditional coverage framework and in VaR/ES ratio.

13. Data Set and descriptive statistics

As mentioned earlier, our data set consists of the logarithmic returns (as computed from NAV of each fund) of nine mutual funds from 22/3/1993 to 21/11/2008 that sum up to 3954 daily returns and were obtained from the Association of Greek Institutional Investor's database[6]. The moving windows vary from 100 observations of HS to 1000 of GARCH, EVT and FHS methods, a fact that leaves us 2954 observations for backtesting for all methods, in order to obtain comparable results. The following table includes the descriptive statistics for the whole sample.

	Equity			Balanced			Bond		
	Alpha	Dilos	Inter/EFG	Alpha	Dilos	Inter/EFG	Alpha	Delos	Inter/EFG
Observations	3954	3954	3954	3954	3954	3954	3954	3954	3954
Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
t-stat for Ho:mean=0	1.452	1.184	1.381	1.912	1.714	1.602	2.876	1.266	2.684
P-Value	0.1467	0.2364	0.1675	0.0559	0.0865	0.1093	0.004	0.2056	0.0073
S.D.	0.014	0.015	0.014	0.008	0.010	0.009	0.004	0.012	0.004
Skewness	-0.361	0.072	-0.246	-2.943	-0.147	-0.309	-34.348	-0.166	-35.546
Kurtosis	8.574	11.193	7.465	56.195	7.751	10.947	1562.473	1615.697	1465.021
Maximum	0.080	0.169	0.072	0.039	0.056	0.062	0.052	0.493	0.007
Minimum	-0.106	-0.096	-0.089	-0.160	-0.070	-0.099	-0.217	-0.492	-0.198
Med	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Jarque-Bera	5.2E+03	1.1E+04	3.3E+03	4.7E+05	3.7E+03	1.0E+04	4.0E+08	4.3E+08	3.5E+08
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 2: Descriptive statistics for the whole sample.

The higher moments of the empirical distribution suggest that we have negative skewness and fat tails, especially for the bond funds. Also, the Jarque-Berra test statistic rejects the normality hypothesis in all cases. Another interesting point is that in 7 out of nine cases the mean of the sample is statistically insignificant[7]. This supports our hypothesis of using zero mean in all computations and is in accordance

[6] www.agii.gr
[7] Although the descriptive statistics presented here cover the whole sample, mean was estimated also in a rolling basis and proved that our hypothesis holds, especially for larger window sizes.

with adopting Figlewski's (1994) results and most of the literature mentioned earlier in Volatility Estimation and Forecasting chapter.

Further statistical evidence can be found in the appendix. The Q-Q plots against the normal distribution are in accordance with the properties of the table, whereas Q-Q plots against the student's t distribution support its usage because it has fatter tails than the normal. This is not the case for bond funds though, which exhibit very large kurtosis and in the Q-Q plots seem to have some observations far from what normal or student's t would suggest. It is interesting to see whether EVT that focuses on the tails can capture these large exceedances, especially for the highest threshold (5%).

14. Results

In this part, we present the results, categorized according to the types of mutual funds. In this way, since we know the asset classes in which each fund invests, we will be able to understand why some methods performed better than others. In all cases, the conditional coverage test is the basic criterion, since it includes both unconditional and independence testing. In the case where conditional coverage is not met by any method, as frequently noticed for 95% VaR, we will evaluate the methods by the other two criteria.

14.1 Equity Funds - 95% VaR

In terms of conditional coverage for 95% VaR estimations, the results do not suggest clear superiority. More specifically, the aforementioned criterion was met only by FHS 500 and only for one fund (Alpha), although many methods predicted the correct percentage of violations.

Moreover, correct unconditional coverage rate was achieved by the most of the models, with FHS 500, GARCH (n), EGARCH (n), G-EVT 8% and EWMA performing well, while HS, EVT 10% and FHS 1000 underestimated VaR and EVT 5% and especially G-EVT 5% produced highly overestimated VaRs.

For Delos, the methods with the best unconditional coverage rate are EGARCH (n), EVT 8%, GARCH (n), SMA and EWMA. Again, HS and EVT 10% underestimated VaR, while EVT 5% and G-EVT 5% overestimated it.

Finally, for Interamerican/EFG, again in unconditional coverage evaluation framework, EWMA performs best, followed by GARCH (t), GARCH (n), SMA and EGARCH (n). VaR underestimation was produced by EVT (10%) and HS methods, while EVT 5% and G-EVT 5% gave overestimations.

Equity Funds - 95% VaR – Best performing models		
Alpha	**Delos**	**Interamerican/EFG**
FHS 500 Violations %: 5.08 LRcc P-Value = 0.16	EGARCH (n) Violations %: 4.91 LRuc P-Value =0.89	EWMA Violations %: 5.11 LRuc P-Value =0.78
GARCH (n) Violations %: 5.08 LRuc P-Value =0.85	EVT 8% Violations %: 5.08 LRuc P-Value =0.85	GARCH (t) Violations %: 5.21 LRuc P-Value =0.60
EGARCH (n) Violations %: 5.18 LRuc P-Value =0.66	GARCH (n) Violations %: 4.91 LRuc P-Value =0.82	GARCH (n) Violations %: 4.77 LRuc P-Value =0.57
G-EVT 8% Violations %: 4.77 LRuc P-Value =0.57	SMA Violations %: 5.11 LRuc P-Value =0.78	SMA Violations %: 5.25 LRuc P-Value =0.54
EWMA Violations %: 5.45 LRuc P-Value =0.27	EWMA Violations %: 5.11 LRuc P-Value =0.78	EGARCH (n) Violations %: 5.28 LRuc P-Value =0.49

Table 3: Five best performing methods for equity funds and 95% VaR forecasts, according to LRuc P-Values. In all cases the LRcc P-Values where insignificant (5% significance level) except from FHS 500. Expected violations rate: 5%

Clearly, at 95% confidence level, HS and high and low threshold EVT and G-EVT is not well suited for equity funds. In an unconditional coverage backtesting framework, the GARCH family performs adequately in all tree funds, as does EWMA, EVT and G-EVT with 8% threshold as well. Unfortunately, we cannot conclude in one model for the best overall performance, as the only one that passes conditional coverage test is the FHS 500 model, but only for one fund. It should be also noted that, for all equity funds, FHS 500 performed better than FHS 1000, suggesting that a smaller sample gives more accurate VaR predictions. Also, FHS performed better than simple HS in all cases, a fact that is in accordance with the literature, while the superiority of G-EVT over simple EVT is not clear at this confidence level.

Further information on the performance of equity funds at 95% confidence level can be found in the appendix at pages 98, 100 and 102.

14.2 Balanced Funds – 95% VaR

For the balanced funds, at 95% confidence level no method managed to pass the conditional coverage tests. Thus, all results are again presented in terms of unconditional coverage testing.

For Alpha, the best performing model is EVT 8% (5.01% violations), followed closely by GARCH (t), SMA, EWMA and EGARCH (t). HS and EVT 10% underestimate VaR, while as in equity funds EVT and G-EVT 5% overestimate VaR.

For Delos, the best VaR prediction comes from SMA (5.01%), followed closely by EGARCH (n) and GARCH (t), EWMA, HS 100 and EVT 8%. In this case, HS seems to perform well in comparison to the other funds, while EVT 10% underestimates and EVT and G-EVT 5% overestimates VaR.

Finally, the VaR of Interamerican/EFG is well captured by GARCH (n), EGARCH (n), SMA, EVT 8% and G-EVT 8%. HS, EGARCH (t) and EVT 10% underestimate VaR and as usual EVT and G-EVT 5% methods overestimate it.

Since no method passes the conditional coverage test, violations come clustered in time and raise issues concerning the capital adequacy of the MFMC's that compute 95% VaR with these methods. Except for this fact, many methods succeed in producing the expected violations ratio. Namely, for balanced mutual funds methods like EVT 8%, the GARCH family methods, SMA and EWMA should be used, while, as with equity funds, high and low threshold EVT and some times HS methods do not seem to produce accurate VaR forecasts.

Balanced Funds - 95% VaR – Best performing models		
Alpha	**Delos**	**Interamerican/EFG**
EVT 8% Violations %: 5.01 LRuc P-Value = 0.98	SMA Violations %: 5.01 LRuc P-Value =0.98	GARCH (n) Violations %: 5.04 LRuc P-Value =0.91
GARCH (t) Violations %: 4.98 LRuc P-Value =0.95	GARCH (t) Violations %: 5.04 LRuc P-Value =0.91	EGARCH (n) Violations %: 5.18 LRuc P-Value =0.66
SMA Violations %: 4.91 LRuc P-Value =0.82	EGARCH (n) Violations %: 5.04 LRuc P-Value =0.91	SMA Violations %: 4.81 LRuc P-Value =0.63
EWMA Violations %: 4.87 LRuc P-Value =0.75	EWMA Violations %: 5.08 LRuc P-Value =0.85	EVT-8% Violations %: 5.21 LRuc P-Value =0.60
EGARCH (t) Violations %: 4.77 LRuc P-Value =0.57	HS 100 Violations %: 5.11 LRuc P-Value =0.78	G-EVT 8% Violations %: 4.74 LRuc P-Value =0.51

Table 4: Five best performing methods for balanced funds at 95% VaR forecasts, according to LRuc P-Values. In all cases, the LRcc P-Values where insignificant (5% significance level). Expected violations rate: 5%

Further evidence on the performance and backtesting of these methods can be found in the appendix at pages 104, 106 and 108.

14.3 Bond Funds – 95% VaR

The table of the descriptive statistics shows that the bond funds have the greatest kurtosis of all, and in the Q-Q plots in the appendix even the fat-tailed student's t distribution does not seem to be able to capture the extremes, especially at 95% confidence level. Our expectations materialize, as for most funds all methods fail to pass the conditional coverage test. But for the Delos fund, SMA and EWMA which assume normality perform surprisingly well as they pass even the conditional coverage test.

More specifically, for the Alpha fund only three methods meet the unconditional coverage criterion, namely EWMA (4.57%), SMA (4.47%) and EGARCH (n) (4.4%), although they exhibit some overestimation patterns. The rest of the GARCH models overestimate VaR, while all the others underestimate it heavily. To give some examples, FHS 1000 and G-EVT 10% produce 10.32% violations and HS252 9.38% respectively.

For the Delos fund, as mentioned earlier, SMA (4.37%) and EWMA (4.33%)) perform well, as they manage to pass the conditional coverage test, although VaR is slightly overestimated. EVT 10% (4.33%) is the only method from the others that passes the unconditional coverage test, while GARCH methods overestimate VaR and all others underestimate it. To give some examples, FHS 1000 and G-EVT 10% produce 11.27% and 11.48% violations respectively.

Finally, for the Interamerican/EFG fund the results are different. Two methods succeed in the unconditional coverage, G-EVT 5% (5.42%) and EVT 5% (5.59%). Again, GARCH methods overestimate VaR, as SMA and EWMA do, while all the rest underestimate it, with HS252 producing 9.88% violations.

The aforementioned results suggest that there is no clear best performing method for bond funds at 95% VaR forecasts. There is unanimity though, for the worst methods that overestimate or underestimate VaR. Thus, GARCH family methods, FHS, HS and EVT in some cases, seem less favorable.

Bond Funds - 95% VaR – Best performing models		
Alpha	**Delos**	**Interamerican/EFG**
EWMA Violations %: 4.57 LRuc P-Value = 0.28	SMA Violations %: 4.37 LRcc P-Value =0.22	G-EVT 5% Violations %: 5.42 LRuc P-Value =0.31
SMA Violations %: 4.47 LRuc P-Value =0.18	EWMA Violations %: 4.33 LRcc P-Value =0.22	EVT 5% Violations %: 5.59 LRuc P-Value =0.15
EGARCH (n) Violations %: 4.40 LRuc P-Value =0.13	EVT 5% Violations %: 4.33 LRuc P-Value =0.09	

Table 5: Three (two for Interamerican/EFG) best performing methods for bond funds at 95% VaR forecasts, according to LRuc P-Values (or LRcc if significant at 5% significance level). Expected violations ratio: 5%

Further evidence on the performance of all methods, can be found in the appendix at pages 110, 112and 114.

Afterwards, we present the results for 99% VaR forecasts. At this confidence level, the exceptional performance of some methods is clearer. The basic criterion now is the conditional coverage test, since some methods repeatedly exhibit high forecasting ability.

14.4 Equity Funds – 99% VaR

In contrast to the 95% VaR, the 99% forecasts reveal some methods that perform best for all funds and thus the results can be more easily universalized. In all cases, GARCH family methods with student's t distributional assumption, FHS and G-EVT perform well, with their ranking depending on the fund.

For the Alpha fund, the best performing method is G-EVT 10%, followed by FHS 1000, FHS 500 and GARCH (t) with same LRcc P-Values, EGARCH (t) and G-EVT 8%. All the other methods underestimate VaR, with G-EVT 5% overestimating it.

99% VaR of the Delos fund is well estimated also by G-EVT 10%, followed by GARCH (t), FHS 1000, G-EVT 8%, EGARCH (t) and FHS 500. Again, all the rest methods underestimate VaR, while G-EVT 5% overestimates it and EVT 5% produces 0.91 %violations.

The ranking for the Interamerican/EFG fund is different, since the best performing method is EGARCH (t), followed closely by G-EVT 10%, FHS 1000, GARCH (t), G-EVT 8% and EVT 5%. As usual, all other methods underestimate VaR while G-EVT 5% overestimates it and FHS 500 giving fair percentage of violations (1.12%).

Commenting on the results, we can conclude that G-EVT 10% is the best method for equity funds. This is in accordance with McNeil and Frey (2000), Angelidis and Benos (2004), Kuester et al. (2005) among others, which found G-EVT to perform better than other methods (and unconditional EVT) for equity indices and portfolios. Also, in most of the aforementioned literature, GARCH and EGARCH models with student's t distributed innovations perform adequately, as in our study. Finally, our results are in accordance with Hull and White (1998) and Barone – Adesi and Gianopulos (2001) among others, who state that FHS is for sure a better method than simple HS.

Another conclusion that can be drawn is that FHS 1000 seems to perform slightly better than FHS 500 in all cases. This should be a subject for further investigation, since the reasons for this fact could be two: either the 1000 observations sample for the GARCH filtering allows for better variance estimations, or the HS component gives more accurate results, as the window size increases.

Equity Funds - 99% VaR – Best performing models		
Alpha	**Delos**	**Interamerican/EFG**
G-EVT 10% Violations %: 0.88 LRcc P-Value: 0.38	G-EVT 10% Violations %: 1.05 LRcc P-Value: 0.60	EGARCH (t) Violations %: 1.08 LRcc P-Value: 0.59
FHS 1000 Violations %: 1.08 LRcc P-Value =0.13	GARCH (t) Violations %: 1.18 LRcc P-Value =0.45	G-EVT 10% Violations %: 1.12 LRcc P-Value =0.56
GARCH (t) Violations %: 1.08 LRcc P-Value =0.13	FHS 1000 Violations %: 0.85 LRcc P-Value =0.31	FHS 1000 Violations %: 0.91 LRcc P-Value = 0.45
FHS 500 Violations %: 1.15 LRcc P-Value =0.13	G-EVT 8% Violations %: 0.81 LRcc P-Value =0.24	GARCH (t) Violations %: 1.25 LRcc P-Value =0.32
EGARCH (t) Violations %: 0.98 LRcc P-Value =0.10	FHS 500 Violations %: 1.12 LRcc P-Value =0.13	G-EVT 8% Violations %: 0.78 LRcc P-Value =0.18

Table 6: Five best performing methods for equity funds at 99% VaR forecasts, according to LRcc P-Values and 5% significance level. Expected violations ratio: 1%.

Further evidence on the performance of all methods, can be found in the appendix at pages 99, 101 and 103.

14.5 Balanced Funds – 99% VaR

The same picture comes from the examination of the balanced funds results, except from one. In general, G-EVT performs best, with FHS and GARCH (t) and EGARCH (t) following.

On a fund to fund analysis, G-EVT 10% performs by far better than the other methods for Alpha, followed by G-EVT 8%, FHS 1000, EGARCH (t) and FHS 500. The worst performance comes from SMA, EWMA and HS100 that constantly underestimate VaR, while G-EVT 5% gives no more than 0.37% violations when 1% is expected.

For the Delos fund though, only two methods pass conditional coverage test. They are FHS 500 and GARCH (t), while several other methods succeed only in unconditional coverage (in these terms, G-EVT 10% with 1.02% of violations, followed by EVT 8% with 1.15% of violations). Again, the worst performers are SMA, EWMA and HS 100.

Finally, for the Interamerican/EFG balanced fund G-EVT 10% performs best, followed closely by FHS 1000, EVT 5%, GARCH (t) and G-EVT 8%. The usual "worst performers" apply here as well.

Balanced Funds - 99% VaR – Best performing models		
Alpha	**Delos**	**Interamerican/EFG**
G-EVT 10% Violations %: 1.02 LRcc P-Value: 0.72	FHS 500 Violations %: 0.95 LRcc P-Value: 0.52	G-EVT 10% Violations %: 1.02 LRcc P-Value: 0.59
G-EVT 8% Violations %: 0.85 LRcc P-Value =0.55	GARCH (t) Violations %: 0.98 LRcc P-Value =0.10	FHS 1000 Violations %: 1.12 LRcc P-Value =0.56
FHS 1000 Violations %: 1.39 LRcc P-Value =0.12	G-EVT 10% Violations %: 1.02 LRuc P-Value =0.93	EVT 5% Violations %: 0.95 LRcc P-Value = 0.52
EGARCH (t) Violations %: 1.05 LRcc P-Value =0.12	EVT 8% Violations %: 1.15 LRuc P-Value =0.42	GARCH (t) Violations %: 1.29 LRcc P-Value =0.26
FHS 500 Violations %: 1.02 LRcc P-Value =0.11	EVT 5% Violations %: 0.85 LRuc P-Value =0.39	G-EVT 8% Violations %: 0.78 LRcc P-Value =0.18

Table 7: Five best performing methods for balanced funds at 99% VaR forecasts, according to LRcc P-Values and 5% significance level. Expected violations ratio: 1%. For Delos fund, G-EVT 10%, EVT 8% and EVT 5% are presented in terms of unconditional coverage, since conditional coverage P-Values are insignificant.

G-EVT 10% seems to perform well for balanced funds, except from one, for which it produces almost 1% violations though. Also, FHS seems to perform well, followed by the GARCH and EGARCH with student's t distributed innovations. Since results are not common for all funds, we can conclude that the best methods for the balanced funds of our sample are G-EVT 10% and FHS methods, with the former producing slightly better violations ratio.

Further evidence on the performance of all methods can be found in the appendix at pages 105, 107 and 109.

14.6 Bond Funds – 99% VaR

As noted in the descriptive statistics table and the Q-Q plots in the appendix, bond funds exhibit the largest kurtosis and have "fatter" tails than the rest of the funds. Thus, in order to model these exceedances, we would expect that EVT, G-EVT or GARCH (t) models would produce the best results. This expectation is actually true for two out of three funds.

More specifically, GARCH (t) performs well for the Alpha fund, followed by G-EVT 5%, EVT 5% and EGARCH (t), which gives overestimated VaR though (0.64% violations). As expected, the rest of the methods underestimate VaR with the worst result coming from HS 100 and FHS 1000.

GARCH (t) and G-EVT 5% work well for the Delos fund as well, followed by GARCH (n), EVT 8% and EGARCH (t). Again, all other methods underestimate VaR, with FHS 1000 being the worst.

The results are a bit different for the Interamerican/EFG fund though, since the best performance is achieved by GARCH (n), followed by EVT 5%, EGARCH (n), GARCH (t) and G-EVT 5%. The worst performers are the same for this fund.

Generally, the best results come from the GARCH (t) models. This is in contrast with Vlaar (2000) who concludes that the student's t assumption produces the worst VaR estimates for Dutch bonds. Our results are this way probably due to the fatter tails of the t distribution, although in the Q-Q plots in the appendix it does not seem to capture well the extremes. G-EVT 5% and EVT 5% threshold perform well as well, but it is of great interest to notice that for the rest of the funds, lower thresholds gave the best performance. The fact that the higher threshold gives good results for the bond funds, is probably attributed to the large kurtosis these funds exhibit.

Bond Funds - 99% VaR – Best performing models		
Alpha	**Delos**	**Interamerican/EFG**
GARCH (t) Violations %: 1.02 LRcc P-Value: 0.59	GARCH (t) Violations %: 0.88 LRcc P-Value: 0.63	GARCH (n) Violations %: 0.91 LRcc P-Value: 0.45
G-EVT 5% Violations %: 1.12 LRcc P-Value =0.13	G-EVT 5% Violations %: 1.18 LRcc P-Value =0.45	EVT 5% Violations %: 1.22 LRcc P-Value =0.33
EVT 5% Violations %: 1.15 LRcc P-Value =0.13	GARCH (n) Violations %: 0.78 LRuc P-Value =0.38	EGARCH (n) Violations %: 0.85 LRcc P-Value = 0.31
EGARCH (t) Violations %: 0.64 LRcc P-Value =0.10	EVT 5% Violations %: 0.78 LRuc P-Value =0.38	GARCH (t) Violations %: 0.71 LRcc P-Value =0.21

Table 8: Four best performing methods for bond funds at 99% VaR forecasts, according to LRcc P-Values and 5% significance level. Expected violations ratio: 1%.

Furthermore, GARCH (n) worked surprisingly well for one fund, leaving behind EVT or GARCH (t), a fact that was not expected. Also, in all cases, although both HS 100 and HS 252 do not perform well, HS 252 produces violations ratios closer to the expected ones. Thus, our results are in accordance with Vlaar (2000), who states that HS performs better for bonds as sample size increases.

The complete backtesting tables with 99% VaR for bond funds are in the appendix, namely tables A14, A16 and A18 at pages 111,113 and 115 respectively.

14.7 Expected Shortfall

HS based ES is computed in this paper, for confidence levels of 95% and 99% and for two sample sizes, 100 and 252 observations. Since, by definition (eqn. 5), ES expresses the expected losses when VaR is exceeded, there are no expected violations ratios to be fulfilled. The best method will be the one which is more rarely violated, since ES is primarily computed to give some intuition to the reader.

In these terms, for the equity funds ES 252 is the best method since it is not violated as often as ES 100. The same results apply for the balanced and the bond funds as well. The results are also confirmed by the VaR/ES ratio.

95% ES Assumptions Free Window length: 100 observations Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations)									
Mutual Fund	Alpha Equity	Delos Equity	Intramerican /EFG Equity	Alpha Balanced	Delos Balanced	Interamerican /EFG Balanced	Alpha Bond	Delos Bond	Interamerican /EFG Bond
Violations	96	99	96	92	92	92	87	90	90
%	3.25	3.35	3.25	3.11	3.11	3.11	2.95	3.05	3.05
VaR/ES Ratio	0.76	0.75	0.74	0.73	0.75	0.75	0.62	0.65	0.49
99% ES Assumptions Free									
Violations	55	52	55	58	55	55	61	51	53
%	1.86	1.76	1.86	1.96	1.86	1.86	2.06	1.73	1.79
VaR/ES Ratio	0.85	0.87	0.88	0.84	0.89	0.90	0.59	0.66	0.42

Table 9: 95% & 99% ES forecasts with sample of 100 observations

95% ES Assumptions Free Window length: 252 observations Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations)									
Mutual Fund	Alpha Equity	Delos Equity	Intramerican /EFG Equity	Alpha Balanced	Delos Balanced	Interamerican /EFG Balanced	Alpha Bond	Delos Bond	Interamerican/ EFG Bond
Violations	75	74	77	72	70	71	77	88	71
%	2.54	2.51	2.61	2.44	2.37	2.40	2.61	2.98	2.40
VaR/ES Ratio	0.70	0.67	0.67	0.65	0.68	0.68	0.54	0.35	0.41
99% ES Assumptions Free									
Violations	21	21	23	18	23	23	23	36	28
%	0.71	0.71	0.78	0.61	0.78	0.78	0.78	1.22	0.95
VaR/ES Ratio	0.83	0.85	0.86	0.79	0.85	0.86	0.45	0.23	0.32

Table 10: 95% & 99% ES forecasts with sample of 252 observations

15. Conclusion

The primer purpose of this dissertation is to find the best methods in determining 95% and 99% Value at Risk for Greek mutual funds. Several methods were applied and some of the results can be universalized. Generally, we should agree that the ability of a method to produce reliable VaR estimations depends heavily on the type of mutual fund and the confidence level. The performance of each method was determined in terms of three tests, proposed by Cristoffersen (2003), namely unconditional coverage, i.e. having the right total number of violations, independence testing, i.e. the violations should not be clustered in time and conditional coverage test, which tests jointly the two aforementioned hypotheses.

At 95% confidence level, the results were a bit disappointing, sine most of the methods failed to pass the conditional coverage tests. For equity funds, only one method and for one fund made it (FHS 500), for balanced funds no method and for bond funds only SMA and EWMA for also one fund. On the other hand, many methods performed well in unconditional coverage basis, with GARCH (n), EGARCH (n) and EWMA performing well for equity funds. The same holds for balanced funds as well, with EVT 8% and SMA giving the right violations ratio. Finally, EWMA, SMA and G-EVT 5% work acceptably for bond funds.

For 99% VaR forecasts, the results were far more satisfying, since many methods performed well in a conditional coverage basis. For equity funds, G-EVT 10% worked well for two out of three funds, followed by GARCH (t) and EGARCH (t). FHS also showed good predictive ability. Most of the other methods underestimate VaR, while G-EVT 5% overestimates it. For the balanced funds, the best results came also from G-EVT 10%, followed by FHS and GARCH (t). The worst performers for this category of funds are SMA, EWMA and HS that constantly underestimate VaR, while G-EVT-5% overestimates it. Finally, for the bond funds the best performance is achieved by GARCH (t) and GARCH (n) models (in one case), followed by G-EVT 5% and EVT 5% methods. The worst performance for bond funds comes from HS and FHS methods.

Finally, due to some criticism on VaR, we computed Expected Shortfall that has been proposed as an alternative measure, in order to give some intuition to the reader. It was computed in HS based way, for two confidence intervals (95% and 99%) and for two sample sizes (100 and 252 observations). Since, by definition, ES is larger than VaR, the best method should be the one produces the fewer violations. In these terms, the larger sample size (252) seems to give ES 252 better performance than ES 100.

Value at Risk is a good and widely used method in estimating the downside risk of many asset classes. As every method using historical data, relying on the past may not give the best results. For instance, an asset that has low volatility for a while equal to the sample of a VaR model, will probably lead to violations on its' first high volatility days. Generally, the notion of Value at Risk, as every other quantitative method, could be described by Albert Einstein's quote: "Not everything that can be counted counts, and not everything that counts can be counted". But, using the "right" models could give the risk manager the means to deal with the uncertainty of adverse price changes.

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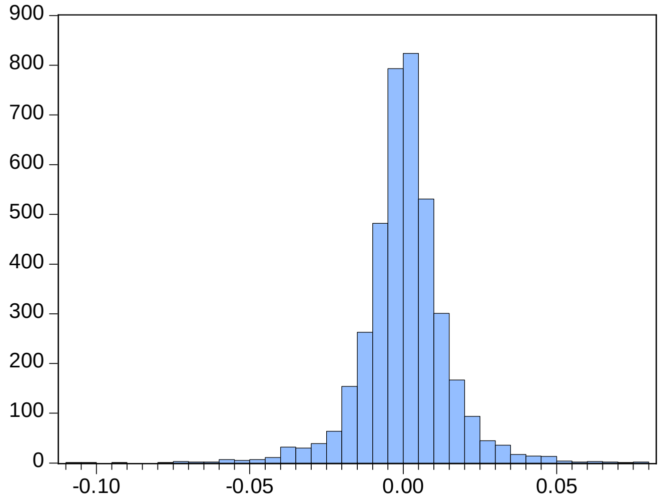
Appendix
Alpha Domestic Equities Fund
Figure A1 – Histogram and stats



Series: ALPHA_EQUITY
Sample 3/23/1993 11/21/2008
Observations 3954

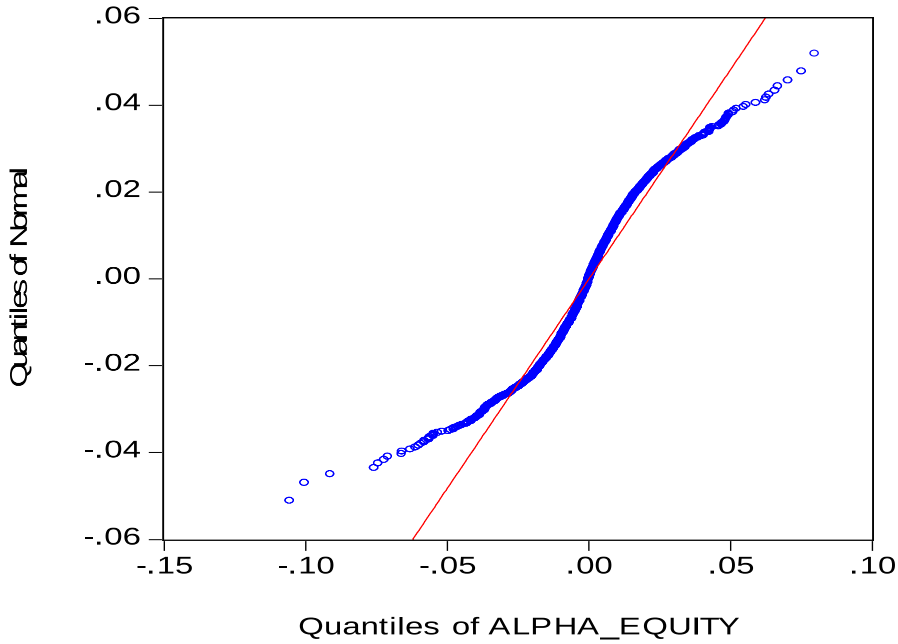
Mean	0.000325
Median	0.000306
Maximum	0.079872
Minimum	-0.105514
Std. Dev.	0.014059
Skewness	-0.360785
Kurtosis	8.574443
Jarque-Bera	5205.289
Probability	0.000000

Figure A2 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:36
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.146	0.146	84.583	0.000
		2	0.001	-0.021	84.589	0.000
		3	0.013	0.017	85.305	0.000
		4	0.019	0.015	86.754	0.000
		5	0.024	0.020	89.111	0.000
		6	0.015	0.009	90.017	0.000
		7	0.001	-0.002	90.025	0.000
		8	0.011	0.010	90.465	0.000
		9	0.008	0.004	90.734	0.000
		10	0.024	0.022	93.033	0.000
		11	0.000	-0.007	93.034	0.000
		12	0.011	0.012	93.484	0.000
		13	0.067	0.064	111.20	0.000
		14	0.027	0.007	114.09	0.000
		15	0.036	0.032	119.16	0.000
		16	0.014	0.003	119.98	0.000
		17	-0.004	-0.008	120.03	0.000
		18	0.014	0.012	120.80	0.000
		19	0.009	0.001	121.09	0.000
		20	-0.000	-0.004	121.09	0.000
		21	-0.013	-0.015	121.74	0.000
		22	0.011	0.014	122.23	0.000
		23	-0.002	-0.010	122.24	0.000
		24	0.038	0.040	127.86	0.000
		25	0.031	0.018	131.62	0.000
		26	0.042	0.032	138.50	0.000
		27	0.033	0.021	142.95	0.000
		28	0.001	-0.013	142.96	0.000
		29	0.014	0.013	143.79	0.000
		30	0.000	-0.008	143.79	0.000

Figure A3 – Q-Q Plots of the empirical against the Normal and the student's t distribution



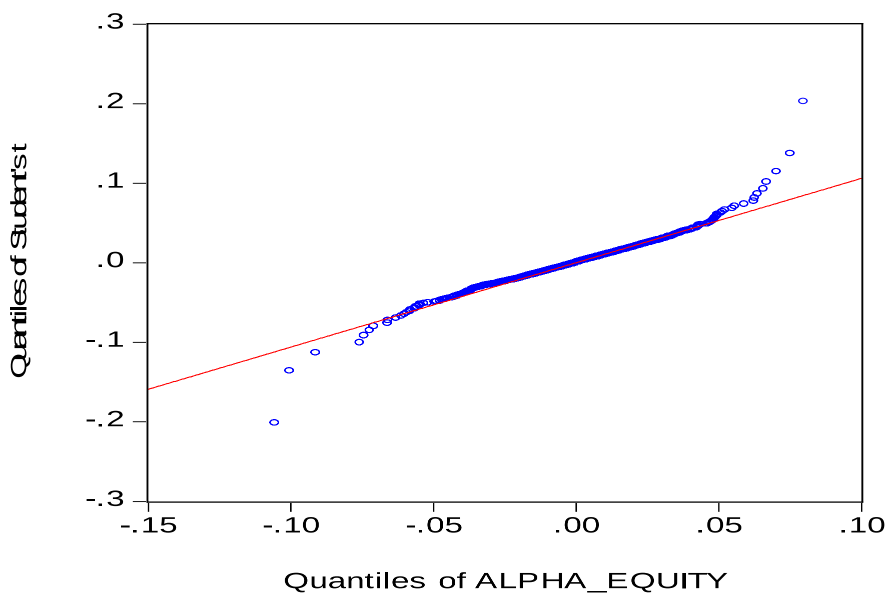
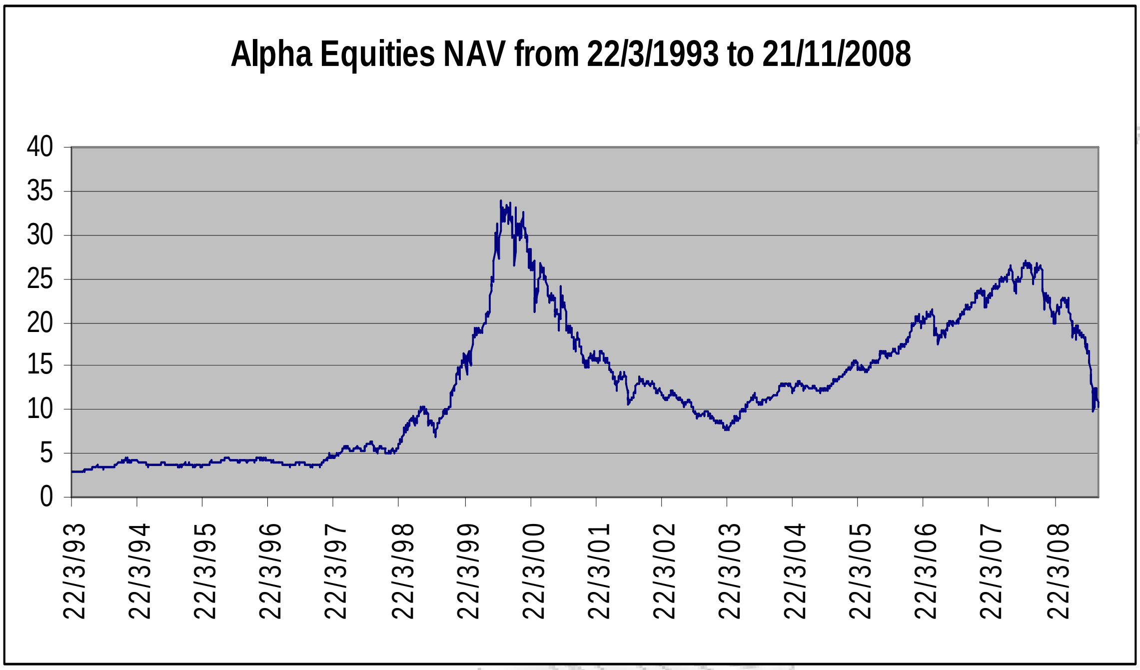
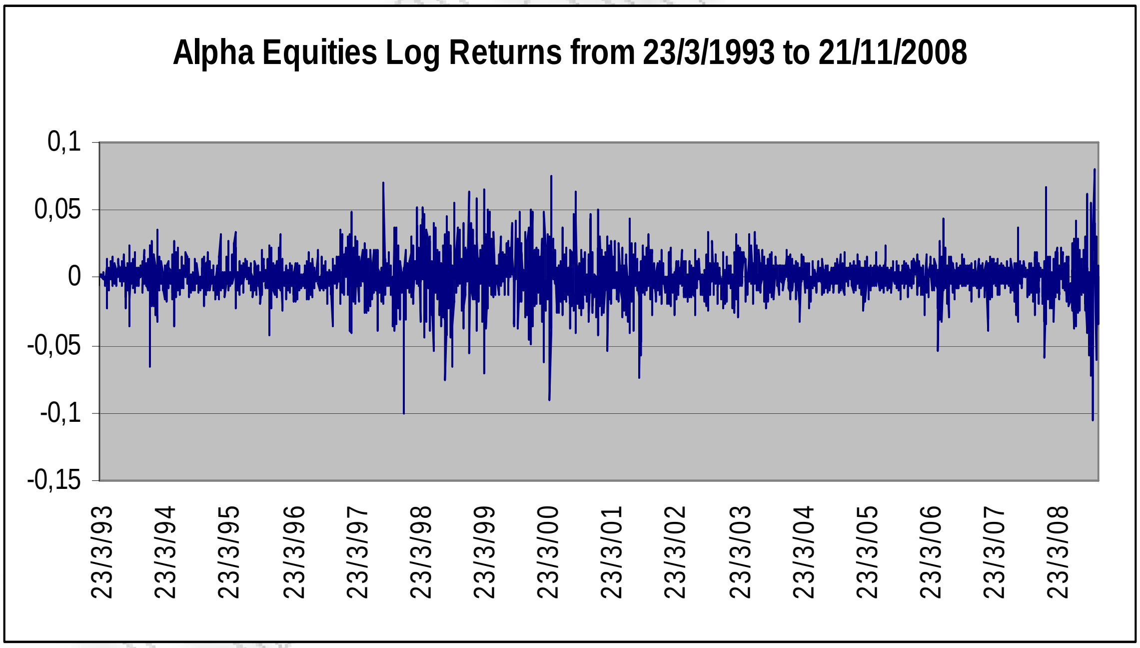
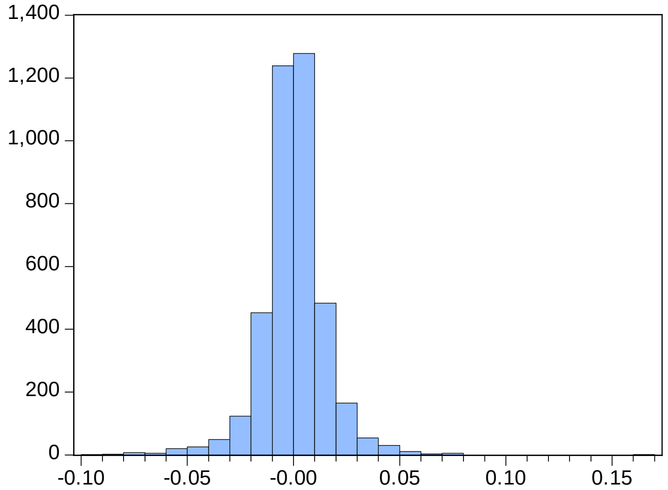


Figure A4 – Net Asset Value and Logarithmic Returns





Delos Blue Chips Domestic Fund
Figure A5 – Histogram and stats

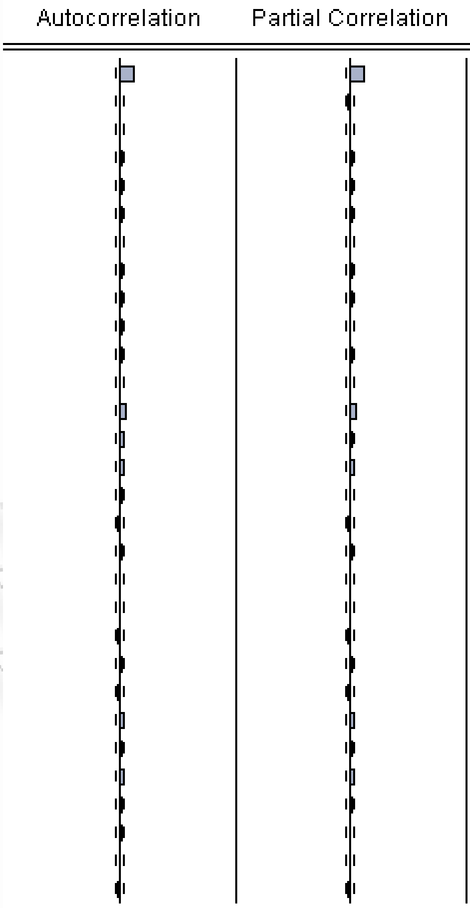


Series: DELOS_EQUITY
Sample 3/23/1993 11/21/2008
Observations 3954

Mean	0.000283
Median	0.000191
Maximum	0.168992
Minimum	-0.095877
Std. Dev.	0.015054
Skewness	0.072219
Kurtosis	11.19291
Jarque-Bera	11062.09
Probability	0.000000

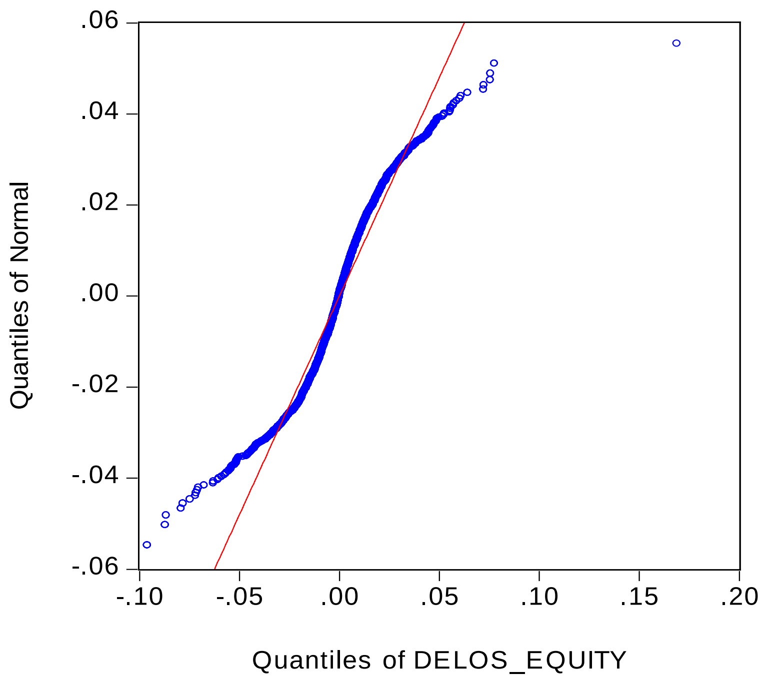
Figure A6 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:38
Sample: 3/23/1993 11/21/2008
Included observations: 3954



	AC	PAC	Q-Stat	Prob
1	0.125	0.125	61.608	0.000
2	-0.002	-0.018	61.628	0.000
3	0.005	0.008	61.738	0.000
4	0.017	0.015	62.840	0.000
5	0.021	0.017	64.506	0.000
6	0.017	0.013	65.617	0.000
7	0.003	-0.000	65.656	0.000
8	0.013	0.013	66.316	0.000
9	0.014	0.010	67.082	0.000
10	0.008	0.005	67.357	0.000
11	0.014	0.012	68.139	0.000
12	-0.003	-0.007	68.174	0.000
13	0.043	0.044	75.370	0.000
14	0.025	0.013	77.849	0.000
15	0.036	0.031	82.865	0.000
16	0.011	0.003	83.382	0.000
17	-0.010	-0.013	83.820	0.000
18	0.015	0.017	84.771	0.000
19	0.004	-0.003	84.847	0.000
20	0.005	0.003	84.946	0.000
21	-0.010	-0.014	85.378	0.000
22	0.009	0.010	85.668	0.000
23	-0.009	-0.014	86.016	0.000
24	0.035	0.036	90.973	0.000
25	0.020	0.011	92.544	0.000
26	0.036	0.032	97.785	0.000
27	0.023	0.014	99.943	0.000
28	0.010	0.003	100.37	0.000
29	0.008	0.003	100.60	0.000
30	-0.012	-0.016	101.16	0.000

Figure A7 – Q-Q Plots of the empirical against the Normal and the student's t distribution



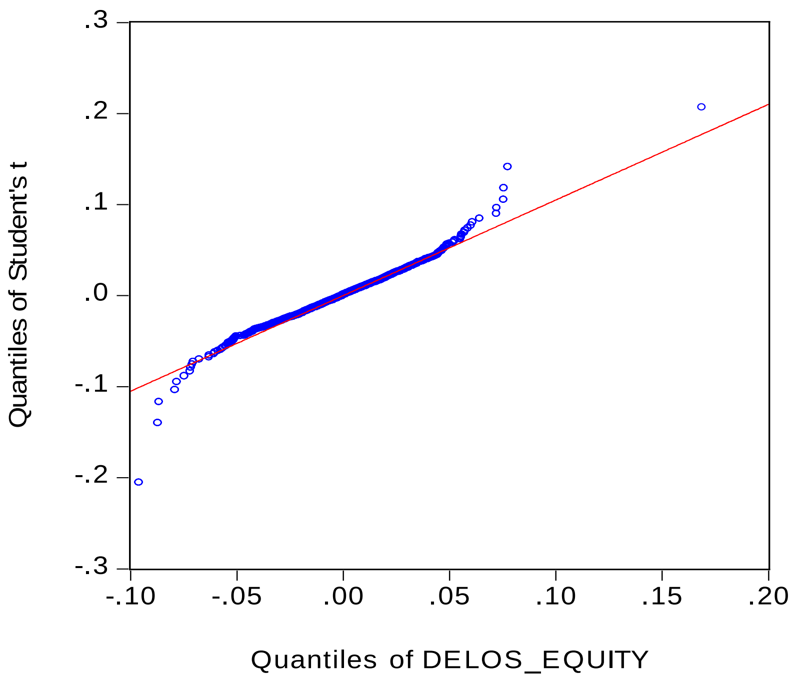
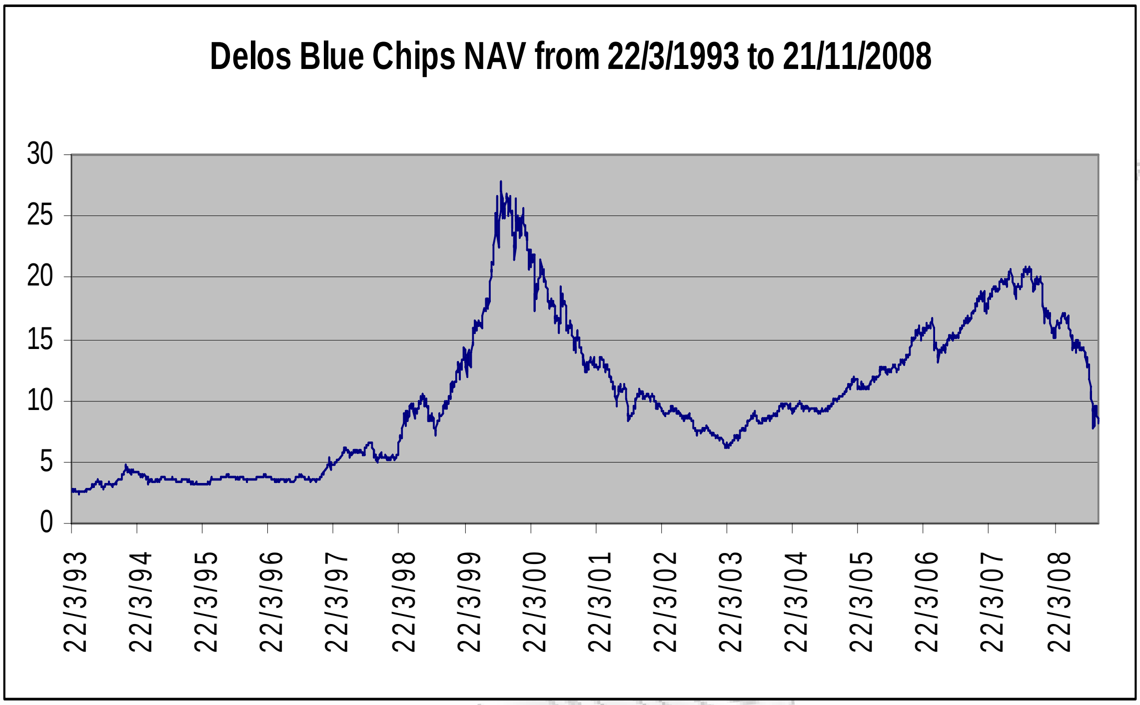
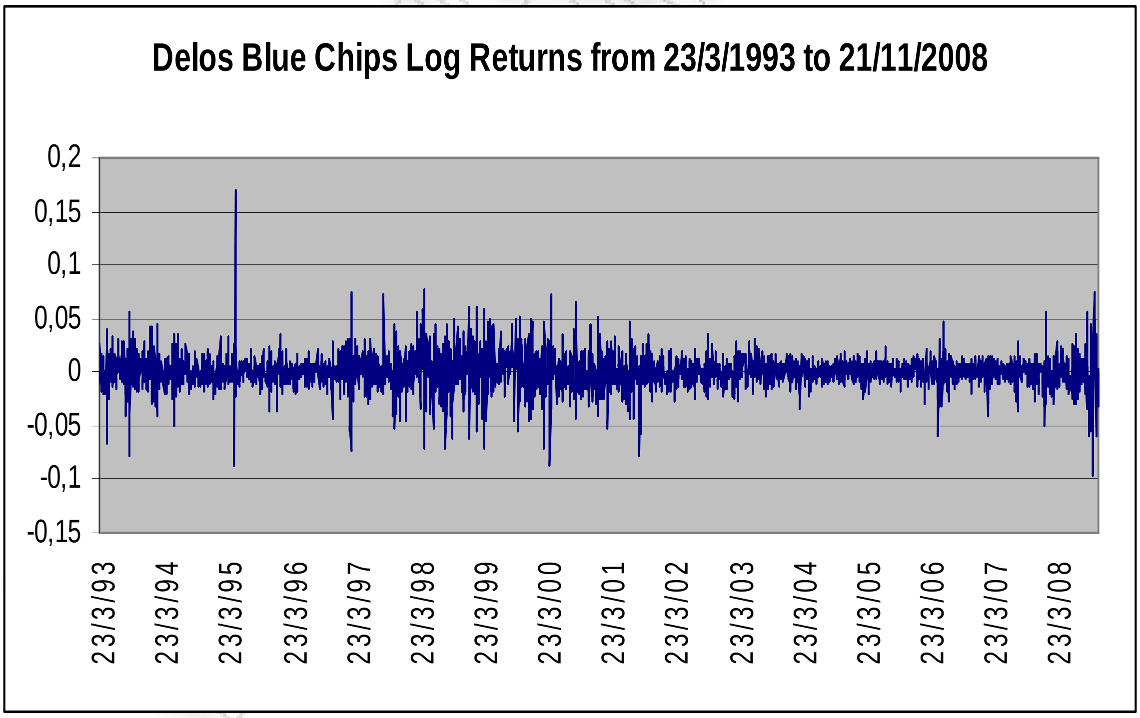
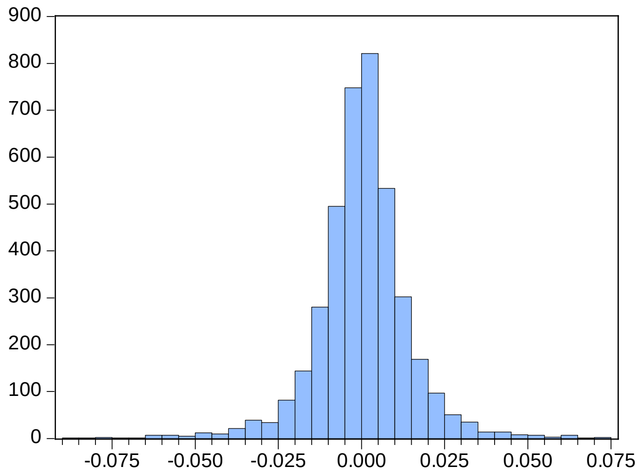


Figure A8 – Net Asset Value and Logarithmic Returns





Interamerican/EFG Dynamic Domestic Equity Fund
Figure A9 – Histogram and stats



Series: INTERAMERICAN_EQUITY
Sample 3/23/1993 11/21/2008
Observations 3954

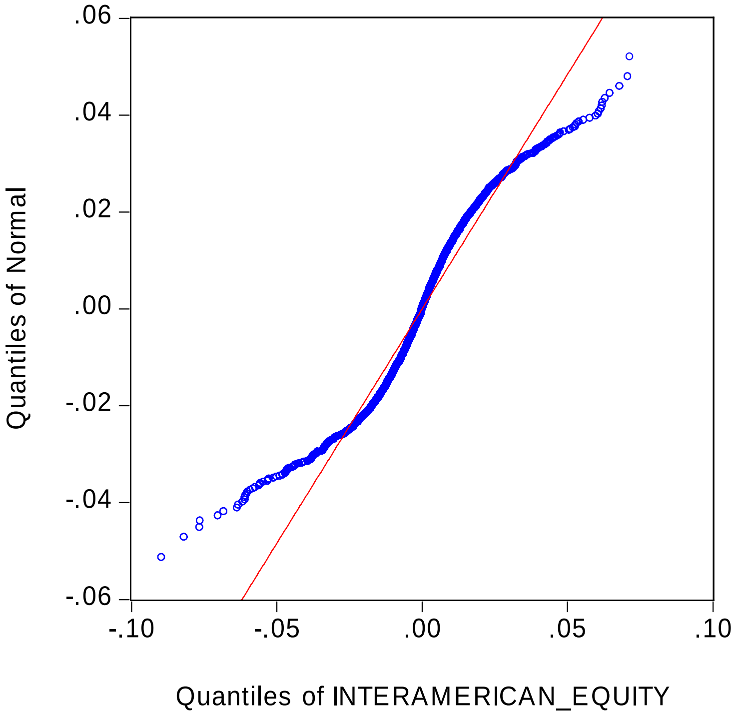
Mean	0.000310
Median	0.000356
Maximum	0.071574
Minimum	-0.089426
Std. Dev.	0.014119
Skewness	-0.245881
Kurtosis	7.465466
Jarque-Bera	3325.020
Probability	0.000000

Figure A10 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:39
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.144	0.144	82.555	0.000
		2	-0.002	-0.023	82.564	0.000
		3	0.009	0.013	82.907	0.000
		4	0.008	0.005	83.144	0.000
		5	0.006	0.004	83.273	0.000
		6	0.016	0.015	84.260	0.000
		7	0.017	0.013	85.431	0.000
		8	0.021	0.017	87.133	0.000
		9	0.023	0.018	89.157	0.000
		10	0.006	0.001	89.316	0.000
		11	0.006	0.005	89.449	0.000
		12	-0.001	-0.004	89.456	0.000
		13	0.043	0.044	96.746	0.000
		14	0.018	0.005	98.068	0.000
		15	0.032	0.029	102.02	0.000
		16	0.010	0.000	102.45	0.000
		17	-0.008	-0.011	102.71	0.000
		18	0.010	0.012	103.14	0.000
		19	0.011	0.006	103.65	0.000
		20	0.001	-0.003	103.66	0.000
		21	-0.015	-0.017	104.55	0.000
		22	0.010	0.012	104.93	0.000
		23	-0.011	-0.017	105.44	0.000
		24	0.029	0.032	108.67	0.000
		25	0.027	0.019	111.66	0.000
		26	0.034	0.027	116.28	0.000
		27	0.028	0.019	119.30	0.000
		28	0.018	0.009	120.56	0.000
		29	0.022	0.017	122.42	0.000
		30	-0.008	-0.014	122.67	0.000

Figure A11 – Q-Q Plots of the empirical against the Normal and the student's t distribution



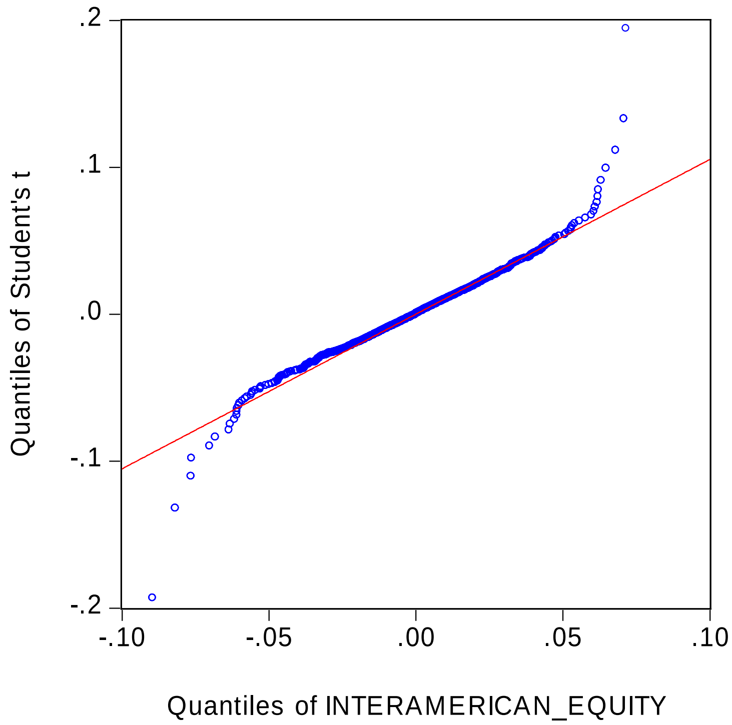
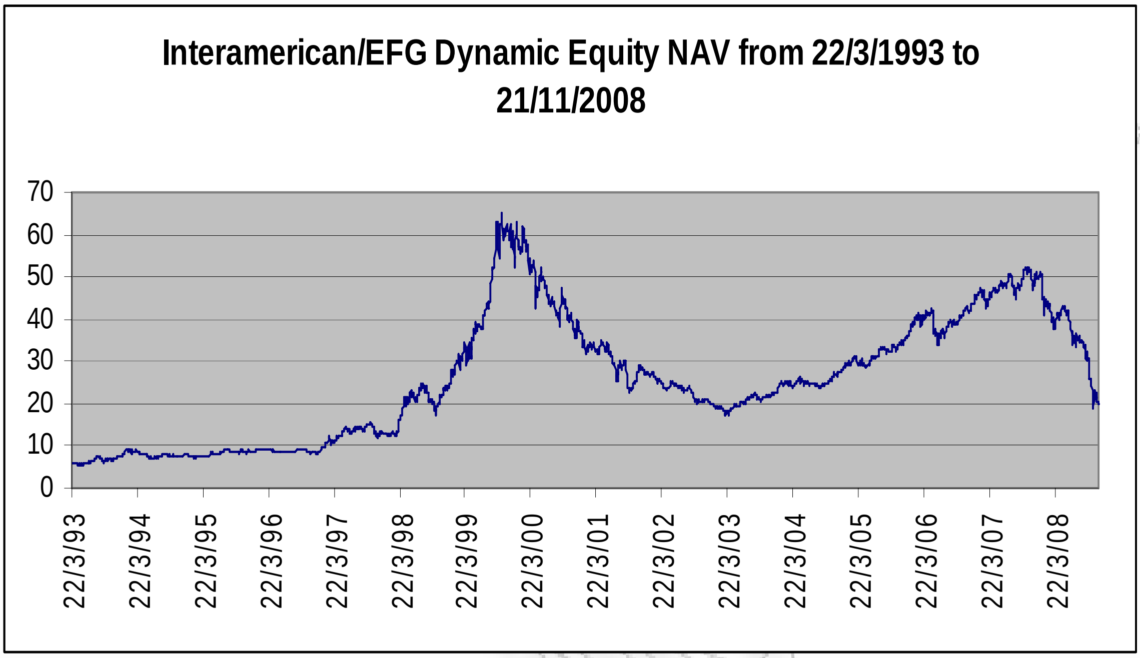
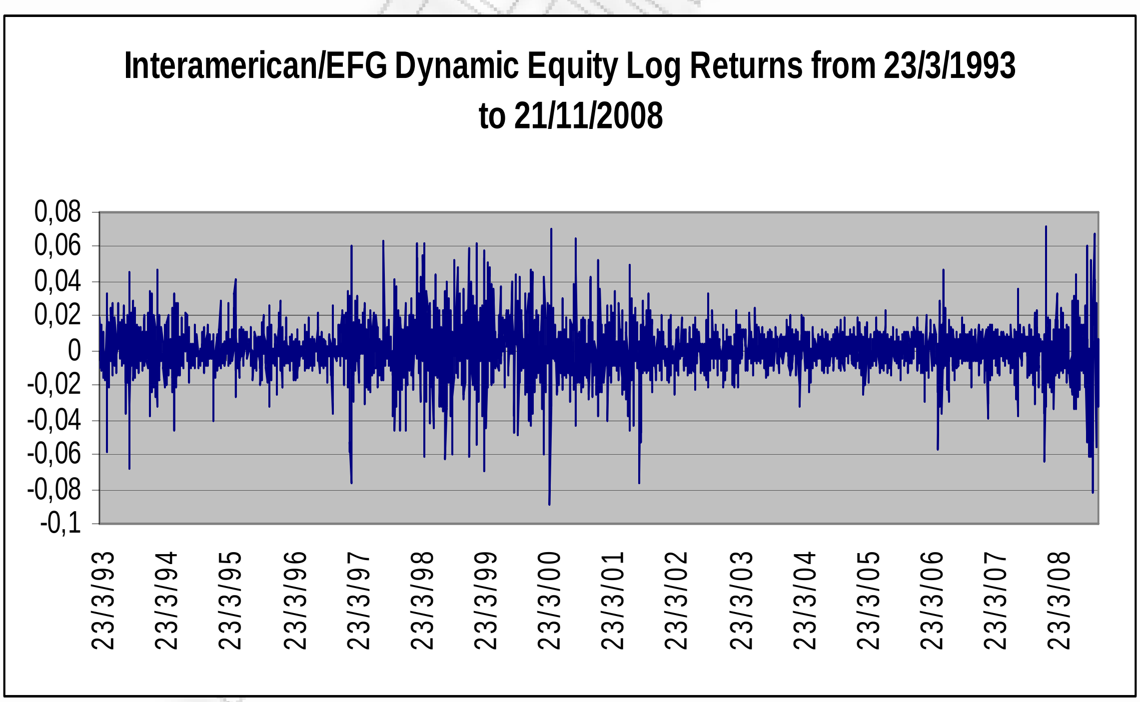


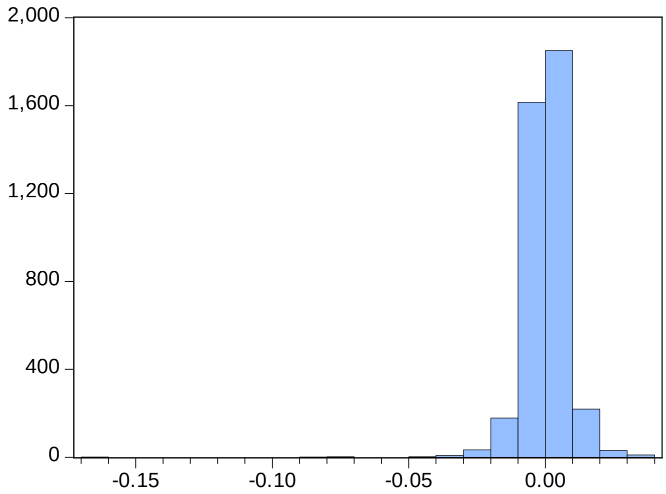
Figure A12 – Net Asset Value and Logarithmic Returns





Alpha Domestic Balanced Fund

Figure A13 – Histogram and stats



Series: ALPHA_BALANCED
Sample 3/23/1993 11/21/2008
Observations 3954

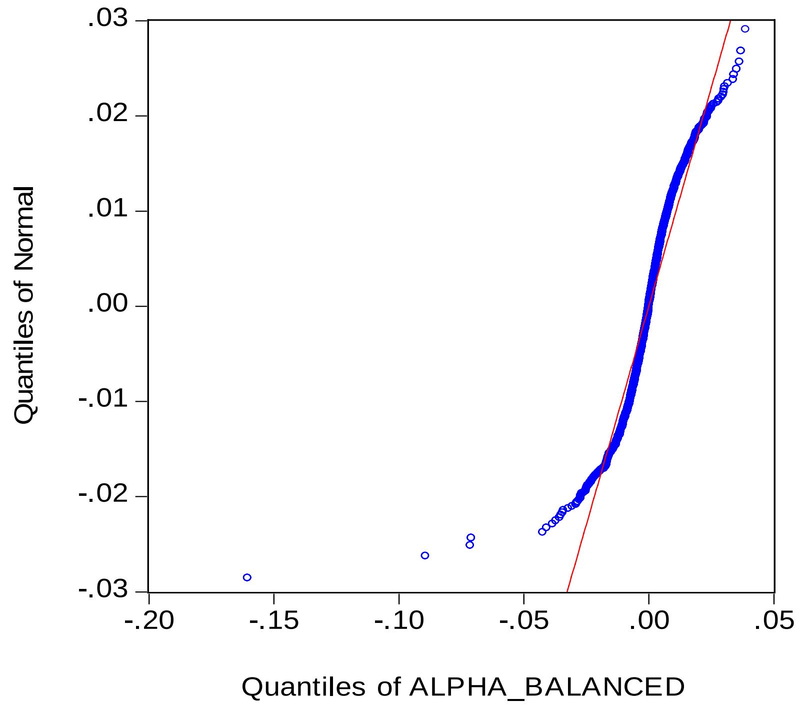
Mean	0.000239
Median	0.000348
Maximum	0.038842
Minimum	-0.160415
Std. Dev.	0.007876
Skewness	-2.943258
Kurtosis	56.19527
Jarque-Bera	471907.9
Probability	0.000000

Figure A14 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:43
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.081	0.081	25.703	0.000
		2	0.000	-0.006	25.703	0.000
		3	0.012	0.013	26.293	0.000
		4	0.014	0.012	27.092	0.000
		5	0.014	0.012	27.837	0.000
		6	0.009	0.006	28.126	0.000
		7	0.005	0.003	28.207	0.000
		8	0.015	0.014	29.084	0.000
		9	-0.011	-0.014	29.555	0.001
		10	-0.007	-0.005	29.748	0.001
		11	-0.004	-0.004	29.820	0.002
		12	0.008	0.008	30.047	0.003
		13	0.055	0.054	42.137	0.000
		14	0.024	0.016	44.494	0.000
		15	0.025	0.022	46.899	0.000
		16	0.022	0.018	48.895	0.000
		17	-0.004	-0.008	48.953	0.000
		18	0.011	0.010	49.411	0.000
		19	0.023	0.019	51.489	0.000
		20	0.012	0.007	52.055	0.000
		21	0.003	-0.001	52.090	0.000
		22	0.003	0.003	52.123	0.000
		23	-0.019	-0.020	53.500	0.000
		24	0.018	0.021	54.758	0.000
		25	0.028	0.025	57.952	0.000
		26	0.031	0.024	61.796	0.000
		27	0.020	0.013	63.364	0.000
		28	0.035	0.030	68.249	0.000
		29	-0.018	-0.027	69.502	0.000
		30	-0.009	-0.008	69.853	0.000

Figure A15 – Q-Q Plots of the empirical against the Normal and the student's t distribution



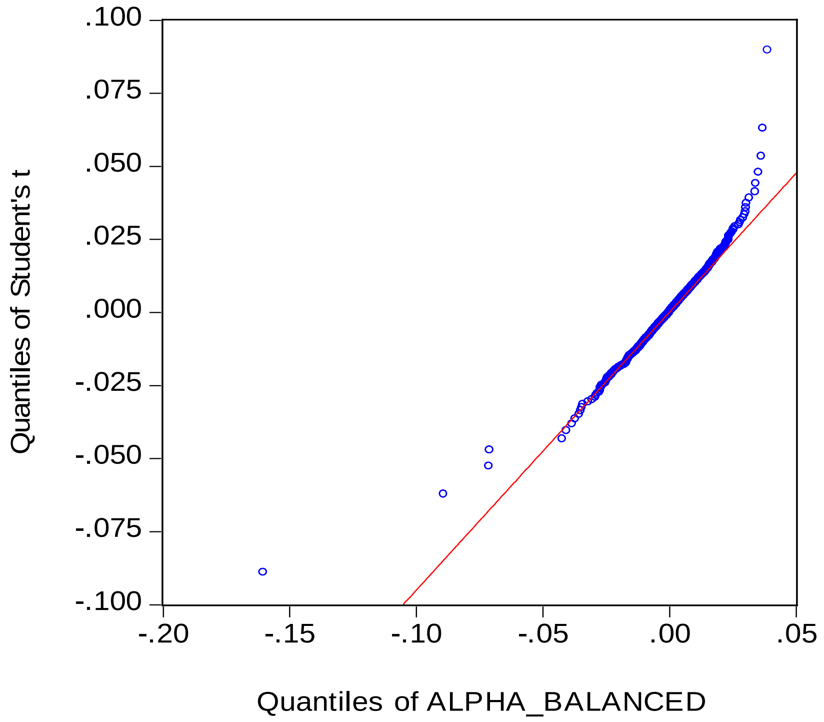
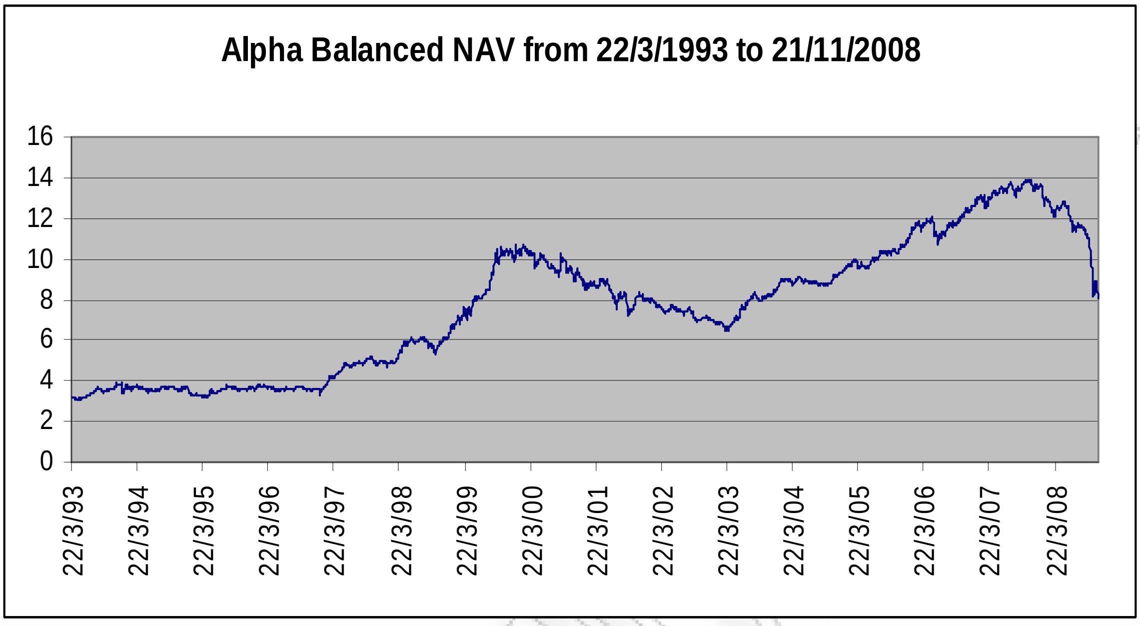
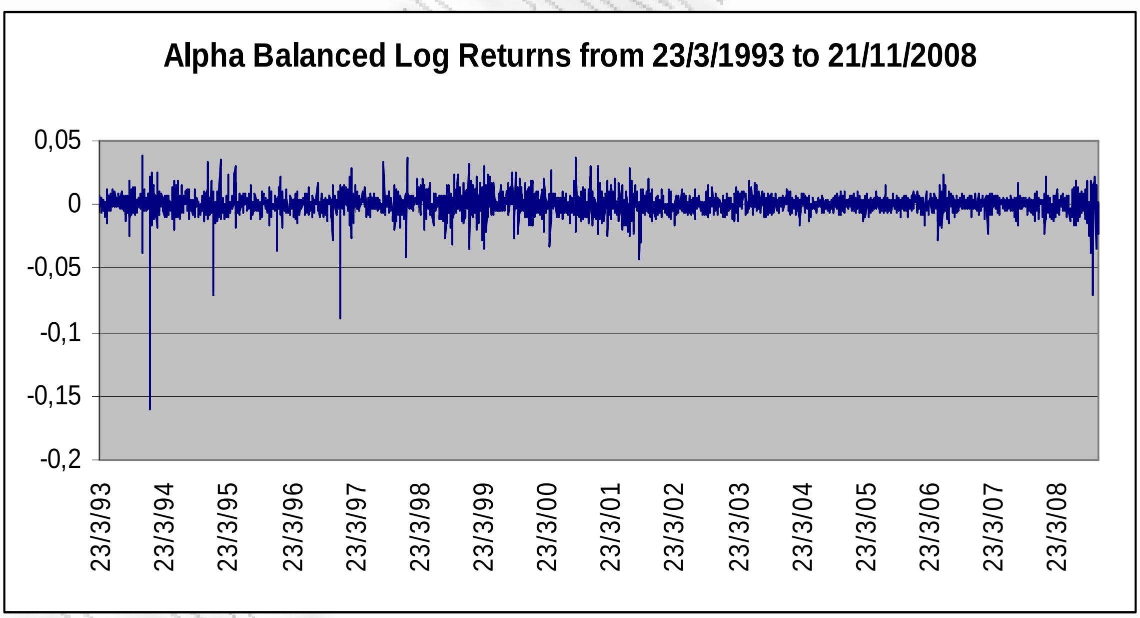


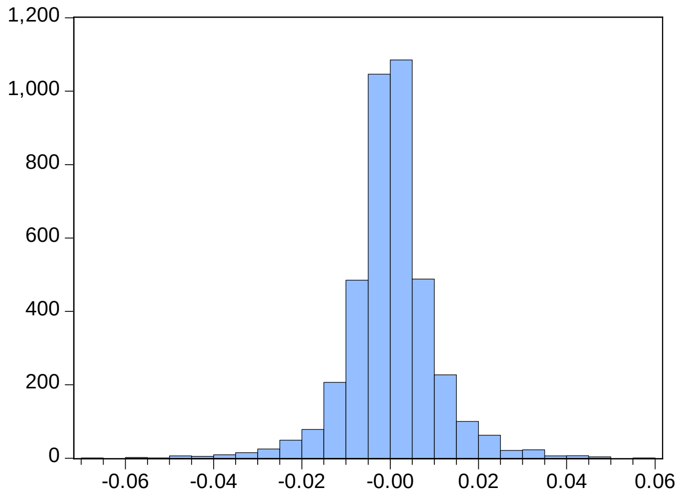
Figure A16 – Net Asset Value and Logarithmic Returns





Delos Domestic Balanced Fund

Figure A17 – Histogram and stats



Series: DELOS_BALANCED
Sample 3/23/1993 11/21/2008
Observations 3954

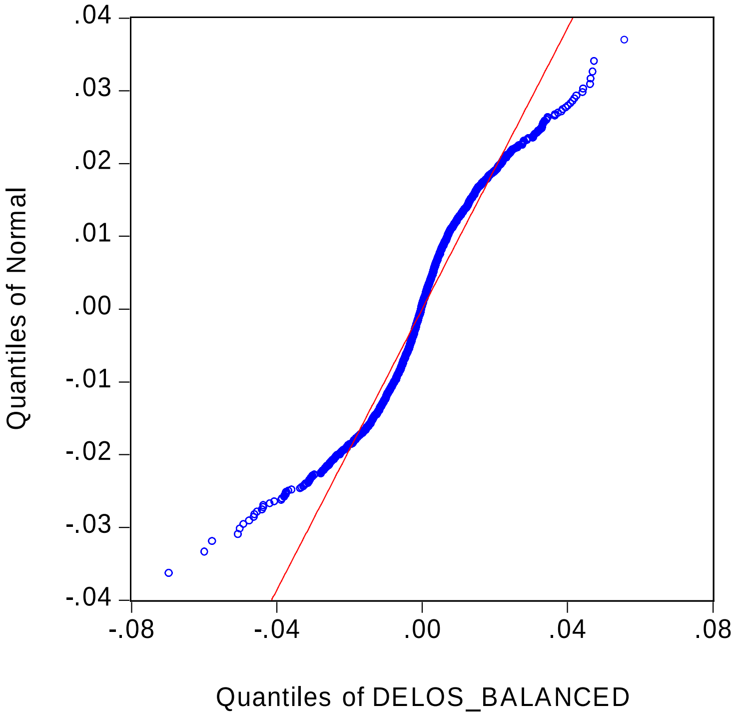
Mean	0.000273
Median	0.000104
Maximum	0.055871
Minimum	-0.069551
Std. Dev.	0.010005
Skewness	-0.147101
Kurtosis	7.751279
Jarque-Bera	3733.434
Probability	0.000000

Figure A18 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:44
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.170	0.170	114.51	0.000
		2	-0.005	-0.035	114.59	0.000
		3	-0.006	0.001	114.74	0.000
		4	-0.010	-0.009	115.12	0.000
		5	0.007	0.011	115.32	0.000
		6	0.022	0.020	117.32	0.000
		7	0.022	0.016	119.27	0.000
		8	0.016	0.011	120.29	0.000
		9	0.016	0.012	121.27	0.000
		10	0.009	0.006	121.61	0.000
		11	0.018	0.016	122.85	0.000
		12	0.003	-0.003	122.88	0.000
		13	0.035	0.037	127.86	0.000
		14	0.014	0.001	128.62	0.000
		15	0.023	0.022	130.72	0.000
		16	0.019	0.011	132.11	0.000
		17	-0.001	-0.006	132.12	0.000
		18	0.013	0.014	132.79	0.000
		19	0.007	0.001	132.97	0.000
		20	0.009	0.007	133.33	0.000
		21	-0.014	-0.019	134.06	0.000
		22	0.000	0.004	134.06	0.000
		23	-0.015	-0.018	134.94	0.000
		24	0.033	0.037	139.16	0.000
		25	0.026	0.012	141.75	0.000
		26	0.047	0.041	150.48	0.000
		27	0.022	0.008	152.49	0.000
		28	0.013	0.010	153.13	0.000
		29	0.021	0.017	154.83	0.000
		30	0.001	-0.005	154.84	0.000

Figure A19 – Q-Q Plots of the empirical against the Normal and the student's t distribution



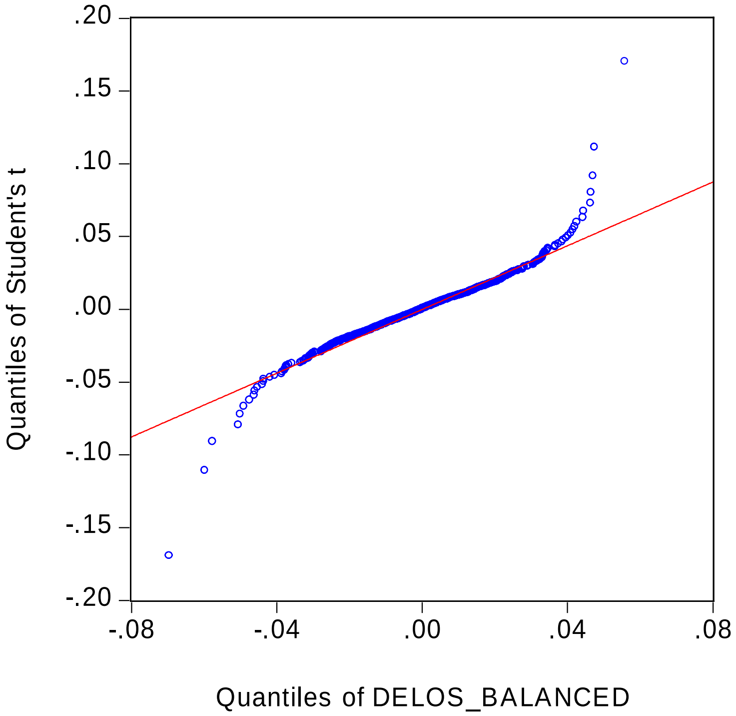
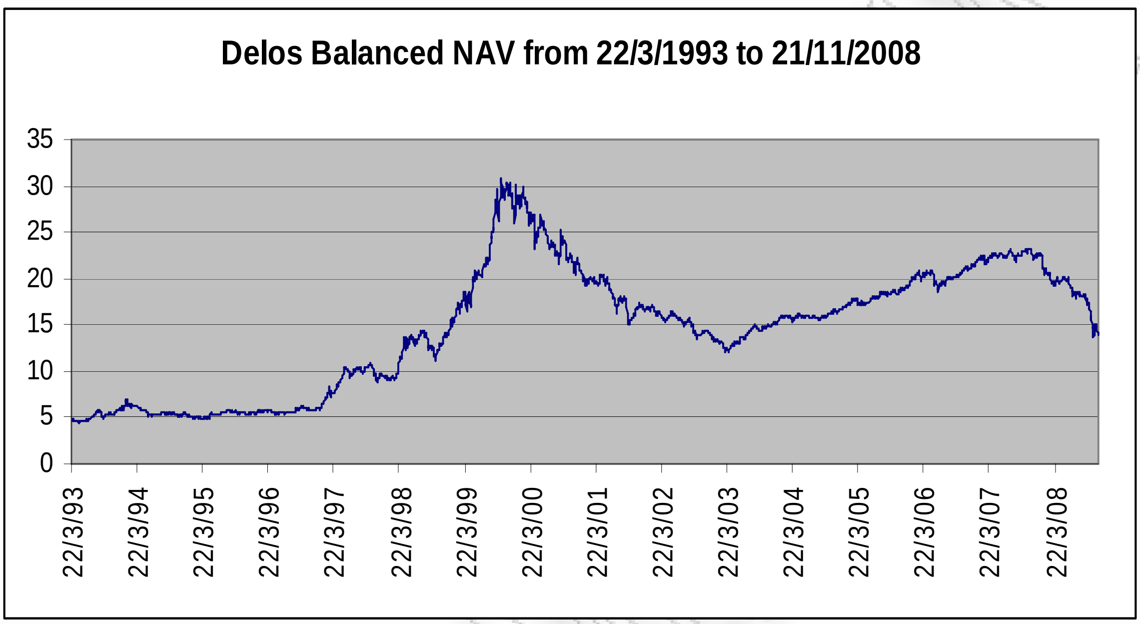
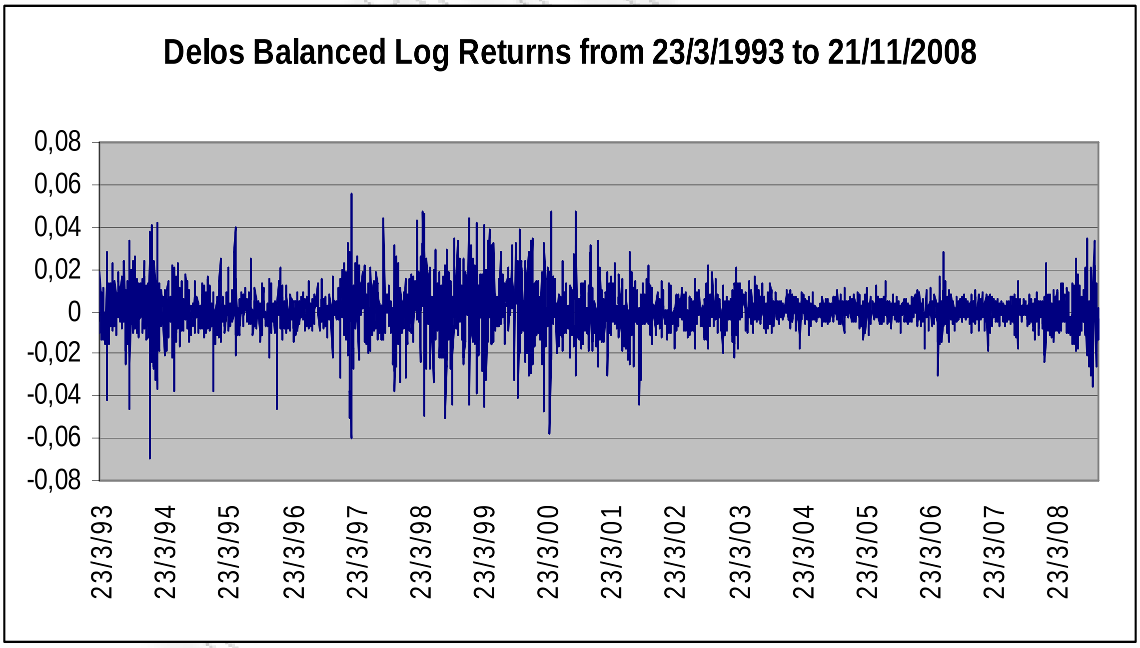


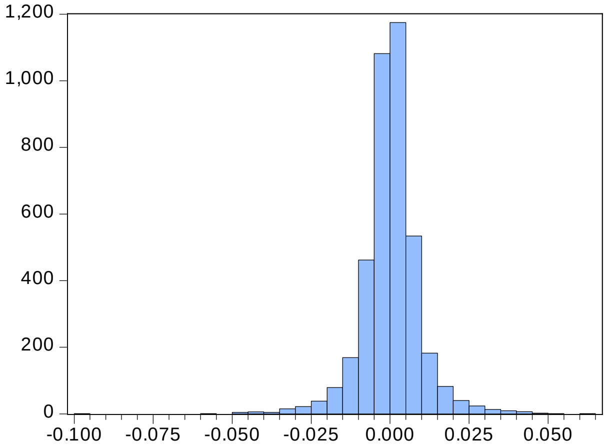
Figure A20 – Net Asset Value and Logarithmic Returns





Interamerican/EFG Hellenic Domestic Balanced Fund

Figure A21 – Histogram and stats



Series: INTERAMERICAN_BALANCED
Sample 3/23/1993 11/21/2008
Observations 3954

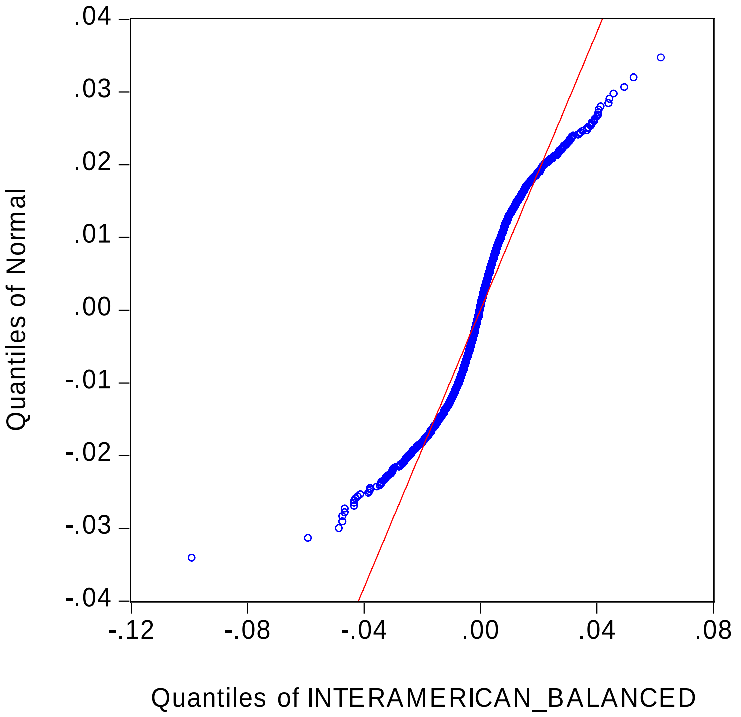
Mean	0.000240
Median	0.000206
Maximum	0.062337
Minimum	-0.098912
Std. Dev.	0.009405
Skewness	-0.309255
Kurtosis	10.94690
Jarque-Bera	10467.52
Probability	0.000000

Figure A22 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:45
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.134	0.134	71.502	0.000
		2	0.001	-0.018	71.503	0.000
		3	0.004	0.006	71.552	0.000
		4	0.012	0.011	72.138	0.000
		5	-0.003	-0.006	72.180	0.000
		6	0.010	0.012	72.609	0.000
		7	0.019	0.016	73.991	0.000
		8	0.014	0.010	74.773	0.000
		9	0.014	0.011	75.513	0.000
		10	-0.002	-0.005	75.524	0.000
		11	-0.004	-0.003	75.586	0.000
		12	-0.007	-0.007	75.805	0.000
		13	0.039	0.041	81.866	0.000
		14	0.000	-0.011	81.866	0.000
		15	0.024	0.027	84.215	0.000
		16	0.022	0.014	86.053	0.000
		17	-0.012	-0.018	86.587	0.000
		18	0.009	0.014	86.887	0.000
		19	0.010	0.006	87.284	0.000
		20	0.005	0.002	87.399	0.000
		21	-0.011	-0.012	87.846	0.000
		22	0.002	0.003	87.861	0.000
		23	-0.024	-0.026	90.086	0.000
		24	0.020	0.027	91.687	0.000
		25	0.021	0.015	93.386	0.000
		26	0.039	0.033	99.407	0.000
		27	0.027	0.019	102.23	0.000
		28	0.010	0.002	102.60	0.000
		29	0.021	0.019	104.40	0.000
		30	0.000	-0.004	104.40	0.000

Figure A23 – Q-Q Plots of the empirical against the Normal and the student's t distribution



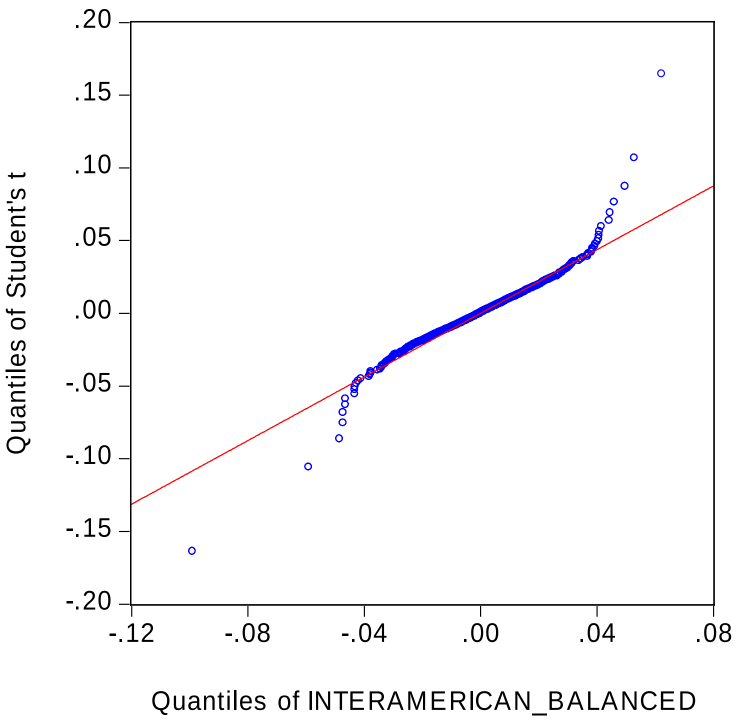
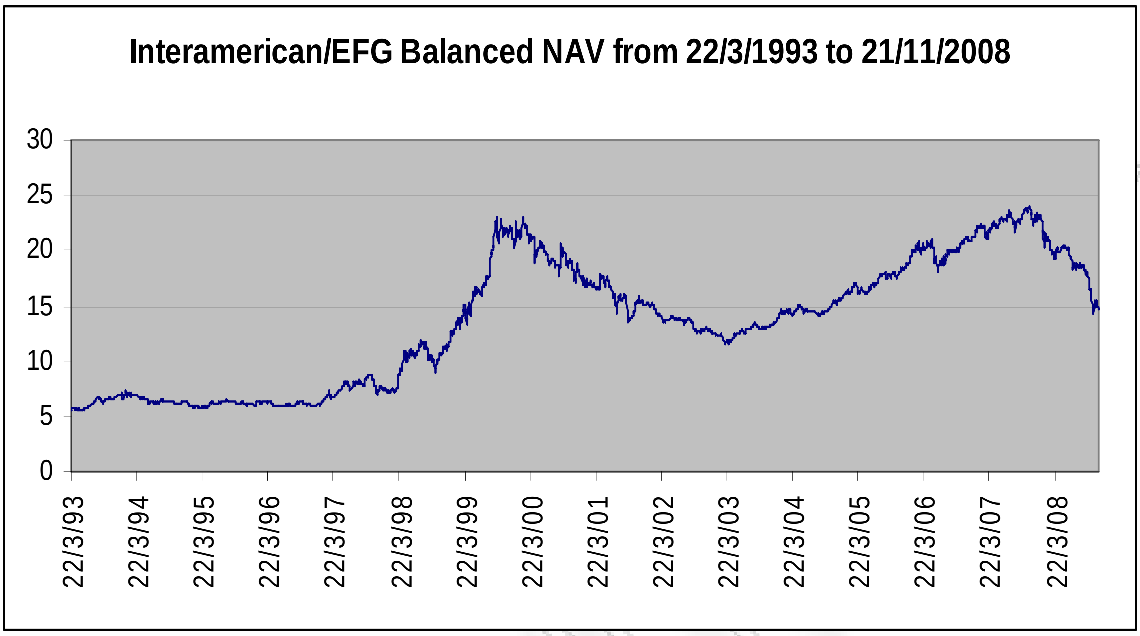
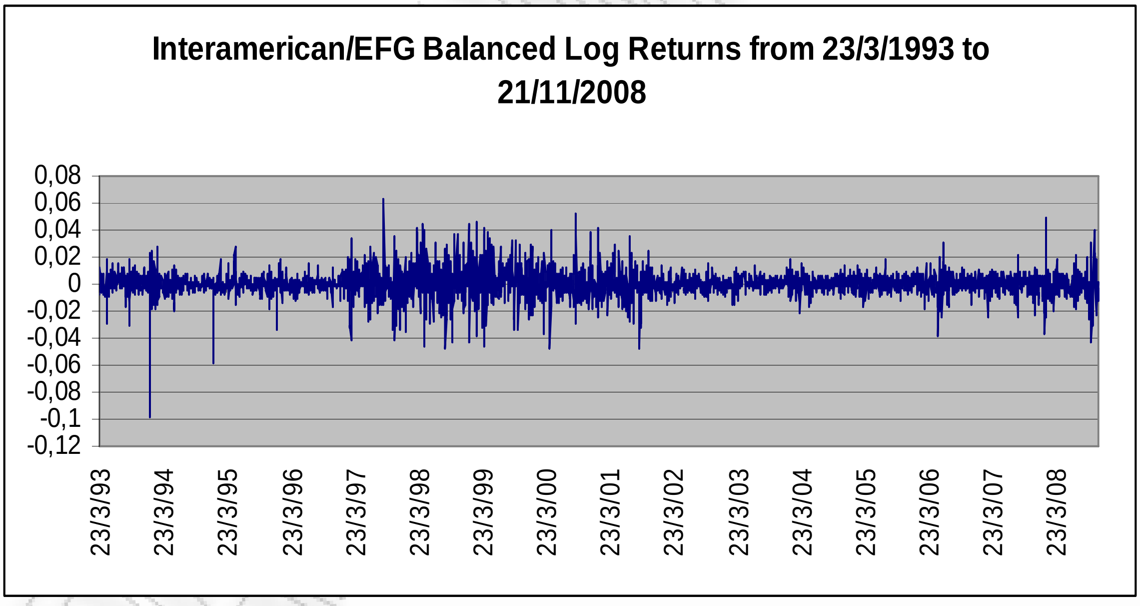
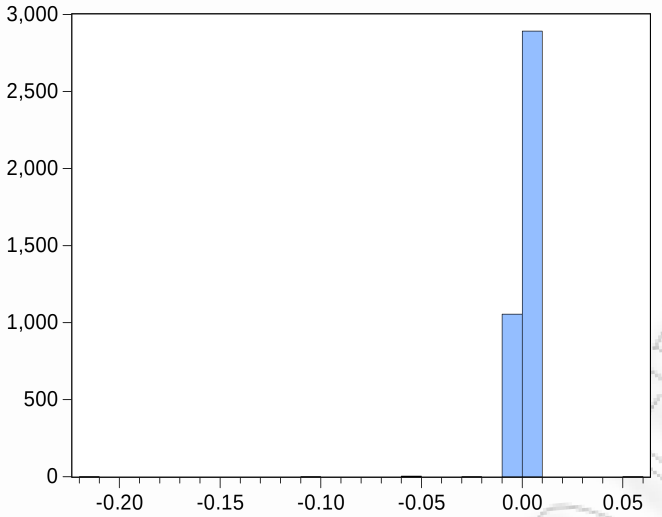


Figure A24 – Net Asset Value and Logarithmic Returns





Alpha Domestic Bonds Fund
Figure A25 – Histogram and stats



Series: ALPHA_BOND
Sample 3/23/1993 11/21/2008
Observations 3954

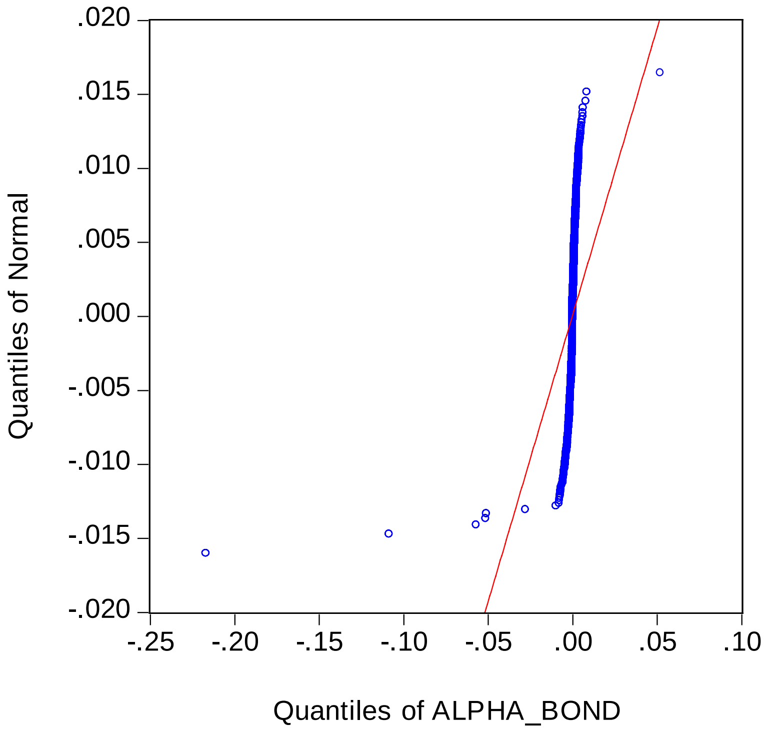
Mean	0.000203
Median	0.000346
Maximum	0.052023
Minimum	-0.216908
Std. Dev.	0.004437
Skewness	-34.34807
Kurtosis	1562.473
Jarque-Bera	4.01e+08
Probability	0.000000

Figure A26 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:48
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.034	-0.034	4.6261	0.031
		2	-0.002	-0.003	4.6467	0.098
		3	0.002	0.001	4.6559	0.199
		4	-0.003	-0.003	4.6957	0.320
		5	-0.010	-0.010	5.0664	0.408
		6	-0.003	-0.003	5.0944	0.532
		7	0.003	0.002	5.1223	0.645
		8	-0.004	-0.004	5.1932	0.737
		9	0.001	0.001	5.2005	0.816
		10	-0.008	-0.008	5.4291	0.861
		11	0.000	-0.000	5.4294	0.909
		12	0.001	0.001	5.4310	0.942
		13	-0.000	-0.000	5.4311	0.964
		14	0.001	0.001	5.4390	0.979
		15	-0.009	-0.009	5.7518	0.984
		16	0.002	0.002	5.7705	0.990
		17	0.005	0.005	5.8659	0.994
		18	0.001	0.001	5.8683	0.997
		19	0.003	0.003	5.9132	0.998
		20	-0.008	-0.008	6.1906	0.999
		21	0.002	0.002	6.2106	0.999
		22	0.002	0.002	6.2250	1.000
		23	-0.000	-0.000	6.2251	1.000
		24	0.006	0.006	6.3806	1.000
		25	-0.012	-0.011	6.9091	1.000
		26	-0.003	-0.004	6.9461	1.000
		27	-0.001	-0.001	6.9492	1.000
		28	0.000	-0.000	6.9492	1.000
		29	0.006	0.006	7.0702	1.000
		30	-0.007	-0.007	7.2878	1.000

Figure A27 – Q-Q Plots of the empirical against the Normal and the student's t distribution



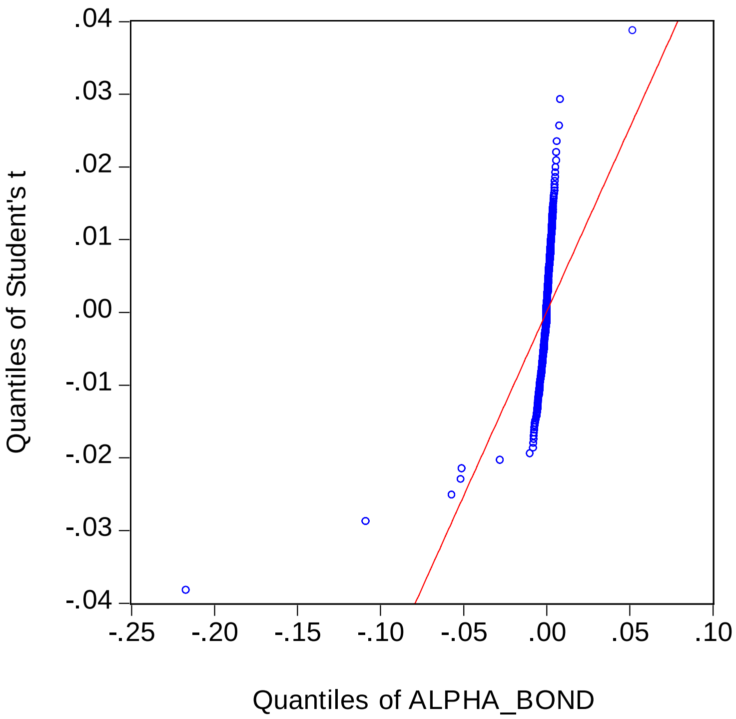
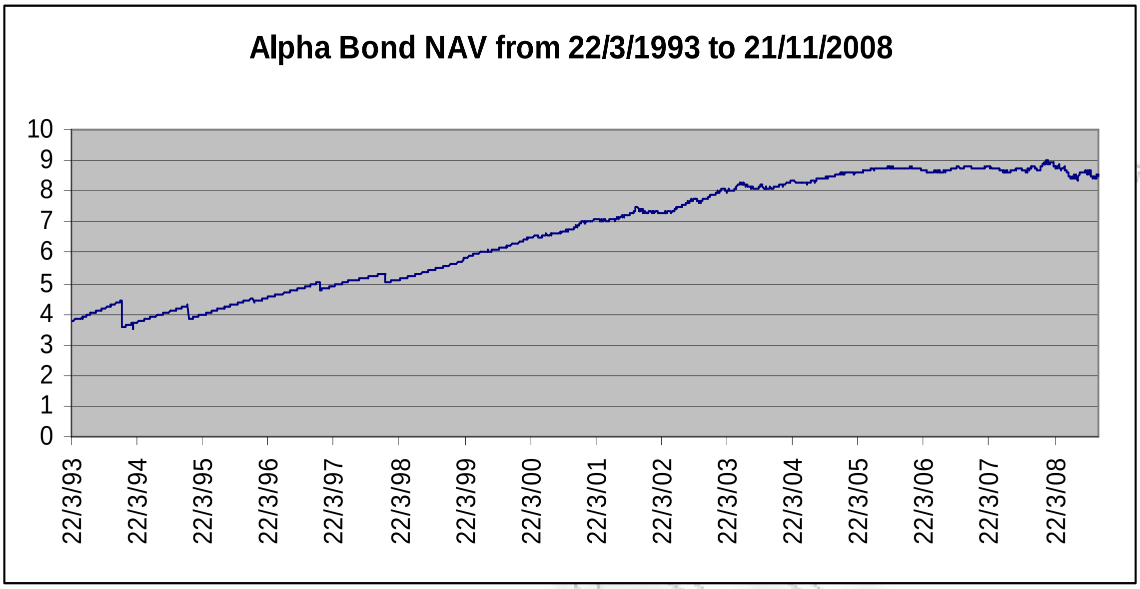
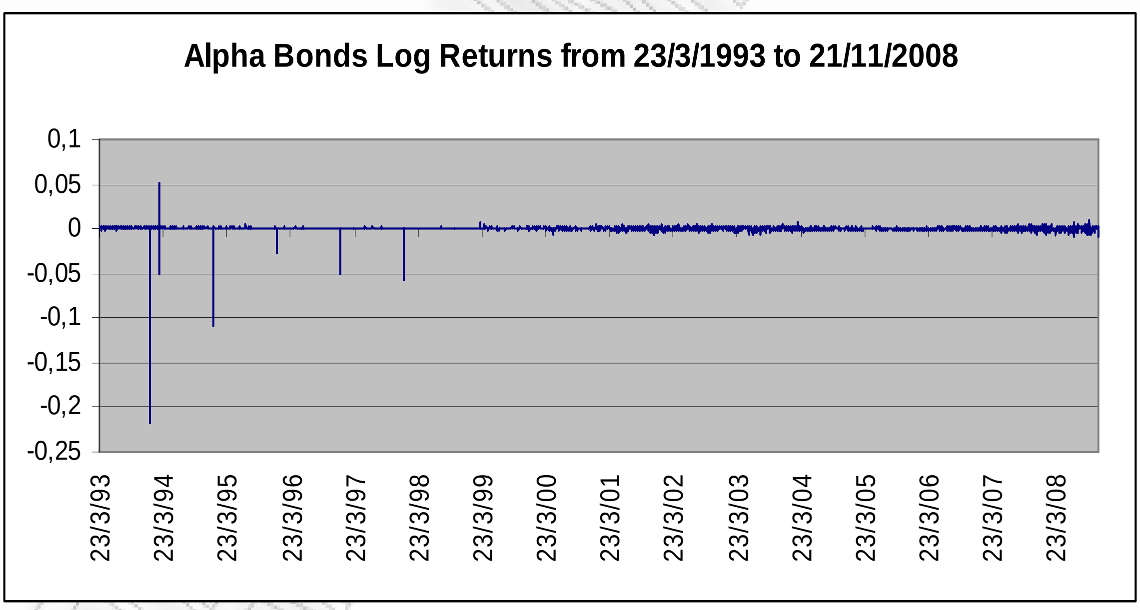
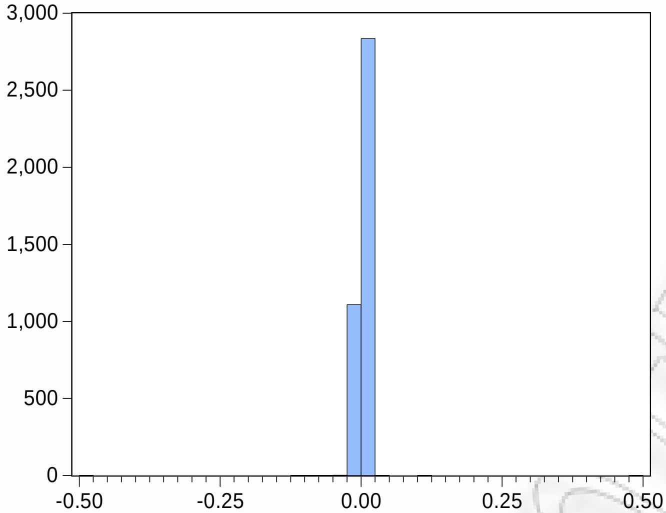


Figure A28 – Net Asset Value and Logarithmic Returns





Delos Income Domestic Bonds Fund
Figure A29 – Histogram and stats



Series: DELOS_BOND
Sample 3/23/1993 11/21/2008
Observations 3954

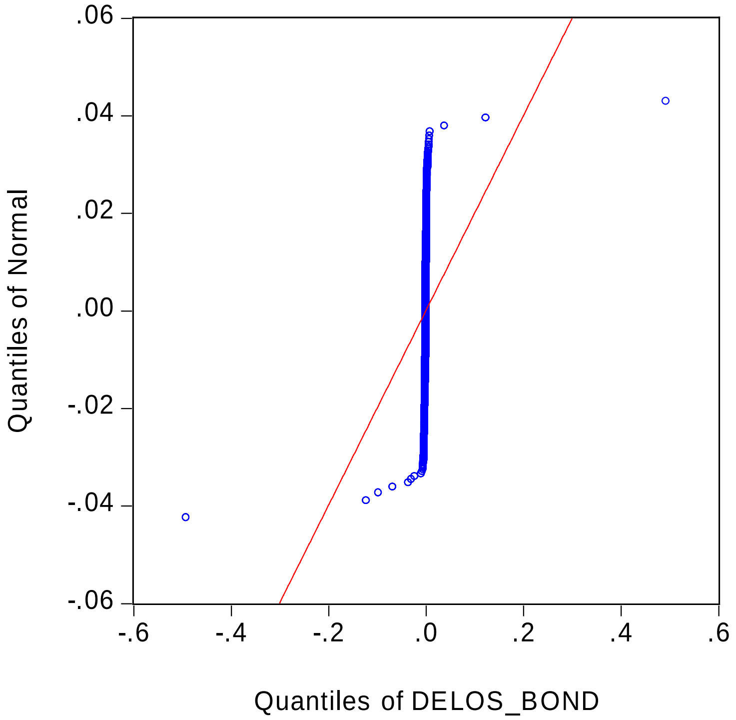
Mean	0.000235
Median	0.000348
Maximum	0.492535
Minimum	-0.491789
Std. Dev.	0.011657
Skewness	-0.166078
Kurtosis	1615.697
Jarque-Bera	4.28e+08
Probability	0.000000

Figure A30 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:51
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.486	-0.486	935.48	0.000
		2	0.001	-0.309	935.48	0.000
		3	0.001	-0.215	935.49	0.000
		4	-0.001	-0.158	935.49	0.000
		5	0.000	-0.119	935.49	0.000
		6	0.000	-0.090	935.49	0.000
		7	0.001	-0.068	935.49	0.000
		8	0.001	-0.051	935.49	0.000
		9	-0.001	-0.038	935.49	0.000
		10	0.000	-0.029	935.49	0.000
		11	0.000	-0.021	935.49	0.000
		12	0.000	-0.015	935.50	0.000
		13	0.002	-0.008	935.51	0.000
		14	-0.001	-0.005	935.51	0.000
		15	0.000	-0.002	935.51	0.000
		16	0.001	0.001	935.51	0.000
		17	0.000	0.003	935.51	0.000
		18	0.001	0.006	935.52	0.000
		19	-0.001	0.007	935.52	0.000
		20	-0.000	0.006	935.52	0.000
		21	0.001	0.007	935.52	0.000
		22	0.001	0.007	935.52	0.000
		23	0.001	0.009	935.53	0.000
		24	-0.000	0.010	935.53	0.000
		25	-0.001	0.009	935.53	0.000
		26	0.000	0.008	935.53	0.000
		27	0.001	0.009	935.53	0.000
		28	0.001	0.010	935.53	0.000
		29	-0.001	0.009	935.54	0.000
		30	0.000	0.008	935.54	0.000

Figure A31 – Q-Q Plots of the empirical against the Normal and the student's t distribution



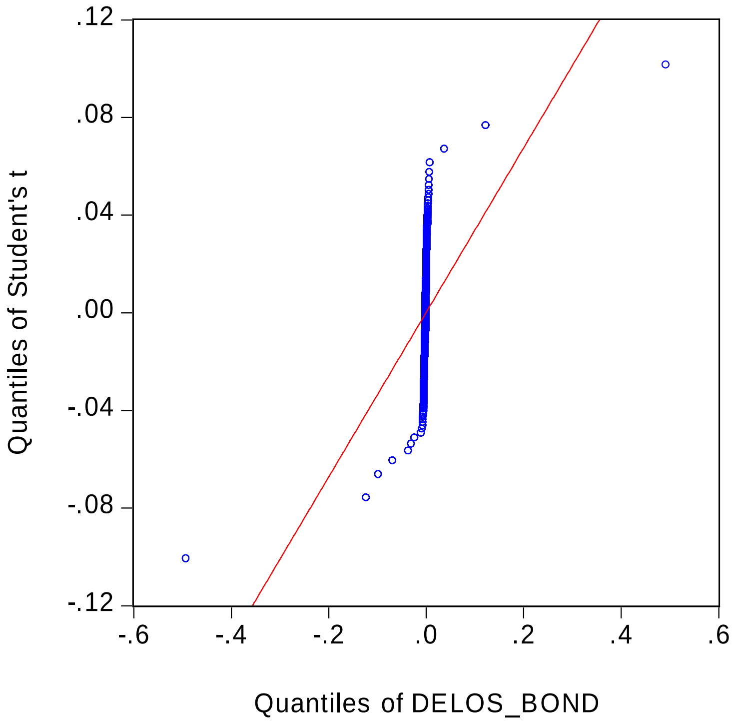
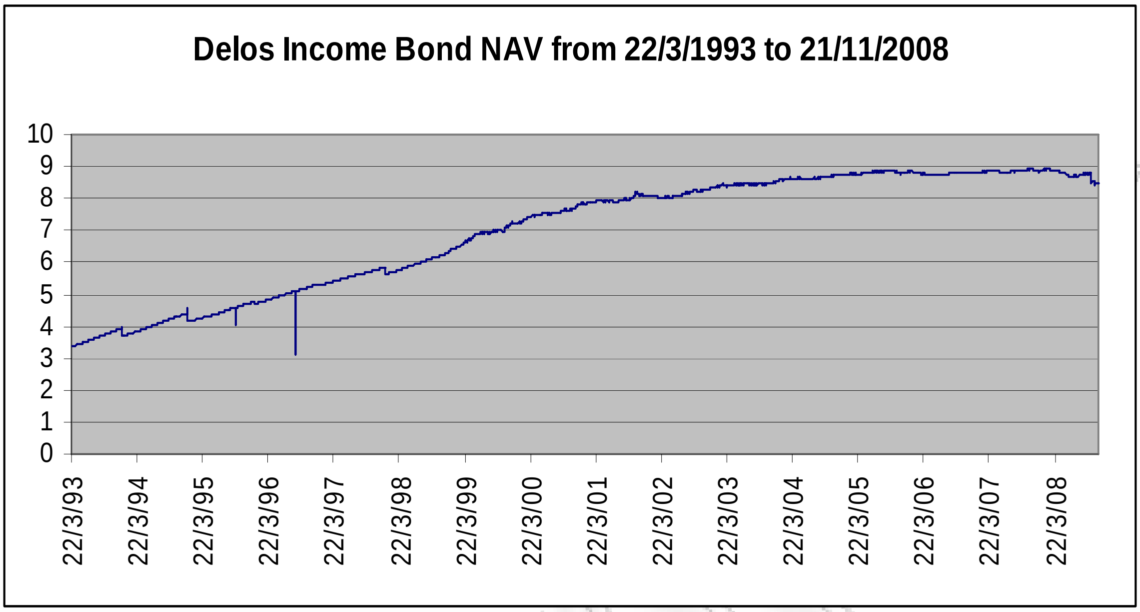
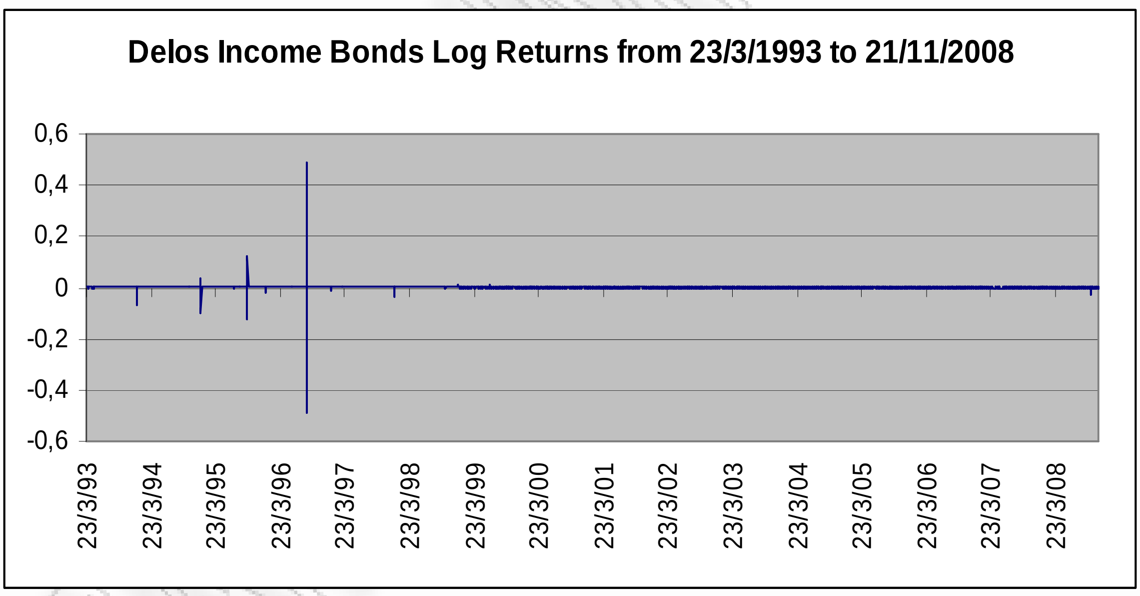
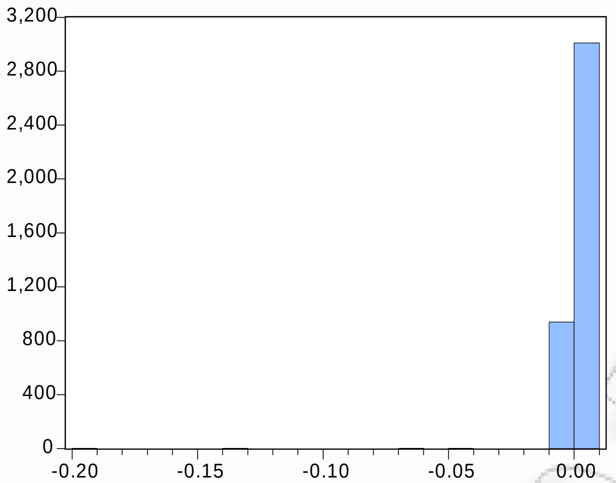


Figure A32 – Net Asset Value and Logarithmic Returns





Interamerican/EFG Fixed Income Domestic Bonds Fund
Figure A33 – Histogram and stats



Series: INTERAMERICAN_BOND
Sample 3/23/1993 11/21/2008
Observations 3954

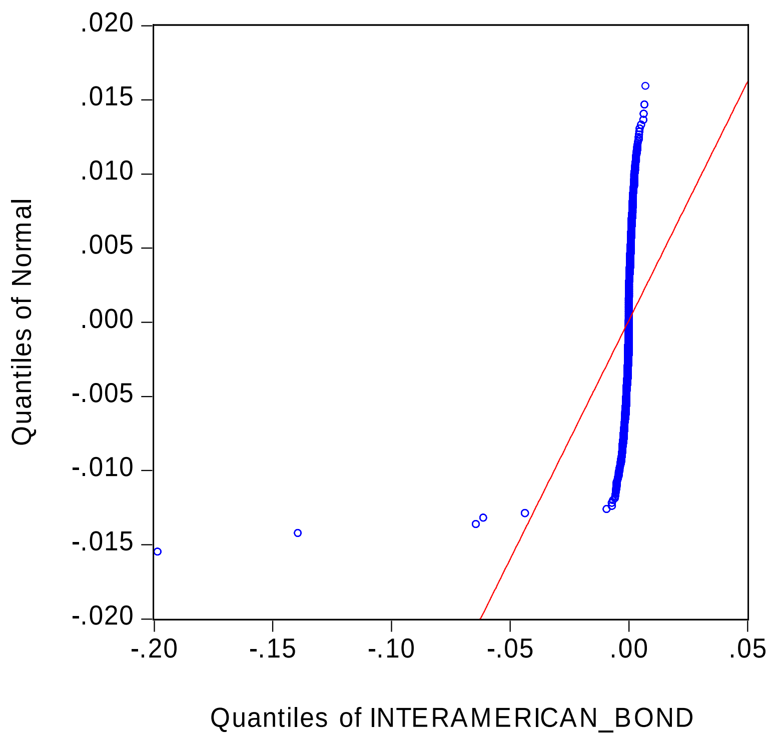
Mean	0.000183
Median	0.000356
Maximum	0.007301
Minimum	-0.198284
Std. Dev.	0.004291
Skewness	-35.54566
Kurtosis	1465.021
Jarque-Bera	3.53e+08
Probability	0.000000

Figure A34 – Ljung-Box autocorrelation test

Date: 06/23/09 Time: 02:50
Sample: 3/23/1993 11/21/2008
Included observations: 3954

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.006	-0.006	0.1211	0.728
		2	-0.006	-0.006	0.2690	0.874
		3	0.002	0.002	0.2811	0.964
		4	-0.008	-0.008	0.5211	0.971
		5	-0.002	-0.002	0.5357	0.991
		6	-0.007	-0.007	0.7235	0.994
		7	-0.000	-0.000	0.7236	0.998
		8	0.002	0.002	0.7351	0.999
		9	-0.004	-0.004	0.7956	1.000
		10	-0.000	-0.001	0.7963	1.000
		11	-0.007	-0.007	0.9715	1.000
		12	0.000	0.000	0.9725	1.000
		13	0.003	0.003	1.0203	1.000
		14	-0.002	-0.002	1.0343	1.000
		15	-0.002	-0.002	1.0454	1.000
		16	-0.001	-0.001	1.0521	1.000
		17	0.006	0.006	1.1753	1.000
		18	0.002	0.002	1.1855	1.000
		19	-0.005	-0.005	1.2904	1.000
		20	-0.001	-0.002	1.2993	1.000
		21	-0.003	-0.003	1.3252	1.000
		22	-0.001	-0.001	1.3289	1.000
		23	-0.000	-0.000	1.3289	1.000
		24	-0.001	-0.001	1.3357	1.000
		25	-0.004	-0.004	1.4082	1.000
		26	-0.006	-0.006	1.5566	1.000
		27	-0.003	-0.003	1.5957	1.000
		28	0.001	0.001	1.6018	1.000
		29	0.000	0.000	1.6018	1.000
		30	-0.003	-0.003	1.6302	1.000

Figure A35 – Q-Q Plots of the empirical against the Normal and the student's t distribution



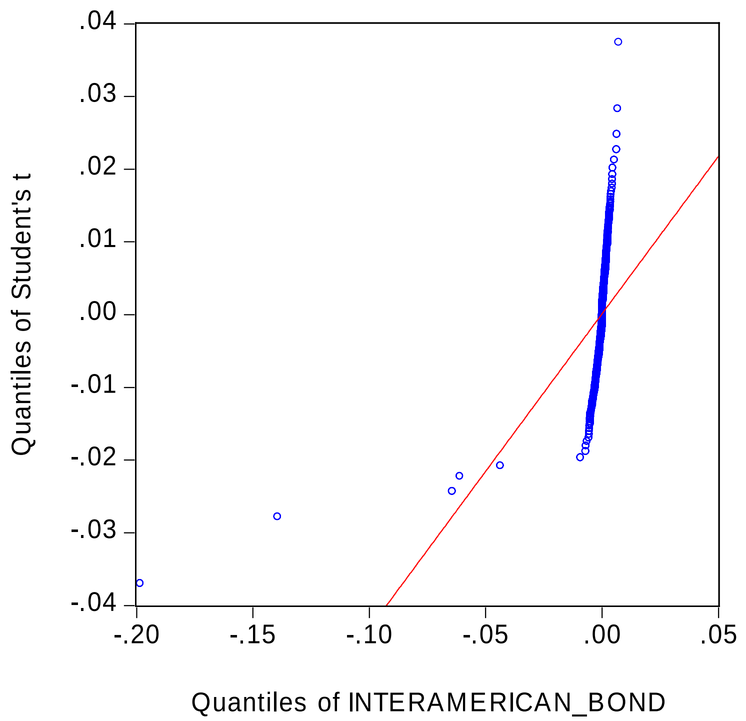
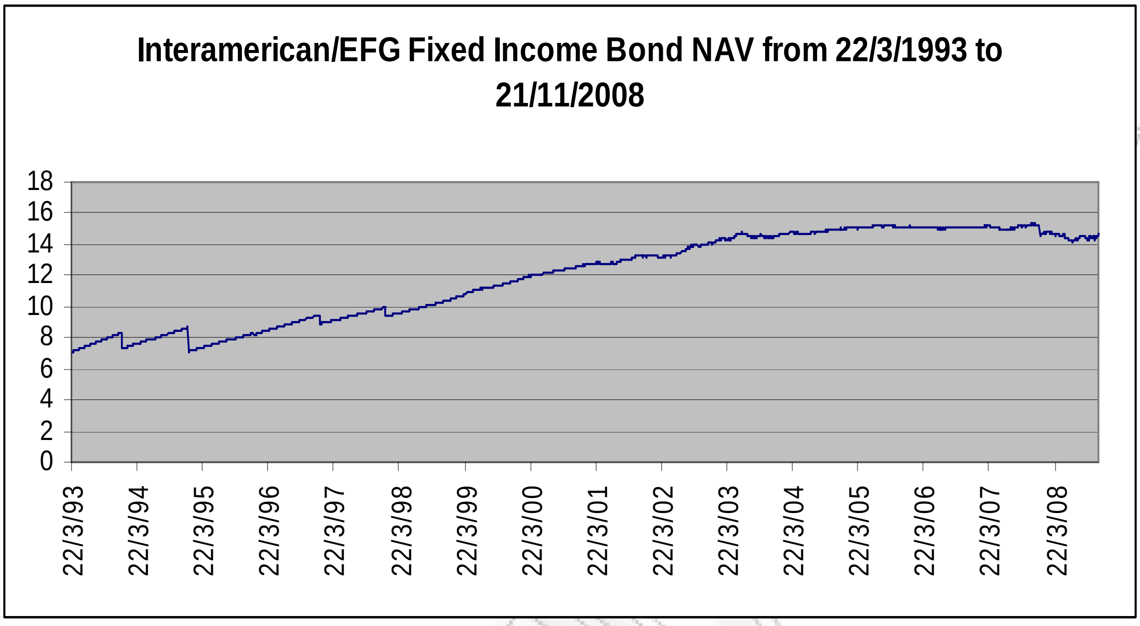
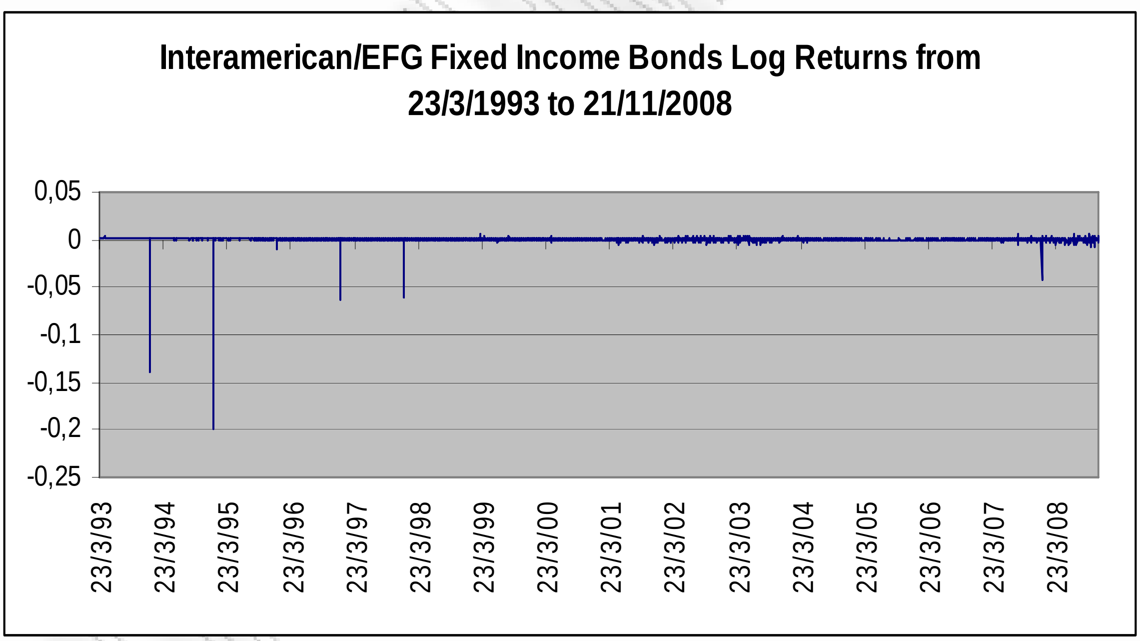


Figure A36 – Net Asset Value and Logarithmic Returns





95% VaR for MF Alpha Equity Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc&` LRind: 3.84 / Critical value for LRcc: 5.99								
Method	**SMA**	**EWMA**	**Historical Simulation**		**GARCH (n)**	**EGARCH (n)**	**GARCH (t)**	**EGARCH (t)**
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-2.24	-2.25	-2.28	-2.18	-2.32	-2.29	-2.22	-2.17
σ(VaR)	0.83	0.84	1.00	0.85	1.10	1.06	1.11	1.02
Min %	-3.81	-5.30	-5.63	-4.25	-9.70	-8.88	-9.27	-12.46
Max %	-1.12	-1.10	-0.74	-0.99	-0.90	-0.75	-0.89	-0.74
Violations	167	161	166	184	150	153	170	173
%	5.65	5.45	5.62	6.23	5.08	5.18	5.75	5.86
LRuc P-Value	**0.11**	**0.27**	**0.13**	0.00	**0.85**	**0.66**	**0.07**	0.04
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-2.10	-2.33	-2.81	-2.23	-2.44	-2.83	-2.35	-2.28
σ(VaR)	0.62	0.69	0.81	1.19	1.31	1.51	1.36	1.25
Min %	-3.23	-3.53	-4.07	-10.95	-11.98	-13.89	-12.69	-11.50
Max %	-1.25	-1.39	-1.74	-0.80	-0.87	-1.00	-0.83	-0.78
Violations	196	165	120	178	141	84	150	172
%	6.64	5.59	4.06	6.03	4.77	2.84	5.08	5.82
LRuc P-Value	0.00	**0.15**	0.02	0.01	**0.57**	0.00	**0.85**	**0.05**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	**0.06**	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	**0.16**	0.00

Table A1: 95% VaR for Alpha Domestic Equities Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Alpha Equity Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-3.16	-3.18	-3.22	-3.73	-3.28	-3.24	-3.60	-3.51
σ(VaR)	1.17	1.19	1.47	1.47	1.55	1.50	1.83	1.68
Min %	-5.38	-7.48	-7.21	-6.56	-13.69	-12.54	-15.04	-20.99
Max %	-1.59	-1.55	-1.09	-1.64	-1.27	-1.06	-1.46	-1.22
Violations	67	63	80	47	51	47	32	29
%	2.27	2.13	2.71	1.59	1.73	1.59	1.08	0.98
LRuc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	**0.65**	**0.92**
LRind P-Value	0.00	**0.05**	0.00	**0.22**	**0.07**	0.01	**0.05**	**0.03**
LRcc P-Value	0.00	0.00	0.00	0.01	0.00	0.00	**0.13**	**0.10**
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-3.79	-4.06	-4.56	-3.98	-4.17	-4.67	-3.83	-3.72
σ(VaR)	1.11	1.17	1.23	2.23	2.31	2.59	2.24	2.00
Min %	-5.59	-5.82	-6.36	-17.96	-18.80	-19.88	-20.06	-16.63
Max %	-2.17	-2.27	-2.50	-1.29	-1.34	-1.44	-1.36	-1.29
Violations	60	51	34	26	21	13	34	32
%	2.03	1.73	1.15	0.88	0.71	0.44	1.15	1.08
LRuc P-Value	0.00	0.00	**0.42**	**0.50**	**0.10**	0.00	**0.42**	**0.65**
LRind P-Value	0.00	0.00	0.00	**0.23**	**0.14**	**0.05**	**0.06**	**0.05**
LRcc P-Value	0.00	0.00	0.00	**0.38**	**0.08**	0.00	**0.13**	**0.13**

Table A2: 99% VaR for Alpha Domestic Equities Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Delos Equity Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-2.29	-2.30	-2.32	-2.18	-2.31	-2.26	-2.23	-2.18
σ(VaR)	0.85	0.86	1.04	0.87	1.15	1.05	1.12	1.03
Min %	-3.92	-4.85	-5.38	-3.94	-9.17	-8.32	-8.82	-8.30
Max %	-1.17	-1.14	-0.71	-0.98	-0.94	-0.83	-0.96	-0.81
Violations	151	151	168	173	145	146	154	161
%	5.11	5.11	5.69	5.86	4.91	4.94	5.21	5.45
LRuc P-Value	**0.78**	**0.78**	**0.09**	0.04	**0.82**	**0.89**	**0.60**	**0.27**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-2.20	-2.45	-2.99	-2.27	-2.48	-2.97	-2.31	-2.26
σ(VaR)	0.67	0.75	0.91	1.29	1.41	1.70	1.35	1.28
Min %	-3.42	-3.75	-4.43	-9.95	-10.92	-12.72	-11.18	-10.54
Max %	-1.27	-1.45	-1.77	-0.79	-0.85	-0.99	-0.83	-0.79
Violations	175	150	104	162	128	86	160	163
%	5.92	5.08	3.52	5.48	4.33	2.91	5.42	5.52
LRuc P-Value	0.02	**0.85**	0.00	**0.23**	**0.09**	0.00	**0.31**	**0.20**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A3: 95% VaR for Delos Blue Chips Domestic Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Delos Equity Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-3.23	-3.24	-3.36	-3.92	-3.26	-3.19	-3.65	-3.56
σ(VaR)	1.20	1.22	1.62	1.51	1.63	1.48	1.86	1.70
Min %	-5.53	-6.85	-7.14	-7.06	-12.95	-11.75	-15.15	-13.27
Max %	-1.65	-1.61	-1.09	-1.67	-1.32	-1.17	-1.59	-1.34
Violations	71	72	78	42	56	52	35	33
%	2.40	2.44	2.64	1.42	1.90	1.76	1.18	1.12
LRuc P-Value	0.00	0.00	0.00	0.03	0.00	0.00	**0.33**	**0.53**
LRind P-Value	0.00	0.00	0.00	0.00	0.02	**0.08**	**0.43**	**0.05**
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	**0.45**	**0.13**
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-3.99	-4.27	-4.83	-3.97	-4.23	-4.85	-4.05	-4.09
σ(VaR)	1.13	1.19	1.29	2.30	2.45	2.84	2.34	2.47
Min %	-5.67	-5.91	-6.49	-16.49	-17.63	-20.70	-21.21	-17.77
Max %	-2.22	-2.29	-2.49	-1.26	-1.37	-1.52	-1.42	-1.29%
Violations	55	45	27	31	24	12	33	25
%	1.86	1.52	0.91	1.05	0.81	0.41	1.12	0.85
LRuc P-Value	0.00	0.01	**0.63**	**0.79**	**0.29**	0.00	**0.53**	**0.39**
LRind P-Value	0.00	0.00	0.00	**0.33**	**0.19**	0.04	**0.05**	**0.21**
LRcc P-Value	0.00	0.00	0.01	**0.60**	**0.24**	0.00	**0.13**	**0.31**

Table A4: 99% VaR for Delos Blue Chips Domestic Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Interamerican/EFG Equity Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-2.22	-2.22	-2.23	-2.09	-2.25	-2.18	-2.18	-2.13
σ(VaR)	0.81	0.82	0.97	0.80	1.10	0.99	1.08	1.01
Min %	-3.78	-4.79	-5.55	-3.75	-8.29	-7.57	-8.30	-7.96
Max %	-1.20	-1.18	-0.72	-1.06	-0.94	-0.82	-0.98	-0.85
Violations	155	151	170	176	141	156	154	167
%	5.25	5.11	5.75	5.96	4.77	5.28	5.21	5.65
LRuc P-Value	**0.54**	**0.78**	**0.07**	0.02	**0.57**	**0.49**	**0.60**	**0.11**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-2.08	-2.31	-2.81	-2.18	-2.39	-2.85	159	-2.18
σ(VaR)	0.62	0.70	0.85	1.20	1.32	1.60	5.38	1.21
Min %	-3.18	-3.50	-4.11	-9.00	-9.85	-11.49	-2.23	-9.20
Max %	-1.25	-1.34	-1.54	-0.78	-0.85	-0.98	1.28	-0.77
Violations	193	160	111	165	131	84	159	168
%	6.53	5.42	3.76	5.59	4.43	2.84	5.38	5.69
LRuc P-Value	0.00	**0.31**	0.00	**0.15**	**0.15**	0.00	**0.35**	**0.09**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A5: 95% VaR for Interamerican/EFG Dynamic Equity Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Interamerican/EFG Equity Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-3.13	-3.14	-3.27	-3.82	-3.18	-3.08	-3.53	-3.44
σ(VaR)	1.15	1.16	1.54	1.46	1.55	1.40	1.76	1.63
Min %	-5.33	-6.76	-6.16	-6.16	-11.71	-10.70	-13.24	-12.70
Max %	-1.70	-1.66	-1.14	-1.53	-1.33	-1.16	-1.60	-1.38
Violations	70	66	74	39	55	56	37	32
%	2.37	2.23	2.51	1.32	1.86	1.90	1.25	1.08
LRuc P-Value	0.00	0.00	0.00	**0.10**	0.00	0.00	**0.18**	**0.65**
LRind P-Value	0.03	**0.25**	0.01	0.01	**0.85**	**0.39**	**0.48**	**0.35**
LRcc P-Value	0.00	0.00	0.00	0.01	0.00	0.00	**0.32**	**0.59**
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-3.75	-4.02	-4.59	-3.73	-3.99	-4.52	-3.87	-3.80
σ(VaR)	1.06	1.12	1.21	2.08	2.24	2.52	2.15	2.11
Min %	-5.28	-5.63	-6.17	-15.11	-16.33	-18.39	-15.43	-15.04
Max %	-1.91	-2.02	-2.22	-1.26	-1.33	-1.51	-1.48	-1.35
Violations	55	49	33	33	23	14	33	27
%	1.86	1.66	1.12	1.12	0.78	0.47	1.12	0.91
LRuc P-Value	0.00	0.00	**0.53**	**0.53**	**0.21**	0.00	**0.53**	**0.63**
LRind P-Value	0.00	0.00	**0.05**	**0.38**	**0.17**	**0.05**	0.01	**0.24**
LRcc P-Value	0.00	0.00	**0.13**	**0.56**	**0.18**	0.00	0.02	**0.45**

Table A6: 99% VaR for Interamerican/EFG Dynamic Equity Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Alpha Balanced Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-1.13	-1.13	-1.08	-1.02	-1.14	-1.17	-1.09	-1.07
σ(VaR)	0.34	0.34	0.42	0.32	0.47	1.39	0.47	0.40
Min %	-1.74	-3.23	-2.71	-2.08	-5.47	-70.11	-4.91	-4.41
Max %	-0.66	-0.64	-0.41	-0.55	-0.49	-0.48	-0.51	-0.47
Violations	145	144	180	188	132	135	147	141
%	4.91	4.87	6.09	6.36	4.47	4.57	4.98	4.77
LRuc P-Value	**0.82**	**0.75**	0.01	0.00	**0.18**	**0.28**	**0.95**	**0.57**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-1.03	-1.14	-1.38	-1.02	-1.12	-1.32	-1.05	-1.04
σ(VaR)	0.22	0.24	0.31	0.46	0.51	0.61	0.53	0.46
Min %	-1.45	-1.61	-1.95	-6.07	-6.66	-7.89	-7.57	-6.11
Max %	-0.71	-0.78	-0.89	-0.43	-0.47	-0.54	-0.43	-0.45
Violations	174	148	98	168	136	83	169	163
%	5.89	5.01	3.32	5.69	4.60	2.81	5.72	5.52
LRuc P-Value	0.03	**0.98**	0.00	**0.09**	**0.32**	0.00	**0.08**	**0.20**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A7: 95% VaR for Alpha Domestic Balanced Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Alpha Balanced Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-1.60	-1.60	-1.59	-1.87	-1.61	-1.65	-1.79	-1.77
σ(VaR)	0.48	0.49	0.69	0.67	0.66	1.96	0.80	0.69
Min %	-2.45	-4.56	-3.70	-3.43	-7.73	-99.01	-8.45	-7.59
Max %	-0.93	-0.90	-0.61	-0.95	-0.70	-0.68	-0.84	-0.76
Violations	67	65	80	46	52	50	34	31
%	2.27	2.20	2.71	1.56	1.76	1.69	1.15	1.05
LRuc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	**0.42**	**0.79**
LRind P-Value	0.00	**0.23**	**0.09**	**0.71**	**0.08**	**0.27**	0.01	0.04
LRcc P-Value	0.00	0.00	0.00	0.02	0.00	0.00	0.02	**0.12**
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-1.93	-2.08	-2.43	-1.89%	-2.03%	-2.36%	-1.89%	-1.78%
σ(VaR)	0.45	0.49	0.59	0.90%	0.99%	1.19%	0.95%	0.81%
Min %	-2.55	-2.71	-3.18	-9.93%	-10.69%	-13.38%	-10.56%	-9.46%
Max %	-1.10	-1.13	-1.24	-0.72%	-0.76%	-0.82%	-0.74%	-0.74%
Violations	44	38	26	30	25	11	30	41
%	1.49	1.29	0.88	1.02	0.85	0.37	1.02	1.39
LRuc P-Value	0.01	**0.13**	**0.50**	**0.93**	**0.39**	0.00	**0.93**	**0.05**
LRind P-Value	0.00	0.00	0.02	**0.43**	**0.51**	**0.76**	**0.04**	**0.58**
LRcc P-Value	0.00	0.00	**0.05**	**0.72**	**0.55**	0.00	**0.11**	**0.12**

Table A8: 99% VaR for Alpha Domestic Balanced Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Delos Balanced Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-1.49	-1.49	-1.49	-1.41	-1.49	-1.47	-1.46	-1.45
σ(VaR)	0.68	0.69	0.74	0.64	0.76	0.73	0.79	0.76
Min %	-2.73	-3.34	-2.96	-2.71	-6.09	-4.84	-6.26	-5.16
Max %	-0.65	-0.64	-0.45	-0.54	-0.52	-0.49	-0.52	-0.47
Violations	148	150	151	171	138	149	149	159
%	5.01	5.08	5.11	5.79	4.67	5.04	5.04	5.38
LRuc P-Value	**0.98**	**0.85**	**0.78**	**0.05**	**0.41**	**0.91**	**0.91**	**0.35**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-1.47	-1.64	-2.00	-1.43	-1.55	-1.85	-1.42	-1.42
σ(VaR)	0.51	0.57	0.69	0.80	0.87	1.05	0.83	0.80
Min %	-2.29	-2.51	-2.99	-5.53	-6.04	-7.30	-5.25	-5.70
Max %	-0.72	-0.81	-1.00	-0.42	-0.46	-0.54	-0.42	-0.43
Violations	181	141	91	160	130	76	166	164
%	6.13	4.77	3.08	5.42	4.40	2.57	5.62	5.55
LRuc P-Value	0.01	**0.57**	0.00	**0.31**	**0.13**	0.00	**0.13**	**0.18**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A9: 95% VaR for Delos Balanced Domestiv Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Delos Balanced Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-2.10	-2.11	-2.19	-2.51	-2.10	-2.08	-2.36	-2.33
σ(VaR)	0.97	0.97	1.24	1.17	1.07	1.03	1.27	1.23
Min %	-3.85	-4.72	-5.05	-4.51	-8.60	-6.84	-10.47	-8.49
Max %	-0.92	-0.90	-0.58	-1.00	-0.73	-0.69	-0.84	-0.77
Violations	72	70	77	42	45	39	29	24
%	2.44	2.37	2.61	1.42	1.52	1.32	0.98	0.81
LRuc P-Value	0.00	0.00	0.00	0.03	0.01	**0.10**	**0.92**	**0.29**
LRind P-Value	0.00	0.01	0.00	0.00	0.00	0.00	0.03	0.01
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	**0.10**	0.03
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-2.66	-2.84	-3.22	-2.50	-2.66	-3.10	-2.59	-2.63
σ(VaR)	0.90	0.95	1.07	1.46	1.58	1.90	1.61	1.60
Min %	-3.91	-4.14	-4.52	-10.64	-11.71	-14.84	-11.09	-11.39
Max %	-1.31	-1.42	-1.61	-0.68	-0.73	-0.80	-0.70	-0.70
Violations	38	34	25	30	23	12	28	23
%	1.29	1.15	0.85	1.02	0.78	0.41	0.95	0.78
LRuc P-Value	**0.13**	**0.42**	**0.39**	**0.93**	**0.21**	0.00	**0.77**	**0.21**
LRind P-Value	0.00	0.00	0.00	0.00	0.01	0.04	**0.27**	0.00
LRcc P-Value	0.00	0.00	0.00	0.01	0.02	0.00	**0.52**	0.00

Table A10: 99% VaR for Delos Balanced Domestic Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Interamerican/EFG Balanced Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-1.50	-1.50	-1.50	-1.43	-1.49	-1.48	-1.44	-1.44
σ(VaR)	0.63	0.63	0.72	0.60	0.79	0.76	0.78	0.74
Min %	-2.77	-3.23	-3.24	-2.73	-7.47	-12.50	-5.80	-5.05
Max %	-0.70	-0.68	-0.40	-0.64	-0.51	-0.43	-0.54	-0.45
Violations	142	137	174	173	149	153	163	177
%	4.81	4.64	5.89	5.86	5.04	5.18	5.52	5.99
LRuc P-Value	**0.63**	**0.36**	0.03	0.04	**0.91**	**0.66**	**0.20**	0.02
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-1.43	-1.60	-1.97	-1.43	-1.56	-1.84	-1.50	-1.43
σ(VaR)	0.49	0.55	0.67	0.80	0.88	1.05	0.90	0.81
Min %	-2.28	-2.50	-3.02	-6.22	-6.91	-8.17	-6.07	-6.41
Max %	-0.79	-0.85	-0.98	-0.44	-0.48	-0.56	-0.46	-0.44
Violations	184	154	103	169	140	89	170	171
%	6.23	5.21	3.49	5.72	4.74	3.01	5.75	5.79
LRuc P-Value	0.00	**0.60**	0.00	**0.08**	**0.51**	0.00	**0.07**	**0.05**
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A11: 95% VaR for Interamerican/EFG Hellenic Domestic Balanced Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Interamerican/EFG Balanced Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-2.12	-2.12	-2.21	-2.50	-2.11	-2.09	-2.35	-2.34
σ(VaR)	0.89	0.90	1.09	1.02	1.12	1.07	1.28	1.21
Min %	-3.92	-4.56	-4.63	-4.62	-10.55	-17.65	-10.06	-8.76
Max %	-0.98	-0.95	-0.71	-1.17	-0.72	-0.61	-0.90	-0.74
Violations	67	65	80	44	49	54	38	36
%	2.27	2.20	2.71	1.49	1.66	1.83	1.29	1.22
LRuc P-Value	0.00	0.00	0.00	0.01	0.00	0.00	**0.13**	**0.25**
LRind P-Value	**0.08**	**0.23**	0.00	**0.17**	**0.78**	0.00	**0.50**	0.01
LRcc P-Value	0.00	0.00	0.00	0.02	0.00	0.00	**0.26**	0.02
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-2.58	-2.76	-3.14	-2.49	-2.65	-3.01	-2.53	-2.44
σ(VaR)	0.76	0.80	0.84	1.47	1.57	1.82	1.47	1.43
Min %	-3.68	-3.85	-4.21	-12.48	-13.72	-16.54	-10.39	-11.37
Max %	-1.26	-1.31	-1.47	-0.73	-0.78	-0.88	-0.72	-0.70
Violations	46	41	28	30	23	16	33	33
%	1.56	1.39	0.95	1.02	0.78	0.54	1.12	1.12
LRuc P-Value	0.00	**0.05**	**0.77**	**0.93**	**0.21**	0.01	**0.53**	**0.53**
LRind P-Value	0.01	**0.13**	**0.27**	**0.31**	**0.17**	**0.07**	**0.05**	**0.38**
LRcc P-Value	0.00	0.04	**0.52**	**0.59**	**0.18**	0.00	**0.13**	**0.56**

Table A12: 99% VaR for Interamerican/EFG Balanced Domestic Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Alpha Bond Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-0.28	-0.28	-0.18	-0.17	-0.40	-0.94	-0.53	-3.23
σ(VaR)	0.14	0.14	0.15	0.13	0.32	13.71	2.50	9.58
Min %	-0.80	-2.42	-0.68	-0.50	-9.35	-585.37	-102.80	-162.90
Max %	-0.08	-0.08	0.03	0.03	-0.17	-0.04	-0.09	-0.02
Violations	132	135	222	277	101	130	117	84
%	4.47	4.57	7.52	9.38	3.42	4.40	3.96	2.84
LRuc P-Value	**0.18**	**0.28**	0.00	0.00	0.00	**0.13**	0.01	0.00
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-0.14	-0.16	-0.20	-0.14	-0.15	-0.19	-0.18	-0.14
σ(VaR)	0.09	0.11	0.13	0.12	0.13	0.15	0.15	0.11
Min %	-0.29	-0.33	-0.41	-0.86	-0.94	-1.10	-0.92	-0.88
Max %	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Violations	287	242	188	305	269	190	215	305
%	9.72	8.19	6.36	10.32	9.11	6.43	7.28	10.32
LRuc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A13: 95% VaR for Alpha Domestic Bonds Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Alpha Bond Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-0.40	-0.40	-0.26	-0.28	-0.57	-1.33	-0.91	-5.46
σ(VaR)	0.20	0.20	0.20	0.20	0.46	19.35	4.39	15.92
Min %	-1.13	-3.42	-0.73	-0.76	-13.20	-826.61	-180.51	-270.37
Max %	-0.12	-0.12	0.03	0.02	-0.23	-0.06	-0.15	-0.03
Violations	49	47	88	58	39	50	30	19
%	1.66	1.59	2.98	1.96	1.32	1.69	1.02	0.64
LRuc P-Value	0.00	0.00	0.00	0.00	**0.10**	0.00	**0.93**	0.04
LRind P-Value	**0.05**	**0.74**	0.02	**0.13**	0.00	0.01	**0.31**	**0.61**
LRcc P-Value	0.00	0.01	0.00	0.00	0.00	0.00	**0.59**	**0.10**
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-0.28	-0.31	-0.39	-0.28	-0.31	-0.39	-0.31	-0.27
σ(VaR)	0.15	0.15	0.13	0.17	0.17	0.20	0.25	0.19
Min %	-0.55	-0.59	-0.67	-1.36	-1.59	-2.89	-1.59	-1.40
Max %	0.00	-0.01	-0.04	0.00	0.00	-0.03	0.00	0.00
Violations	74	61	34	73	51	33	52	78
%	2.51	2.06	1.15	2.47	1.73	1.12	1.76	2.64
LRuc P-Value	0.00	0.00	**0.42**	0.00	0.00	**0.53**	0.00	0.00
LRind P-Value	0.00	0.00	**0.06**	0.00	0.00	**0.05**	**0.31**	0.00
LRcc P-Value	0.00	0.00	**0.13**	0.00	0.00	**0.13**	0.00	0.00

Table A14: 99% VaR for Alpha Domestic Bonds Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Delos Bond Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-0.48	-0.47	-0.14	-0.13	-0.90	-0.83	-0.27	-1.46
σ(VaR)	1.37	1.33	0.10	0.09	1.11	1.06	0.21	9.32
Min %	-7.24	-7.03	-0.35	-0.30	-6.39	-7.25	-3.20	-450.26
Max %	-0.06	-0.06	0.02	0.03	-0.08	-0.03	-0.07	-0.03
Violations	129	128	183	235	66	113	99	82
%	4.37	4.33	6.19	7.96	2.23	3.83	3.35	2.78
LRuc P-Value	**0.11**	**0.09**	0.00	0.00	0.00	0.00	0.00	0.00
LRind P-Value	**0.51**	**0.72**	0.00	0.00	0.00	0.04	**0.06**	0.03
LRcc P-Value	**0.22**	**0.22**	0.00	0.00	0.00	0.00	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-0.13	-0.15	-0.18	-0.10	-0.11	-0.13	-0.13	-0.10
σ(VaR)	0.07	0.08	0.09	0.09	0.10	0.13	0.12	0.10
Min %	-0.22	-0.24	-0.29	-3.01	-3.34	-4.10	-3.84	-3.16
Max %	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Violations	214	179	128	339	290	213	213	333
%	7.24	6.06	4.33	11.48	9.82	7.21	7.21	11.27
LRuc P-Value	0.00	0.01	**0.09**	0.00	0.00	0.00	0.00	0.00
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A15: 95% VaR for Delos Income Bonds Domestic Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Delos Bond Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-0.68	-0.67	-0.21	-0.24	-1.28	-1.17	-0.45	-2.54
σ(VaR)	1.93	1.87	0.14	0.15	1.57	1.50	0.37	16.38
Min %	-10.22	-9.93	-0.52	-0.50	-9.02	-10.24	-5.62	-790.74
Max %	-0.08	-0.08	0.02	0.02	-0.11	-0.04	-0.11	-0.04
Violations	49	44	80	70	23	44	26	22
%	1.66	1.49	2.71	2.37	0.78	1.49	0.88	0.74
LRuc P-Value	0.00	0.01	0.00	0.00	**0.21**	0.01	**0.50**	**0.14**
LRind P-Value	**0.05**	**0.17**	**0.09**	0.03	**0.54**	**0.17**	**0.49**	**0.15**
LRcc P-Value	0.00	0.02	0.00	0.00	**0.38**	0.02	**0.63**	**0.13**
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-0.28	-0.31	-0.40	-0.21	-0.24	-0.34	-0.24	-0.19
σ(VaR)	0.12	0.13	0.14	0.19	0.21	0.27	0.22	0.19
Min %	-0.48	-0.55	-0.82	-5.98	-6.57	-7.94	-6.90	-6.08
Max %	-0.03	-0.05	-0.15	-0.03	-0.05	-0.07	0.00	0.00
Violations	34	23	11	79	56	35	59	98
%	1.15	0.78	0.37	2.67	1.90	1.18	2.00	3.32
LRuc P-Value	**0.42**	**0.21**	0.00	0.00	0.00	**0.33**	0.00	0.00
LRind P-Value	0.01	**0.54**	**0.76**	**0.08**	**0.39**	**0.43**	0.03	0.00
LRcc P-Value	0.02	**0.38**	0.00	0.00	0.00	**0.45**	0.00	0.00

Table A16: 99% VaR for Delos Income Bonds Domestic Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

95% VaR for MF Interamerican/EFG Bond Expected violations: 148 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc& LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-0.26	-0.26	-0.13	-0.11	-0.43	-0.40	-0.45	-1.37
σ(VaR)	0.20	0.20	0.13	0.11	0.37	0.42	2.27	2.42
Min %	-0.92	-2.62	-0.48	-0.38	-2.57	-2.72	-79.04	-25.65
Max %	-0.07	-0.06	0.03	0.03	-0.09	-0.01	-0.07	-0.03
Violations	116	111	204	292	78	80	88	75
%	3.21	3.76	6.91	9.88	2.64	2.71	2.98	2.54
LRuc P-Value	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRind P-Value	0.01	**0.08**	0.00	0.00	**0.21**	**0.09**	0.00	0.01
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-0.11	-0.12	-0.15	-0.11	-0.12	-0.15	-0.14	-0.11
σ(VaR)	0.08	0.09	0.11	0.13	0.15	0.18	0.17	0.14
Min %	-0.22	-0.24	-0.29	-2.01	-2.19	-2.61	-2.11	-2.05
Max %	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Violations	266	218	165	265	235	160	194	265
%	9.00	7.38	5.59	8.97	7.96	5.42	6.57	8.97
LRuc P-Value	0.00	0.00	**0.15**	0.00	0.00	**0.31**	0.00	0.00
LRind P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LRcc P-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A17: 95% VaR for Interamerican/EFG Fixed Income Domestic Bond Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

99% VaR for MF Interamerican/EFG Bond Expected violations: 30 / Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations) Backtesting significance level 5% / Critical value for LRuc & LRind: 3.84 / Critical value for LRcc: 5.99								
Method	SMA	EWMA	Historical Simulation		GARCH (n)	EGARCH (n)	GARCH (t)	EGARCH (t)
Window length	**252**	**100**	**100**	**252**	**1000**	**1000**	**1000**	**1000**
E(VaR) %	-0.37	-0.37	-0.19	-0.21	-0.61	-0.56	-0.78	-2.37
σ(VaR)	0.29	0.29	0.17	0.17	0.52	0.59	3.98	4.23
Min %	-1.30	-3.70	-0.67	-0.67	-3.63	-3.84	-138.86	-45.04
Max %	-0.09	-0.09	0.03	0.03	-0.12	-0.01	-0.12	-0.05
Violations	45	44	86	69	27	25	21	12
%	1.52	1.49	2.91	2.34	0.91	0.85	0.71	0.41
LRuc P-Value	0.01	0.01	0.00	0.00	**0.63**	**0.39**	**0.10**	0.00
LRind P-Value	0.03	**0.66**	0.01	0.10	**0.24**	**0.21**	**0.57**	**0.74**
LRcc P-Value	0.00	0.04	0.00	0.00	**0.45**	**0.31**	**0.21**	0.00
Method	EVT Thr=10%	EVT Thr=8%	EVT Thr=5%	G-EVT Thr=10%	G-EVT Thr=8%	G-EVT Thr=5%	FHS 500	FHS 1000
Window length	**1000**	**1000**	**1000**	**1000**	**1000**	**1000**	**500**	**1000**
E(VaR) %	-0.22	-0.24	-0.29	-0.23	-0.25	-0.32	-0.25	-0.22
σ(VaR)	0.13	0.14	0.15	0.25	0.27	0.42	0.27	0.22
Min %	-0.44	-0.49	-0.73	-3.94	-4.14	-5.16	-3.09	-3.23
Max %	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Violations	80	62	36	75	66	36	48	80
%	2.71	2.10	1.22	2.54	2.23	1.22	1.62	2.71
LRuc P-Value	0.00	0.00	**0.25**	0.00	0.00	**0.25**	0.00	0.00
LRind P-Value	0.00	0.01	**0.34**	0.01	0.00	**0.08**	0.01	**0.09**
LRcc P-Value	0.00	0.00	**0.33**	0.00	0.00	**0.11**	0.00	0.00

Table A18: 99% VaR for Interamerican/EFG Fixed Income Domestic Bond Fund. The methods applied are Simple Moving Average (SMA), Exponentially Weighted Moving Average (EWMA or RiskMetrics model), Historical Simulation (HS for two window sizes), GARCH (1,1) and EGARCH (1,1) with normally and student's t distributed innovations, unconditional and GARCH filtered Extreme Value Theory (EVT and G-EVT) for thresholds of 10%, 8% and 5% and Filtered Historical Simulation (FHS) for two window sizes. The methods accepted under Unconditional Coverage, Independence and Conditional Coverage (5% significance level) tests are marked with bold font.

Expected Shortfall

Mutual Fund	Alpha Equity	Delos Equity	Intramerican /EFG Equity	Alpha Balanced	Delos Balanced	Interamerican /EFG Balanced	Alpha Bond	Delos Bond	Interamerican /EFG Bond
95% ES Assumptions Free. Window length: 100 observations. Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations)									
E(ES) %	-3.01	-3.10	-3.00	-1.48	-1.97	-1.99	-0.30	-0.22	-0.26
σ(ES) %	1.36	1.41	1.37	0.65	1.04	0.94	0.25	0.16	0.32
Min %	-7.06	-6.49	-6.29	-3.97	-4.10	-3.87	-1.12	-0.86	-1.26
Max %	-1.05	-0.97	-1.08	-0.59	-0.56	-0.56	0.03	0.02	0.03
Violations	96	99	96	92	92	92	87	90	90
%	3.25	3.35	3.25	3.11	3.11	3.11	2.95	3.05	3.05
VaR/ES Ratio	0.76	0.75	0.74	0.73	0.75	0.75	0.62	0.65	0.49
99% ES Assumptions Free									
E(ES) %	-3.77	-3.86	-3.73	-1.90	-2.45	-2.47	-0.44	-0.31	-0.44
σ(ES) %	1.82	1.84	1.79	0.99	1.36	1.19	0.57	0.34	0.76
Min %	-8.88	-7.86	-7.48	-5.81	-5.51	-4.67	-2.83	-1.79	-3.19
Max %	-1.13	-1.16	-1.15	-0.63	-0.63	-0.75	0.03	0.02	0.03
Violations	55	52	55	58	55	55	61	51	53
%	1.86	1.76	1.86	1.96	1.86	1.86	2.06	1.73	1.79
VaR/ES Ratio	0.85	0.87	0.88	0.84	0.89	0.90	0.59	0.66	0.42

Table A19: Expected Shortfall for 95% and 99% confidence levels for window size of 100 observations.

Mutual Fund	Alpha Equity	Delos Equity	Intramerican /EFG Equity	Alpha Balanced	Delos Balanced	Interamerican /EFG Balanced	Alpha Bond	Delos Bond	Interamerican/ EFG Bond
95% ES Assumptions Free. Window length: 252 observations. Backtesting period: 6/3/1997 – 21/11/2008 (2954 observations)									
E(ES)	-3.12	-3.24	-3.11	-1.56	-2.07	-2.10	-0.31	-0.39	-0.27
σ(ES)	1.18	1.22	1.16	0.52	0.93	0.84	0.14	0.77	0.20
Min	-5.95	-5.58	-5.51	-3.03	-3.80	-3.80	-0.89	-4.16	-1.02
Max	-1.40	-1.45	-1.47	-0.79	-0.81	-0.95	0.02	0.00	0.02
Violations	75	74	77	72	70	71	77	88	71
%	2.54	2.51	2.61	2.44	2.37	2.40	2.61	2.98	2.40
VaR/ES Ratio	0.70	0.67	0.67	0.65	0.68	0.68	0.54	0.35	0.41
99% ES Assumptions Free									
E(ES)	-4.48	-4.61	-4.46	-2.35	-2.94	-2.90	-0.61	-1.05	-0.66
σ(ES)	1.82	1.76	1.70	1.00%	1.38	1.09	0.54	3.17	0.74
Min	-8.05	-7.16	-6.86	-4.74	-4.93	-4.66	-3.61	-16.7	-4.16
Max	-1.99	-2.04	-1.92	-1.11	-1.10	-1.26	0.02	-0.04	0.02
Violations	21	21	23	18	23	23	23	36	28
%	0.71	0.71	0.78	0.61	0.78	0.78	0.78	1.22	0.95
VaR/ES Ratio	0.83	0.85	0.86	0.79	0.85	0.86	0.45	0.23	0.32

Table A20: Expected Shortfall for 95% and 99% confidence levels for window size of 252 observations.