Comments solicited

Value at Risk as a Diagnostic Tool for Corporates:

The Airline Industry

Winfried Hallerbach and Bert Menkveld*

Erasmus University Rotterdam
Tinbergen Institute
P.O. Box 1738
NL-3000 DR Rotterdam
The Netherlands
Phone: +31 10 4088900
Fax: +31 10 4089031
Email: menkveld@few.eur.nl

KLM Royal Dutch Airlines
Investor Relations (AMS/IR)
P.O. Box 7700
NL-1117 ZL Schiphol Airport
The Netherlands

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* Corresponding author

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Abstract

In recent years the Value at Risk (VaR) concept for measuring downside risk has been widely studied. VaR basically is a summary statistic that quantifies the exposure of an asset or portfolio to market risk, or the risk that a position declines in value with adverse market price changes. Three parties have been particularly interested: financial institutions, regulators and corporates.

In this paper, we focus on VaR use for corporates. This field is relatively unexplored. We show how VaR can be helpful to study market value risk -- proxied by share price risk. We develop a methodology to decompose the overall VaR into components that are attributable to underlying external risk factors and a residual idiosyncratic component.

Apart from developing theoretical results, we study the airline industry to show what practical results our 'Component VaR framework' can yield. Like any multinational company, an airline faces significant exposures to external risk factors, e.g. commodity prices, interest rates and exchange rates. In our opinion, Component VaR analysis can enrich discussions in the company on financial risk management and shareholder value.

Abstract (extended)

In recent years the Value at Risk (VaR) concept for measuring downside risk has been widely studied. VaR basically is a summary statistic that quantifies the exposure of an asset or portfolio to market risk, or the risk that a position declines in value with adverse market price changes. Three parties have been particularly interested: financial institutions, regulators and corporates. The focus of this paper is VaR use for corporates. This is a relatively unexplored field, which offers many theoretical and empirical challenges.

Using insights from both the VaR and multifactor literature we develop the 'Component Value at Risk' framework. We add two innovative features. First, the framework defines and explores a company's VaR that can be helpful to study market value risk as proxied by share price risk. The Component VaR offers a multidimensional approach to such risk, i.e. we distinguish between several external risk factors and an idiosyncratic risk factor. Second, we develop a methodology to decompose the overall VaR into components attributable to these underlying risk factors. This enables us to evaluate the contribution of each risk factor to the overall VaR.

Apart from developing theoretical results, we investigate the international airline industry to illustrate the relevance of our Component VaR framework to corporate practice. We study exposures to exchange rates, jet fuel prices, interest rates and local stock market indices. This provides us with the shareholders' perception of airline risks. The out of sample performance of Component VaR estimates is compared to the well-known RiskMetrics™ approach. The latter approach is known to suffer from significant underestimation of risk for high VaR confidence levels. We find further evidence of this bias in the airline industry. Component VaR estimates, in contrast, do not seem to suffer from such bias. In addition, our framework provides insight in the source of VaR differences both across airlines and over time. Finally, the decomposition result does not rely on any distributional assumptions and is computationally simple and straightforward.

We focus on KLM Royal Dutch Airlines to show how Component VaR results should be interpreted. The objective of KLM's risk management strategy is to shield shareholders from financial risks and, hence, expose them solely to business risk. In recent years this strategy was implemented and we find that the stock's risk profile changed accordingly. In our opinion, Component VaR analyses can enrich discussions on corporate risk management and shareholder value.

Keywords: Value at Risk, non-financials, factor models, airline industry, risk management, downside risk, out of sample, decomposition.

JEL Classification: G12, G14, G15, G30

1 Introduction

Companies are in the business of managing risk. The ones most adept survive, others fail. Company risk is defined as potential fluctuation in future cash flows or equity value. Jorion (1997) provides a useful taxonomy of company risk, viz. business risk, strategic risk and financial risk. A company willingly assumes business risk in order to create a competitive advantage and to provide value to its shareholders. Strategic risk is caused by fundamental shifts in the economy or the political environment. Financial risk is related to potential losses in financial markets.

This paper contributes to the growing literature on financial risk management. These studies explore various kinds of financial risk: credit risk, liquidity risk, market risk etc. In this paper we focus on market risk, which is caused by changes in exchange rates, commodity prices and interest rates. Adverse movements in these risk factors can seriously damage a company. Orange County, Metallgesellschaft and Barings have become buzzwords in papers that refer to recent empirical evidence. This, combined with increased volatility in financial markets over the last decade and a strong growth of derivative products as tools to manage financial risk, has triggered academic and professional interest. One of the major achievements is the introduction of the Value at Risk (VaR) framework, which provides companies with an easy-to-understand standard of measuring and managing financial risk.

VaR first emerged in the trading community. The objective of VaR was to systematically measure an trading firm's risk exposure across its dealing portfolios. Regulators' interest followed soon after. Both the SEC and the Basle Committee consider VaR a sound approach to meet risk reporting requirements. A relatively new field is VaR for non-financial companies. Most papers in this area explore VaR use at corporate treasury desks, focusing at Cash Flow at Risk or Earnings at Risk. Starting from the premise that shareholders' perceptions are reflected in share price dynamics, we use VaR to analyse their view on a company's downside risk. The main purpose of the paper is to investigate the share price VaR and to disentangle this overall VaR into components attributable to external factors and a company specific component. These 'Component VaRs' offer a multifarious view on a company's risk. We want to stress that this decomposition is a general result and hence does not depend on any distributional assumption.

In a perfect market setting a new hedging strategy should change the risk profile of the stock. In practice, however, shareholders often lack information about risk exposures. When their estimate does not mirror the true company risk, they might experience unpleasant earnings surprises. A recent initiative by the American Stock Exchange illustrates shareholders' concern:

> *"To respond to investors' concern that firm hedging decisions may affect exposures, the American Stock Exchange recently issued options on a new index of gold mining firms that refrain from hedging gold*

price exposure to provide equity derivative investors with a 'purer' play on gold than was available", Hu (1996)

Tufano (1998) studies shareholders' perception of exposures in the gold mining industry and shows how these are affected by hedging strategies. We extend this line of research by studying risk exposures in the airline industry using Component VaR. The reason for studying this particular industry is the significant exposure of airlines to financial risk factors, i.e. fuel prices, exchange rates and interest rates. We generate weekly VaR forecasts for six major international airlines and perform out of sample tests. We focus on KLM Royal Dutch Airlines to show how the results should be interpreted.

This paper is organised as follows. Section 2 briefly discusses the Value at Risk concept and its origin. In section 3 we combine basic VaR techniques with factor models in order to develop the Component VaR framework. This framework will prove useful in finding the contribution of various sources of risk to the stock's overall VaR. Section 4 discusses how this methodology can be applied to the airline industry. Out of sample performance is studied in section 5. To show how to interpret results, section 6 focuses on Component VaR results for KLM. Section 7 contains concluding remarks and directions for future research.

2 Value at Risk

In recent years the Value at Risk concept for measuring downside risk has been widely discussed. Basically, VaR is a summary statistic that quantifies the downside risk exposure of an asset or portfolio to market factors. Jorion (1997) provides an extensive discussion on Value at Risk. His definition is:

"The Value at Risk is the worst expected loss over a given time interval under normal market conditions at a given confidence level".

VaR has been developed for financial firms to evaluate (trading) portfolio risk. The inherent simplicity of the concept greatly facilitated dealers' reporting of risks to senior managers and directors. It allows them to make statements like: "We do not expect losses to exceed $ 1 million on more that one out of the next 20 trading days." The popularity of VaR nowadays owes much to Dennis Weatherstone, former chairman of JP Morgan & Co, Inc., who demanded to know the total market risk exposure of JP Morgan at 4:15pm every day. Weatherstone's request was met with a daily VaR report.

Various methodologies have been developed to estimate VaR. In October 1994, JP Morgan released their RiskMetrics™ methodology, which consists of two steps. First a portfolio's exposure to prespecified risk sources is identified. These sources relate to bond, equity, foreign exchange and money markets. Second, the portfolio VaR can be estimated using JP Morgan's data sets containing variance and covariance forecasts for these risk sources. We refer to the RiskMetrics™ technical documents for an extensive discussion (JPMorgan Bank (1996)).

Statistically, RiskMetrics™ is based on time-weighted moving averages, where the weights decline in an exponential fashion. The covariance matrix forecast is equal to an exponentially weighted sample variance. This is equivalent to an IGARCH(1,1) estimate. Extensive empirical research suggests a decay factor of 0.94 for daily observations and a decay factor of 0.97 for monthly observations.

3 Component Value at Risk for Stocks

The major virtue of the RiskMetrics™ framework is that it provides an integrated and easy-to-use risk estimate. It is an integrated approach, because it keeps track of the correlation between the various financial series. The intuitive appeal of exponential weighting is that it accommodates a time-varying volatility by considering recent shocks more important than remote ones. In this paper we try to keep this virtue when applying the framework to stocks. The major difference between stocks and portfolios, however, is the visibility of exposures. Whereas a portfolio exposure for risk factors is determined by the extent to which a particular security is in the portfolio, the exposure of the stock to the underlying risk factors is hidden. As Stulz (1996) puts it:

> *"It is relatively simple to calculate VaR for a financial institution's portfolio over a horizon of a day or a week. It is much less clear how one would compute VaR associated with, say, an airline's ongoing operating exposure to oil prices."*

In the finance literature, factor models are used to estimate such exposures. Some well-known examples are Sweeney and Warga (1986) and Flannery and James (1984) who estimate the exposure of shares for the market index and the risk-free interest rate. Jorion (1990) uses a factor model to study exchange rate exposures of US multinationals. In general, the exposures of total stock returns for external risk sources can be estimated using the following model:

$$(1)\quad \tilde{r}_t = a + \sum_{i=1}^{k} b_i \tilde{f}_{i,t} + \tilde{\varepsilon}_t$$

where $\tilde{r}_t$ = the total stock return in period t (including dividend payments),

$\tilde{f}_{i,t}$ = the return on underlying factor i in period t,

$\tilde{\varepsilon}_t$ = the disturbance term.

Tildes indicate stochastic variables. The sensitivity coefficients *b* indicate the stock's exposures to the external factors. The major drawback of this simple representation is that exposures are assumed to be constant. However, we know that these exposures are subject to change for a number of reasons. The company's activities might change and therefore its exposures. In addition, the company may initiate a hedging policy or change it. Finally, the perceptions of investors may change over time.

Moving window estimation of the model allows for time-varying exposures. The major drawback of this approach is that the changing exposure might be caused by the new observation that is added to the window as well as by the one that drops out of the window. In the latter case the changing exposure was not triggered by new information. We choose to apply exponential weighting in line with the RiskMetrics™ approach to estimate exposures. We do this by modelling the disturbance term as

(2) $\varepsilon_{-k} \sim N(0,\sigma(1/\lambda)^k)$

where k represents the number of lagged time periods and λ is the decay factor. Intuitively the model emphasises a fit with recent observations because recent residuals should have smallest standard errors.

Suppose we have estimates of the stock's risk exposures at time t. For period t+1 (i.e. from time t to t+1) the stock return and the risk factors are stochastic. If period t+1 is short enough, the factor exposures can be assumed to be constant. Clearly, both the underlying factors and the disturbance term cause stock return risk in period t+1. For convenience, we consider the disturbance term to be one of the factors and rewrite the model as:

(3) $\tilde{r}_{t+1} = a + \sum_{i=1}^{k} b_{i,t}\,\tilde{f}_{i,t+1} + b_{k+1,t}\,\tilde{f}_{k+1,t+1}$

The disturbance term factor should be interpreted as a source of idiosyncratic -- i.e. company specific -- risk. Without loss of generality this idiosyncratic factor $\tilde{f}_{k+1,t}$ can be scaled to obtain $b_{k+1,t}=1$.

Next we consider the VaR concept with the factor model equation (3) in mind. Given an overall VaR, two questions appeal to us:

1. What is the effect on the stock VaR if the exposures for one of the underlying factors were to change?
2. How can we decompose the stock VaR into components attributable to each of the underlying factors?

To answer both questions we have to formalise stock VaR and introduce definitions for the Marginal VaR and Component VaR of factor i.

The return VaR on a stock is defined as:

$$(4)\quad \Pr\left[\tilde{r}_{t+1} < -r^*_{t+1}\right] = 1 - c\%$$

where r^*_{t+1} = the stock return VaR for period t+1,

$\tilde{r}_{t+1}$ = the stock return for period t+1,

c = the VaR confidence level.

The linearity of the factor model enables us to define and estimate the *contribution* of each factor to the overall VaR. The marginal VaR of factor *i*, M-VaR$_i$, is defined as the change in the return VaR r^* that is caused by a marginal change in factor exposure b_i :

$$(5)\quad M - VaR_i \equiv \frac{\partial r^*}{\partial b_i} \qquad i = 1,\ldots,k+1$$

In addition, we consider the total contribution of each factor. Denoting a factor *i* Component VaR by C-VaR$_i$, we require:[1]

$$(6)\quad r^* \equiv \sum_{i \in k+1} C - VaR_i$$

With these definitions in mind, we have to find a model that enables us to calculate the overall VaR, M-VaR and C-VaR. We follow the RiskMetrics™ approach in assuming that the conditional distribution of returns over period t+1 equals a normal density in the left tail ranging from the 1% critical value $Z_{0.01}$ to the 10% critical value $Z_{0.10}$. This distribution is conditional, because the variance and mean estimate are based on all historical returns until and including the return in period t. It is common practice to ignore the mean since its influence is negligible compared to that of the standard deviation.[2] In our empirical work we use detrended series to calculate VaR. Taking either of these two approaches the resulting VaR estimate is:

$$(7)\quad r^*_{t+1} = -N^{-1}(1-c)\cdot\hat{\sigma}_t = Z_c \cdot \hat{\sigma}_t$$

where $\hat{\sigma}_t$ = the standard deviation estimate based on returns until time t

N^{-1} = the inverse cumulative normal distribution function,

c = the VaR confidence level.

The factor model and its inherent linearity allows us to estimate σ_t^2 from the variance of the underlying factors:

(8) $\sigma_t^2 = \underline{b_t}'\Sigma_t \underline{b_t}$

where $\underline{b}_t$ = a vector representing the stock's factor exposures,

Σ_t = the covariance matrix of the underlying factors.

Differentiating this expression to b_i yields[3]:

(9) $$\frac{\partial \ \sigma_t}{\partial \ b_i} = \frac{Cov\left(\tilde{f}_{i,t}, \tilde{r}_t\right)}{\sigma_t}$$

where cov(·,·) is the covariance operator. We use this expression to find M-VaR$_i$ as:

(10) $$M - VaR_i \equiv \frac{\partial r^*}{\partial b_i} = \frac{\partial Z_c.\sigma_t}{\partial b_i} = Z_c \cdot \frac{Cov\left(\tilde{f}_{i,t}, \tilde{r}_t\right)}{\sigma_t}$$

In addition, linearity allows us to find the Component VaR as:

(11) $$C - VaR_i = b_i \cdot M - VaR_i$$

since:

(12)

$$\sum_{i=1}^{k+1} C - VaR_i = \sum_{i=1}^{k+1} b_i \cdot M - VaR_i = Z_c \cdot \sum_{i=1}^{k+1} b_i \cdot \frac{Cov\left(\tilde{f}_{i,t}, \tilde{r}_t\right)}{\sigma_t} = Z_c \cdot \frac{Cov\left(\sum_{i=1}^{k+1}(b_i \cdot \tilde{f}_{i,t}), \tilde{r}_t\right)}{\sigma_t} = Z_c \cdot \sigma_t = r^*$$

One of the virtues of this approach to M- and C-VaR is easy calculation. The expression on the right hand side of equation (10) equals Z_c times the slope coefficient of an OLS regression of return on factor i on the stock return. In the appendix you find a more general derivation of the M- and C-VaR result. We want to stress that this decomposition is a general result and hence does not depend on any distributional assumption.

4 Component VaR in the Airline Industry

> *"An airline, for example, might find VaR helpful in assessing its exposure to jet fuel prices; but for the airline to use VaR to analyse the risk that seats on its aircraft are not all sold makes little sense.", Culp, Miller and Neves (1998)*

This paper follows this suggestion. The airline industry in this decade serves as an appropriate laboratory for a VaR perspective on risk exposures. There are several reasons for this. The most important reason is that airlines are intrinsically heavily exposed to various sources of financial risk. Airline revenues are denominated in many different currencies. Hence, exchange rate risk is an important issue in the industry. Furthermore, jet fuel expenses constitute a significant part of airline costs. This generates commodity price risk. In addition, the degree of leverage in the industry is substantial. Considerable tax benefits can be achieved through debt financing of aircraft. Widespread use of financial lease constructions illustrates airlines' interest in debt finance. The result of this is that airlines face a substantial exposure to interest rate levels. Another reason for studying the airline industry is the creation of global airline alliances in this decade. Such alliances will have changed the stock profile. Finally the relatively high liquidity and volatility of airline stocks ensures sufficient share price dynamics to study. Our Component VaR framework provides the proper tools to study this dynamics.

We use a factor model that relates share price returns to returns on exchange rates, jet fuel and government bonds. The local market index is added to account for the fact that the stock is part of the local market portfolio. This index should be purged of the other factors' effects, since we want to measure the pure effect of each of these factors on stock return. This can be achieved by a regression of the index on all other factors. The residual is added to the factor model and is referred to as the residual market index.[4] The resulting factor model is:

$$(13)\quad \tilde{r}_{t,airline} = \alpha + b_{JetFuel}\tilde{r}_{t,JetFuel} + b_{\$-DEM}\tilde{r}_{t,\$-DEM} + b_{\$-GBP}\tilde{r}_{t,\$-GBP} + b_{BOND}\tilde{r}_{t,BOND} + b_{M}\tilde{r}_{t,M} + \tilde{\varepsilon}_t$$

where $r_{t,\,airline}$ = the total return on the airline stock in dollars,

$r_{t,\,jet\,fuel}$ = the return on jet fuel in dollars,

$r_{t,\,\$-DEM}$ and $r_{t,\,\$-GBP}$ = the returns on the German Mark and British Pound denominated in dollars,

$r_{t,\,BOND}$ = the return on the local government bond index in local currency,

$r^{*}_{t,\,M}$ = the residual local market index return, and

ε_t = the disturbance term.

The factor model is estimated using weekly data from Bloomberg in the period January 1st, 1990 until January 1st, 1999. We chose to study Wednesday on Wednesday returns to avoid results being affected by the start- or end-of-the-week effects. Six major international airlines are studied: KLM Royal Dutch Airlines, British Airways, Lufthansa, American Airlines, United Airlines and Delta Airlines. The reason for this choice is twofold. On the one hand, these airline stocks are listed throughout the entire research period and, on the other hand, these stocks provide investors with a pure play on the airline business. Some airline stocks expose investors also to associated business, such as the catering or travel industry.

The following variables are taken from the Bloomberg system to find the desired returns. Airline stock returns are calculated from trading prices at local exchanges, dividend returns included. These returns are converted to dollar returns to facilitate comparability. Jet fuel return is derived from a Bloomberg index representing jet kerosene spot prices in dollars. Government bond returns are derived from the JP Morgan Government Bond index, which contains all traded government bonds. For each airline we selected the local index. One drawback of taking this portfolio is that the duration is likely to be different for different countries and is likely to change over time. It turns out that duration is close to 5 years for all bond portfolios and does not change significantly over time. Nonetheless, we adjust bond returns for duration differences by re-scaling them to a five-year duration return as follows:

$$(14)\quad r_{BOND,t}^{adjusted} = 5 \cdot \frac{r_{BOND,t}^{original}}{Duration_t}$$

As local market indices for the Netherlands, Germany, the UK and US we took the AEX, DAX, FTSE100 and the NYSE Composite, respectively.

In this paper we focus on KLM Royal Dutch Airlines to illustrate what can be learned from the Component VaR results. We regress stock returns on all underlying factors for the sub-periods 1990-1992, 1993-1995, 1996-1998 and the overall period. The results in Table 1 show that exposures for the underlying factors are not constant over time. The other airline stocks are analysed in the same way and this yields similar results. It confirms our intuition that exposures are not stationary. To keep track of changing exposures we use the weighted least squares as described in section *3 Component Value at Risk for Stocks*. In this approach observations are exponentially weighted with a decay factor λ. High values of λ imply that the regression is based on many observations, enhancing estimation efficiency. Low values of λ put more emphasis on recent observations, thus enhancing the accommodation to changing exposures. We believe λ = 0.99 ensures a good balance between these two effects. This value of λ can be said to focus on a 2-year history, since approximately 90% of total variance of all historical disturbance terms added up can be calculated to fall within the last two years.

Figure 1 presents estimation results for KLM. The exposures in the first year are not very informative, since the rolling regression has too few data to estimate coefficients. To illustrate what we can learn from these results, an elucidation is given below. Regression coefficients should be interpreted as elasticities, since a coefficient of 0.5 implies that a +10% factor return results, on average, in a +5% stock return.

(i) The elasticity of KLM stock for jet fuel is significant and is on average around –10%. In recent years the exposure has somewhat diminished. This is not surprising, since the company increased the fuel hedge in recent years to around 70% in order to gain from what it considered to be temporary low fuel prices.

(ii) As of January 1991, the elasticity of KLM stock for the dollar value of the German Mark has decreased significantly from 100% to 50%. Three observations can help to understand this result. First, KLM earnings were long in dollars at the start of the decade. Re-financing of aircraft helped to neutralise the dollar effect. Second, KLM stock is listed on both the Amsterdam and the New York Stock Exchange. The number of outstanding shares in New York, and concurrently the number of US shareholders, has increased significantly over the last decade. Today almost half of all common shares are listed as ADR in New York. Third, this decade saw the first global airline alliance when KLM and NorthWest Airlines joined forces. This could have contributed to the fact that KLM is considered a more international stock and hence less exposed to the DEM-USD exchange rate.

(iii) The results for KLM stock exposure to the dollar value of the British Pound are mixed. Until the EMS crash in 1992, this exposure was negative. However, since then the exposure has become slightly positive and again negative at the end of the research period. We consider this effect non-existent, since it clearly lacks significance.

(iv) The elasticity of KLM stock to the local market has decreased substantially over the decade. At the start of the decade it grew to almost 200%. Over the years it decreased to 100%. The decrease in this 'beta' is arguably due to structural changes in the industry during the decade. At the start the airline industry showed over-capacity and perfect competition. Over the years, however, it has become increasingly oligopolistic. The creation of worldwide alliances has contributed strongly to this development. In this case results might be less sensitive to economic cycles.

5 Out of Sample Test Component VaR

Before we elaborate on the airline marginal VaR and the decomposition of VaR, we will study the out of sample properties of this Component VaR. It should at least do as well as the RiskMetrics™ VaR estimate, since the latter is extensively tested and has through its wide use set a standard in the financial industry[5].

The performance of a VaR estimator is judged by out of sample unbiasedness. We can think of an indicator variable l(t), which equals one if the VaR is exceeded and zero otherwise. The estimator is unbiased if the sample mean of l(t) does not differ significantly from 1 minus the VaR confidence level. In terms of formulas:

(15) $$average(l(t)) = 1 - c$$

Unbiasedness is tested for four frequently used confidence levels: 0.90, 0.95, 0.975 and 0.99. Empirical research summarised in the RiskMetrics™ Technical Document has shown that for daily and monthly data the optimal decay factor is 0.94 and 0.97, respectively (JPMorgan Bank (1996)). We apply the 0.94 level to our weekly data. Table 2 presents results for this test on both the RiskMetrics™ VaR and Component VaR. One well-known drawback of the RiskMetrics™ VaR is that it underestimates risk for high confidence levels.

> *"It is our experience that while RiskMetrics VaR estimates provide reasonable results for the 90% confidence interval, the methodology does not do as well at the 95% and 98% confidence intervals", JPMorgan Bank (1996, p.235)*

Our results show that the same applies to our sample. For the 99% confidence level the RiskMetrics™ VaR significantly underestimates the VaR for three out of six airlines. The Component VaR, in contrast, does not lead to significant VaR underestimation. For one airline at a 90% confidence level it significantly overestimates VaR, which, in practice, is less hazardous than underestimation.

Less underestimation for Component VaR can be understood from the different approach it takes. Intuitively, keeping track of exposures and knowing that one of the external factors is getting increasingly volatile allows Component VaR to increase in an early stage.

Since both RiskMetrics™ and Component VaR are based on estimation of the first two moments of the return distribution, we decided to take a closer look at the distribution of standardised returns. The 'out of sample' stock return from t to (t+1) is standardised by subtracting the mean estimate and dividing this result by the standard deviation estimate. Since both mean and standard deviation estimates are based on all historical observations until time t, this standardised return should coincide with the normal distribution in the left tail. GARCH models in general, and RiskMetrics™ in particular, assume this conditional distribution to be standard normal. In figure 2 we illustrate the properties of this standardised return by showing the empirical cumulative distribution and the sample mean, standard deviation, skewness and kurtosis. We also show the results of a Jarque-Bera test for normality.

The solid lines in the graphs show the empirical cumulative distribution of the standardised return. The dashed line shows what it should be for observations taken from a standard normal distribution. If the solid line is above the dashed one, this means that at that point the VaR underestimates risk. The graphs show that underestimation is more severe in the case of the RiskMetrics™ VaR as compared to the Component VaR. The out of sample test results as shown in table 2 indicates whether the solid line -- i.e. the empirical distribution -- significantly differs from the dashed line -- i.e. the normal distribution. For example, we concluded that at a 99% confidence level RiskMetrics™ yielded significant underestimation for three out of six airlines, viz. KLM, Lufthansa and United. This observation is illustrated at the horizontal axis of the graphs at the value -2.65.

The sample mean of the standardised return does not differ more than 0.02% from zero. This is not significantly different from zero for the number of observations we have at a 90% significance level. Only the RiskMetrics™ approach for Delta Airlines finds a significant negative sample mean. For the sample variance we find that on average the sample variance exceeds one. For all six airlines we find that sample variance is larger for the RiskMetrics™ than for the Component VaR approach. The results of the Jarque-Bera test for both RiskMetrics™ and the Component VaR show that we have to reject normality for four out of six airlines at a 90% confidence level. Both positive skewness and fat tails, as evidenced by kurtosis being larger than 3, contribute to this rejection. The assumption of conditional normality for the *full* distribution is not tenable. However, this does not invalidate our results, since are only interested in the left tail ranging from 1% to 10% critical levels.

6 Component VaR Results and Interpretation

The out of sample test showed that the Component VaR framework performed at least as well as the RiskMetrics™ approach. The main advantage of the Component VaR as compared to RiskMetrics™ is that it allows for decomposition. We will present M-VaR and C-VaR results for KLM Royal Dutch Airlines to show how these should be interpreted. The case of KLM is very useful and interesting to study, because the airline has put much effort in recent years to develop a new risk management strategy and practice accordingly. In 1998, Ernst&Young rewarded KLM in this field along with Ford, McDonalds, Microsoft and Nokia.[6] A quote taken from the Ernst&Young report summarises the company's view on risk management:

> *"We would ultimately like to show operational risk to our shareholders and none of the financial risks.", De Die, SVP Finance KLM in Ernst&Young (1998)*

If markets were perfect shareholders would know this and, hence, the risk profile of the stock should have changed accordingly. In the remainder of this section we will apply the M- and C-VaR framework to test this assumption.

In section *4 Component VaR in the Airline Industry* we found the exposures of KLM stock for the underlying factors. To calculate VaR we need to multiply these with the covariance matrix estimates for the external factors. Figure 3 illustrates how volatility of the underlying factors developed throughout the decade. The figure shows that fuel is most volatile with weekly volatility peaking at 12% early 1991. This is the result of the Gulf War. It decreased to around 4% at the end of the period. The idiosyncratic risk is next in line with average volatility between 3 and 4%. Both the German Mark and British Pound exchange rate volatility and the residual market volatility are between 1% and 2%. The sharp increase in market volatility by the midst of 1997 is caused by unrest in international financial markets due to the Asian monetary crisis. The German Government Bond shows least volatility with levels slightly below 1%. This graph only tells part of the story, because it does not provide insight in the development of correlations, or covariances if you will, between external factors over time.

Figure 4 shows the results of the M-VaR analysis for KLM. VaR confidence level was set at 95%. We left out the M-VaR for the idiosyncratic factor, because the exposure to this factor is one by construction. M-VaR can be calculated, but does not have an interpretation in this case. The largest value for M-VaR occurs for jet fuel in March 1991. By that time the M-VaR for jet fuel equaled 8.2%. This means that being 0.1 more exposed to jet fuel results in almost 1% increase in the stock VaR. The M-VaR for fuel decreased over time to a value between 0 and 0.5%. The M-VaR for the residual market index is substantial throughout the sample. It is on average 1% with a sharp increase by the midst of 1998. It ended up above 2% in January 1999. Two developments explain this result. First, the volatility of the residual market index increased substantially by the midst of 1997. Second, initially the 'beta' of KLM stock dropped to compensate for this effect, but then, by the midst of 1998, this changed for an increase in 'beta'. The marginal VaR for both the German Mark and British Pound exchange rate is at most 1% by the start of 1993, but decreased since then to approximately 0.25% by the middle of 1998. The sharp increase for both exchange rates at the end of 1992 to 1% M-VaR is arguably caused by the European Monetary System (EMS) crisis in 1992. This fixed exchange rate system did not allow large movements of the German Mark to the British Pound. However, in September 1992 this 'fixed' rate restriction was lifted, because the Pound left the system. Since then the currencies can be regarded separate risk sources and this explains the jump to 1% M-VaR for both currencies. The M-VaR for the German government bond is the smallest of all factors: on average 0.2%. This can be understood from the low volatility in the German Government Bond.

Figures 5a and 5b illustrate the results of Component VaR calculations for all six carriers. VaR confidence level was set at 95%. Although we study M- and C-VaR for KLM, it is interesting to benchmark the stock profile development against similar airlines. First we evaluate the C-VaR results for KLM and, second, we study the major differences compared to other carriers.
The total weekly Value at Risk in KLM stock ranges from slightly above 2% to almost 12%. In other words, in bad times the share price lost more than 12% on KLM stock every 20 weeks. These turbulent times occurred at the start of the decade and total VaR decreased over time to about a 2% loss every 20 weeks at the start of 1998. The Value at Risk increased again to 5% in the final year. To understand why this happened we study the development of C-VaR for each factor separately. The largest contributor to total VaR is arguably idiosyncratic risk. In relative terms it appears to be quite stable by contributing half of total VaR. This should be interpreted as risk inherent to the company's business. The second largest contributor to total stock VaR is the residual market index. Its effect ranges from 1 to 3%. At the start of the decade it contributes a relatively small amount of total risk. Further throughout the decade its relative influence grew to almost 50% at the end of the decade. An increasingly volatile market index in the final year of the

sample appears to be the main reason for the VaR of KLM increasing from 2 to 5%. The German Mark exchange rate contributes 0.25 to 1% to total VaR. Its relative contribution throughout the decade is about 10%.[7] In 1998, its contribution to total VaR is truly marginal. Jet fuel contribution to total risk is 0.5% at the start due to high volatility caused by the Gulf War. In the rest of the decade its C-VaR is negligible. The Government Bond C-VaR is substantial at the start of the decade amounting to 2%, which is roughly a quarter of total VaR. Its relative contribution decreased to 10% in the rest of the sample period. In the final year of the sample its contribution is marginal. The British Pound does not appear to contribute to overall VaR. At the start of the decade its influence is substantial. However, this is largely due to it being related to the German Mark in the EMS.

If we benchmark KLM Component VaR results to those of the other two European carriers, we observe some remarkable differences. First, total VaR is largest for Lufthansa and smallest for British Airways. However, differences have become smaller over the decade. Second, apart from the first two years of the sample the Government Bond exposure is more substantial and more stable throughout the sample for British Airways and Lufthansa compared to KLM. Third, apart from the first two years the relative contribution of the residual market index to total risk is largest for KLM amounting to almost half of total risk. Although its influence on VaR is also quite substantial for Lufthansa, it is relatively small for British Airways amounting to just a quarter of total VaR. British Airways might be regarded a more international stock, since local market risk tends to be the smaller part of total risk. Generally, we find that throughout the decade commodity price, exchange rate and interest rate risk have become almost non-existent for KLM. This is true for British Airways and Lufthansa as well, albeit to a far lesser degree.

If we now benchmark the results for European carriers to their US rivals we find that over the decade VaR developed in favour of the Europeans. Starting off with a stock VaR that was almost double the VaR of their US rivals they ended up with equal or slightly lower VaR at the end of the sample. Furthermore, we find that the C-VaR of commodity price, exchange rate and interest rate risk is relatively larger for European airlines. However, differences have decreased in the course of the decade.

To complete the picture we study events of an airline exceeding its VaR more closely. We want to know to what extent these shocks occur simultaneously. And, does the event of one of the external factors exceeding its VaR coincide with a shock to the airline stock. To test for concurrence we count the events of two series exceeding VaR at the same time. The null hypothesis is event independence. The test statistic is defined as the number of actual simultaneous events minus the number expected given independence. The confidence level for the test is 97.5%. The results are presented in table 3.

Studying the results for airlines we find that a shock to the British Airways stock coincides with a shock to both the KLM and Lufthansa stock. The mere fact that a shock to KLM does not coincide significantly with a shock to Lufthansa suggests that British Airways is the leading airline stock. In the US, on the other hand, shocks to airline stock occur simultaneously.

Studying the factor shocks to airlines, we find mixed results. The residual market index exceeding its VaR shows the strongest influence. Four out of six airlines exceed their VaR simultaneously. Jet fuel and government bond index shocks coincide significantly with shocks to airline stock for only two out of six airlines. Finally, a shock to the British Pound exchange rate only concurs with a shock to British Airways stock.

7 Conclusion

In this paper we develop the Component Value at Risk framework. It is founded on insights from both the VaR and multifactor literature. This framework has two innovative features. Firstly, it defines and explores a company's VaR in which company value is proxied by share price. Secondly, it enables us to estimate the contribution of underlying risk factors to the overall VaR.

We apply the framework to analyse how shareholders perceive airline risks. We study exposures to exchange rates, jet fuel prices, interest rates and local stock market indices. Out of sample performance is compared to the standard RiskMetrics™ approach. One well-known drawback of the latter approach is the significant underestimation of risk for high VaR confidence levels. We here find similar evidence for airline stocks. The Component VaR estimates, in contrast, do not seem to suffer from this bias. Moreover, our framework provides insight in the sources of VaR differences across airlines and VaR changes over time. Finally, the decomposition does not rely on any distributional assumptions and is computationally simple and straightforward.

We focus on KLM Royal Dutch Airlines to show how Component VaR results should be interpreted. The objective of KLM's risk management strategy is to shield shareholders from financial risks and, hence, expose them solely to business risk. In recent years this strategy was implemented and we find that the stock's risk profile changed accordingly. Markets might be efficient after all…

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Appendix: General linear decomposition of overall VaR

In this Appendix, we derive a general decomposition of overall VaR into component-VaRs. Together with the relationship between marginal and component-VaR, this decomposition result is of a very general nature. Most important, it does not depend on any distributional assumptions made to estimate the overall VaR. The results derived below prevail as long as the security return can be expressed as a linear combination of the factor returns.

the linear factor model

Assume that the security return over period t follows a linear k-factor model:

(A-1) $$\tilde{r}_t = a + \sum_{i=1}^{k} b_i \tilde{f}_{i,t} + b_{k+1} \tilde{f}_{k+1,t}$$

where without loss of generality the idiosyncratic factor $\tilde{f}_{k+1,t}$ (the disturbance) is scaled to obtain $b_{k+1}=1$. When all expected returns are zero – this is justifiable given the short VaR horizon – we have $a=0$. In the following we'll surpress the time index t.

defining Marginal VaR and Component VaR

The marginal return-VaR of factor *i*, M-VaR$_i$, is defined as the change in the return-VaR r^* resulting from a marginal change in factor sensitivity b_i :

(A-2) $$M - VaR_i \equiv \frac{\partial r^*}{\partial b_i} \qquad i = 1,\ldots,k+1$$

In addition, we consider the *total* contribution of each separate factor to the total security's return-VaR. Denoting a factor's *i* component return-VaR by C-VaR$_i$, we require that:

(A-3) $$r^* \equiv \sum_{i \in k+1} C - VaR_i$$

relating Marginal VaRs and Component VaRs

The linear factor model eq.(A-1) implies that the security return $\tilde{r}$, and hence the return-VaR r^*, are linearly homogeneous functions of the factor sensitivities $\{b_i\}_{i \in k+1}$. According to Euler's theorem it then immediately follows that:

(A-4) $$r^* = \sum_{i \in k+1} \frac{\partial r^*}{\partial b_i} b_i = \sum_{i \in k+1} b_i \cdot M-VaR_i = \sum_{i \in k+1} C-VaR_i$$

So the relationship between marginal and component-VaR is of a very general nature. It does not depend on any distributional assumptions and it prevails as long as the underlying factor model is linear in the factor sensitivities.

deriving Marginal VaR and Component VaRs : step 1

Now assume that all relevant return distributions have finite first moments. From eq.(A-1) (with a=0), we have by the very definition of conditional expectations:

(A-5) $$\tilde{r} = E\{\tilde{r} \,|\, \tilde{r}\} = \sum_{i \in k+1} b_i E\{\tilde{f}_i \,|\, \tilde{r}\}$$

Note that $E\{\tilde{f}_i | \tilde{r}\}$ is to be interpreted as the expectation of $\tilde{f}_i$ conditional to the σ-field relative to which $\tilde{r}$ is defined. Hence, this conditional expectation is a random variable. By taking iterated expectations we get:

(A-6) $$r^* = -\sum_{i \in k+1} b_i E\{\tilde{f}_i \,|\, \tilde{r} = -r^*\}$$

Since the security return now takes the particular value $-r^*$, this conditional expectation is now deterministic. Combining eqs.(A-6) & (A-4) yields:

(A-7) $$M-VaR_i = -E\{\tilde{f}_i \,|\, -r^*\} \qquad i = 1, \ldots, k+1$$

and hence,

(A-8) $$C-VaR_i = -b_i \cdot E\{\tilde{f}_i \,|\, -r^*\} \qquad i = 1, \ldots, k+1$$

deriving Marginal VaR and Component VaRs : step 2

Next, we have to link $\tilde{f}_i$ to the security return $\tilde{r}$ in order to obtain $E\{\tilde{f}_i | \tilde{r}\}$, and hence $E\{\tilde{f}_i | \tilde{r} = -r^*\}$.

Suppose that we model the relationship between $\tilde{f}_i$ and $\tilde{r}$ by some function $\varphi_i(\cdot)$:

(A-9) $$\tilde{f}_i = \varphi_i(\tilde{r}) + \tilde{\xi}_i$$

where without loss of generality, we let the additive disturbance term satisfy $E\{\tilde{\xi}_i\} = 0$. Assuming that the relevant first and second moments exist, the choice $\varphi_i(\cdot) = E\{\tilde{f}_i | \tilde{r}\}$ minimizes the mean-squared error of the fit $E\{\tilde{\xi}_i^2\}$.[8] Hence, the least-squares representation of eq.(A-9) is:

(A-10) $$\tilde{f}_i = E\{\tilde{f}_i | \tilde{r}\} + \tilde{\xi}_i$$

which in turn implies the semi-independence of the disturbance term:

(A-11) $$E\{\tilde{\xi}_i | \tilde{r}\} = 0$$

In order to obtain a general insight in $E\{\tilde{f}_i | \tilde{r}\}$, we consider the orthogonal projection of $\tilde{f}_i$ into the subspace spanned by the security return $\tilde{r}$:

(A-12) $$\tilde{f}_i = \alpha_i + \beta_i \tilde{r} + \tilde{\varepsilon}_i \qquad i = 1,\ldots,k+1$$

This construction is always possible. In statistical terms, eq.(A-12) represents an ordinary linear least-squares approximation to the relationship between $\tilde{f}_i$ and $\tilde{r}$, satisfying $E\{\tilde{\varepsilon}_i\} = 0$ and the orthogonality condition $E\{\tilde{\varepsilon}_i \tilde{r}\} = 0$ of the disturbances. The slope coefficient is defined as :

(A-13) $$\beta_i \equiv \frac{\operatorname{cov}(\tilde{f}_i, \tilde{r})}{\operatorname{var}(\tilde{r})}$$

The assumption of zero expected returns again implies a zero intercept.

From eq.(A-12) we thus have:

(A-14) $$E\{\tilde{f}_i | \tilde{r}\} = \beta_i \tilde{r} + E\{\tilde{\varepsilon}_i | \tilde{r}\}$$

When the actual relationship between $\tilde{f}_i$ and $\tilde{r}$ is linear, the conditional expectation eq.(A-14) is linear in $\tilde{r}$. This in turn implies the semi-independence $E\{\tilde{\varepsilon}_i | \tilde{r}\} = 0$. Together with the restriction that $\tilde{r} = -r^*$, eq.(A-14) then transforms into the deterministic expression:

(A-15) $$E\{\tilde{f}_i | \tilde{r} = -r^*\} = -\beta_i r^*$$

Hence, from eqs.(A-7) & (A-8) we obtain:

(A-16) $$M - VaR_i = \beta_i r^*$$

and

(A-17) $$C - VaR_i = b_i \beta_i r^*$$

univariate case

For a single-factor model, we have *k=1* in eq.(A-1). Note that $b\beta = R^2$, where R^2 is the determination coefficient of the OLS regressions (A-1) and (A-12). Hence the systematic factor component-VaR is $R^2 r^*$, whereas the idiosyncratic factor component-VaR is given by $(1 - R^2) r^*$.

multivariate case

Trivially, the same results apply to the case of a multi-factor model where one considers the *total* contribution of the systematic factors to the VaR. When R^2 is now the (unadjusted) determination coefficient of the multivariate regression (A-1), then $R^2 r^*$ is the *aggregated* component-VaR of all k systematic factors together, whereas $(1 - R^2) r^*$ is the idiosyncratic factor component-VaR. For decomposing the aggregated systematic factor component-VaR, note that the (unadjusted) R^2 of regression eq.(A-1) is:

(A-18) $$R^2 = \frac{\sum_i^k \sum_j^k b_i b_j \operatorname{cov}(\tilde{f}_i, \tilde{f}_j)}{\operatorname{var}(\tilde{r})} = \sum_i b_i \left[\sum_j b_j \frac{\operatorname{cov}(\tilde{f}_i, \tilde{f}_j)}{\operatorname{var}(\tilde{r})} \right]$$

Combining eqs.(A-4), (A-16) & (A-17) shows that the term between the square brackets in eq.(A-18) equals the simple regression coefficient β_i. Given the regression coefficients b_i and the covariance matrix of the factors $\tilde{f}_i$ in eq.(A-1), the marginal and component factor-VaRs can now easily be estimated.

validity of the results

The conventional formulas for estimating marginal-VaR and component-VaR rest on the multivariate normality assumption. We have derived general expressions for these risk metrics, assuming only linearity of the underlying return generating process.

Endnotes

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[1] Fong and Vasicek (1997) suggest an approach to decompose overall VaR into components. However, their decomposition does not satisfy equation (6).

[2] Since the mean is of a lower order than the standard deviation, the latter fully dominates the influence of the former. From the results of Jorion (1995), for example, we know that the standard deviation is more than 25 times larger than the mean for a daily series.

[3] We know $\sigma^2 = \underline{b}'\Sigma\underline{b}$ where $\underline{b}$ is a vector that contains the factor exposures and Σ is the covariance matrix of the risk factors. Hence, $\frac{\delta}{\delta\underline{b}}\sigma^2 = 2\Sigma\underline{b}$, and, $\frac{\delta}{\delta\underline{b}}\sigma^2 = 2\sigma \frac{\delta}{\delta\underline{b}}\sigma$. Combining these two expressions gives $2\sigma\frac{\delta}{\delta\underline{b}}\sigma = 2\Sigma\underline{b}$. Taking the i'th element of this vector gives $\frac{\delta}{\delta b_i}\sigma = \frac{\sum_j \sigma_{ij} b_j}{\sigma} = \frac{\text{cov}(\tilde{f}_i, \sum_j b_j \tilde{f}_j)}{\sigma} = \frac{\text{cov}(\tilde{f}_i, r)}{\sigma}$, see also Garman(1996) and Jorion(1997, p.154).

[4] This two-step procedure where residuals generated from an auxiliary regression are used as regressors in a main regression raises some econometric issues. However, Pagan (1984) shows that the OLS estimators for the auxiliary generated residuals in the main regression are both consistent and efficient.

[5] Although actual RiskMetrics™ use will be difficult to estimate and as far as it is known with JPMorgan will be kept confidential, the mere fact that most financial systems e.g. Bloomberg and Reuters, provide RiskMetrics™ or closely related functionality proves that it has gained significant interest.

[6] In 1998 KLM received the Ernst&Young Global Risk Manager of the Year Award.

[7] Before September 1992 the contribution of the German Mark and the British Pound should be added, since both currencies being part of EMS basically means they can be regarded one source of risk.

[8] This follows from applying iterated expectations: $E\left\{\left[\tilde{f}_i - \varphi_i(\cdot)\right]^2\right\} = E\left\{E\left\{\left[\tilde{f}_i - \varphi_i(\cdot)\right]^2 \middle| \tilde{r}\right\}\right\}$.

Table 1: Determinants of KLM Share Price

t-values in brackets

	1990 - 1992	1993 - 1995	1996 - 1998	FY all
Constant	-0.67**	0.36	0.07	-0.08
	(-2.14)	(1.26)	(0.19)	(-0.44)
Jet Fuel	-0.11**	-0.11	-0.06	-0.11**
	(-2.75)	(-1.13)	(-0.75)	(-3.23)
DEM in $	0.62*	0.64**	0.00	0.48**
	(1.88)	(2.38)	(0.00)	(2.73)
GBP in $	-0.09	0.27	-0.23	0.01
	(-0.27)	(0.85)	(-0.57)	(0.06)
German Government Bond	2.49**	1.60**	-0.07	1.47**
	(4.11)	(3.30)	(-0.09)	(4.17)
Residual AEX Index	1.60**	1.44**	0.94**	1.17**
	(9.00)	(7.70)	(7.22)	(13.63)
σ (weekly KLM return, $)	7.92%	2.78%	4.30%	5.40%
Number of Observations	155	156	157	468
R^2	0.45	0.36	0.26	0.33

*: Significant at the 10% level
**: Significant at the 5% level

This table shows the results of a regression with the weekly KLM total share return in dollar as the dependent variable. Explanatory factors are: jet fuel return, the exchange rate of the dollar to the Dutch Guilder, the exchange rate of the dollar to the British Pound, the return on the German government bond index and the residual local market index.

Table 2: Out of Sample test VaR

λ(mean) = 0.94, λ(variance) = 0.94, λ(regression) = 0.99

		RiskMetrics		Component VaR	
		Number of times VaR is exceeded	t-value	Number of times VaR is exceeded	t-value
P=0.90	KLM	0.1106	0.77	0.0830	-1.23
	British Airways	0.1000	0.00	0.0894	-0.77
	Lufthansa	0.1085	0.62	0.0957	-0.31
	American Airlines	0.1213	1.54	0.1085	0.62
	United Airways	0.0872	-0.92	0.0723	-2.00 +
	Delta	0.1170	1.23	0.1128	0.92
	Average	0.1074		0.0936	
P=0.95	KLM	0.0553	0.53	0.0532	0.32
	British Airways	0.0574	0.74	0.0404	-0.95
	Lufthansa	0.0532	0.32	0.0340	-1.59
	American Airlines	0.0617	1.16	0.0404	-0.95
	United Airways	0.0447	-0.53	0.0340	-1.59
	Delta	0.0574	0.74	0.0489	-0.11
	Average	0.0550		0.0418	
P=0.975	KLM	0.0340	1.26	0.0340	1.26
	British Airways	0.0191	-0.81	0.0277	0.37
	Lufthansa	0.0277	0.37	0.0170	-1.11
	American Airlines	0.0255	0.07	0.0213	-0.52
	United Airways	0.0277	0.37	0.0149	-1.40
	Delta	0.0234	-0.22	0.0319	0.96
	Average	0.0262		0.0245	
P=0.99	KLM	0.0234	2.92 -	0.0128	0.60
	British Airways	0.0149	1.07	0.0149	1.07
	Lufthansa	0.0191	1.99 -	0.0064	-0.79
	American Airlines	0.0085	-0.32	0.0128	0.60
	United Airways	0.0234	2.92 -	0.0085	-0.32
	Delta	0.0170	1.53	0.0128	0.60
	Average	0.0177		0.0113	

\+ : Significant overestimation of risk at 90% confidence level
\- : Significant underestimation of risk at 90% confidence level

This table shows the results for an out of sample test on RiskMetrics and the Component VaR. The test statistic is the number of times VaR is exceeded divided by the total number of observations. Exceeding VaR is defined as the return in the interval (t, t+1) being smaller than μ_t - Z(0.05)*σ_t, whereby μ_t equals the conditional mean at time t calculated as the exponentially weighted moving average mean (λ = 0.94). σ_t is the conditional standard deviation at time t calculated as the square root of the exponentially weighted average variance (λ = 0.94) as in RiskMetrics.The null hypothesis is that the test statistic is equal to one minus the confidence level of the VaR measure.

Table 3: Exceeding VaR: Concurrence of Events

VaR confidence level 95%, λ(mean) = 0.94, λ(variance) = 0.94
t-values in brackets

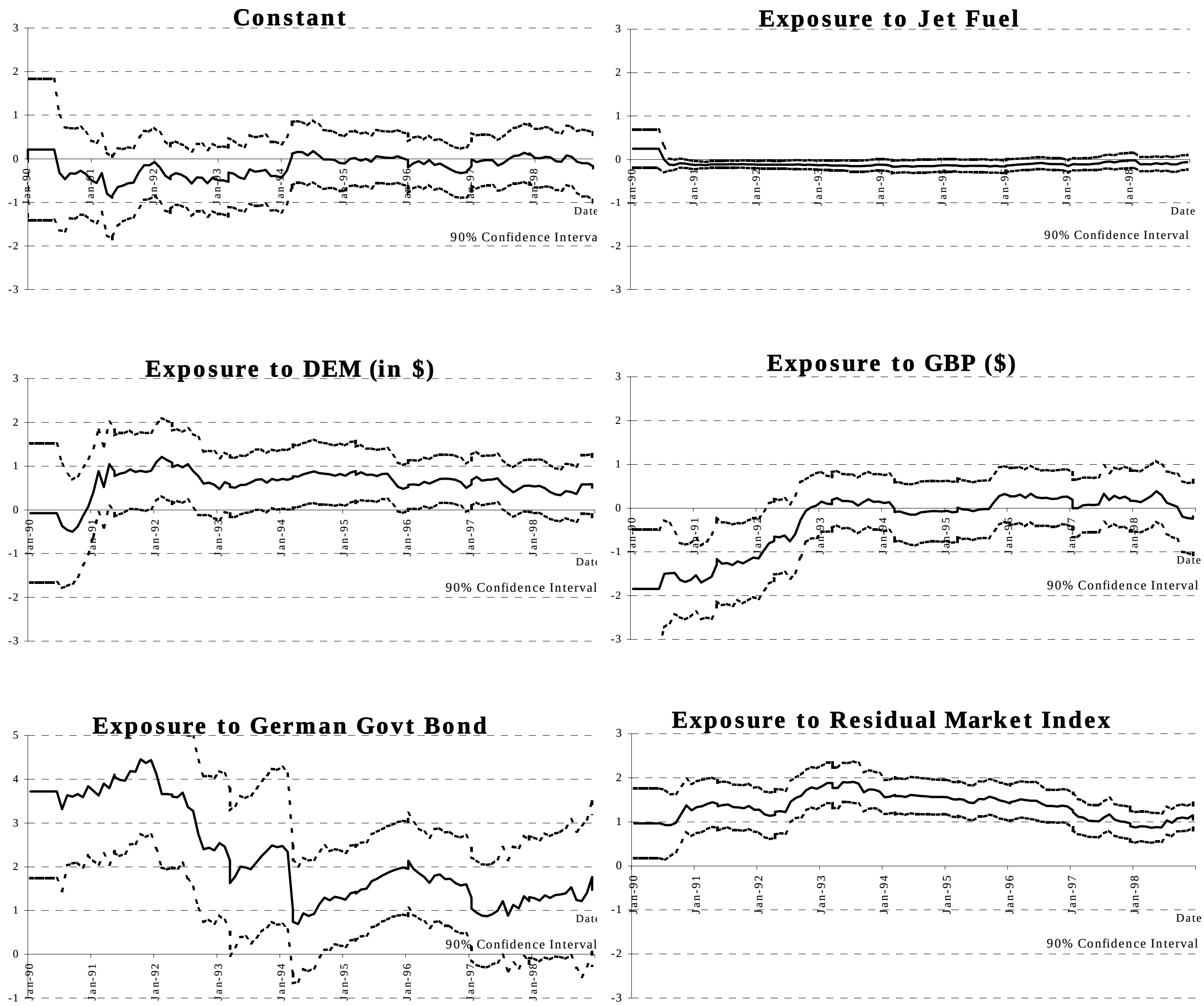
	KLM	British Airways	Lufthansa	American Airlines	United Airlines	Delta Airlines	Jet Fuel	Deutsche Mark ($)	British Pound ($)	Government Bond	Res. Market Index
KLM		3.50** (2.87)	0.62 (0.53)	1.40 (1.10)	1.84 (1.71)	3.51** (2.87)	2.45* (1.97)	0.67 (0.58)	0.62 (0.53)	1.62 (1.38)	10.95** (7.67)
British Airways			5.56** (4.65)	2.33 (1.81)	4.79** (4.37)	4.45** (3.58)	2.39 (1.89)	0.62 (0.53)	2.56** (2.14)	2.45* (1.97)	4.51** (3.69)
Lufthansa				2.46** (1.98)	1.88 (1.78)	-0.44 -(0.36)	1.51 (1.24)	-1.28 (-1.13)	0.67 (0.58)	2.56* (2.14)	1.40 (1.11)
American Airlines					2.70** (2.38)	6.33** (4.92)	3.27* (2.49)	-1.48 (-1.22)	0.46 (0.37)	2.33 (1.81)	7.96** (5.59)
United Airlines						4.79** (4.37)	0.75 (0.67)	-1.07 (-1.04)	-1.12 (-1.06)	1.79 (1.64)	2.53* (2.08)
Delta Airlines							0.39 (0.31)	-1.38 (-1.18)	-1.44 (-1.20)	1.45 (1.17)	0.39 (0.31)
Jet Fuel								1.57 (1.32)	0.51 (0.42)	-0.49 (-0.40)	-0.20 (-0.14)
Deutsche Mark ($)									10.72* (9.50)	-1.28 (-1.13)	-0.89 (-0.65)
British Pound ($)										-0.33 (-0.29)	-1.97 (-1.41)
Government Bond											0.03 (0.02)
Res. Market Index											

* Significant at 97.5% level
** Significant at 99% level

This table shows to what extent VaR levels are exceeded at the same time for the weekly returns of the series studied in the paper. Exceeding VaR is defined as the return in the interval (t, t+1) being smaller than μ_t - Z(0.05)*σ_t, whereby μ_t equals the conditional mean at time t calculated as the exponentially weighted moving average mean (λ = 0.94). σ_t is the conditional standard deviation at time t calculated as the square root of the exponentially weighted average variance (λ = 0.94) as in RiskMetrics. The test statistic is defined as the number of actual concurrent events minus the number expected given event independence.

Figure 1: Exposures KLM share

λ(regression) = 0.99



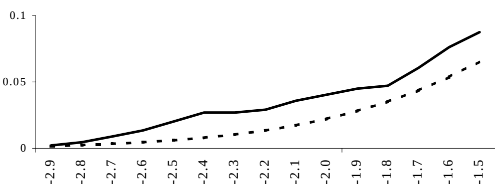
This figures shows the exposure of KLM stock to external factors. Exposures are estimated in the period January 1, 1990 until January 1, 1999. A rolling weighted least squares method is used, whereby recent observations are considered more valuable than remote observations. An exponential scale is applied with λ equal to 0.99.

Figure 2: Out of Sample Test VaR

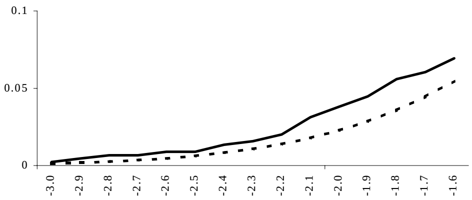
λ(mean) = 0.94, λ(variance) = 0.94, λ(regression) = 0.99

Empirical Cumulative Distribution Standarized Weekly Dollar Returns **JP Morgan Riskmetrics**	Empirical Cumulative Distribution Standarized Weekly Dollar Returns **Component VaR**

KLM Royal Dutch Airlines

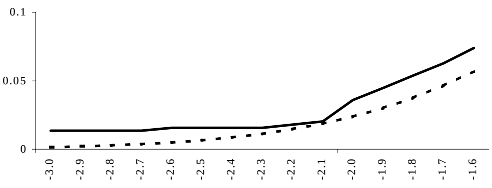


Mean	0.00
St. Dev.	1.06
Skewness	0.03
Kurtosis	3.17
Jarque-Bera	0.60
p-value J-B	0.74

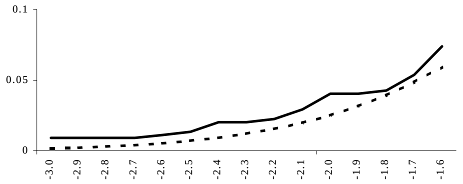


Mean	0.00
St. Dev.	1.01
Skewness	-0.01
Kurtosis	3.46
Jarque-Bera	3.91
p-value	0.14

British Airways

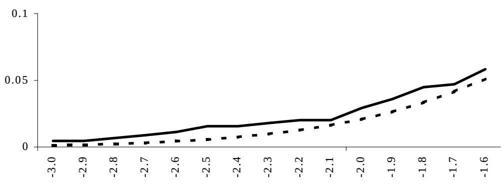


Mean	-0.01
St. Dev.	1.07
Skewness	0.08
Kurtosis	3.80
Jarque-Bera	12.33
p-value	0.00

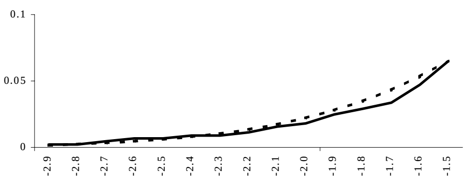


Mean	-0.02
St. Dev.	1.02
Skewness	0.05
Kurtosis	4.23
Jarque-Bera	28.32
p-value	0.00

Lufthansa

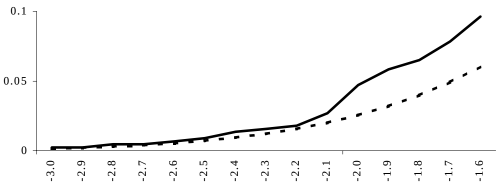


Mean	0.01
St. Dev.	1.06
Skewness	0.22
Kurtosis	3.76
Jarque-Bera	>1000
p-value	0.00

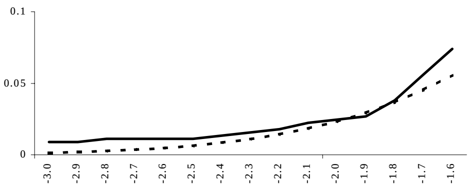


Mean	0.02
St. Dev.	0.99
Skewness	0.37
Kurtosis	3.97
Jarque-Bera	27.64
p-value	0.00

American Airlines

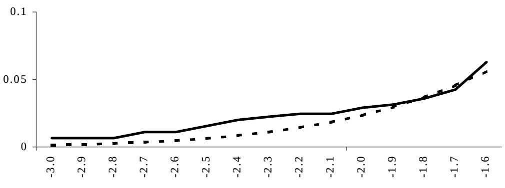


Mean	-0.01
St. Dev.	1.09
Skewness	0.22
Kurtosis	3.77
Jarque-Bera	>1000
p-value	0.00

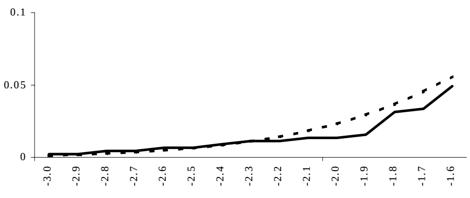


Mean	0.01
St. Dev.	1.07
Skewness	0.19
Kurtosis	4.45
Jarque-Bera	41.87
p-value	0.00

United Airlines

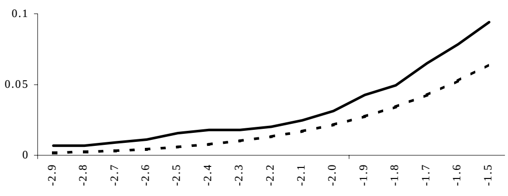


Mean	0.00
St. Dev.	1.06
Skewness	0.31
Kurtosis	3.76
Jarque-Bera	17.73
p-value	0.00

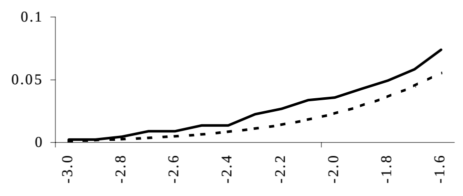


Mean	0.00
St. Dev.	0.96
Skewness	0.31
Kurtosis	3.71
Jarque-Bera	16.25
p-value	0.00

Delta Airlines



Mean	-2.51
St. Dev.	1.09
Skewness	0.17
Kurtosis	3.21
Jarque-Bera	2.83
p-value	0.24



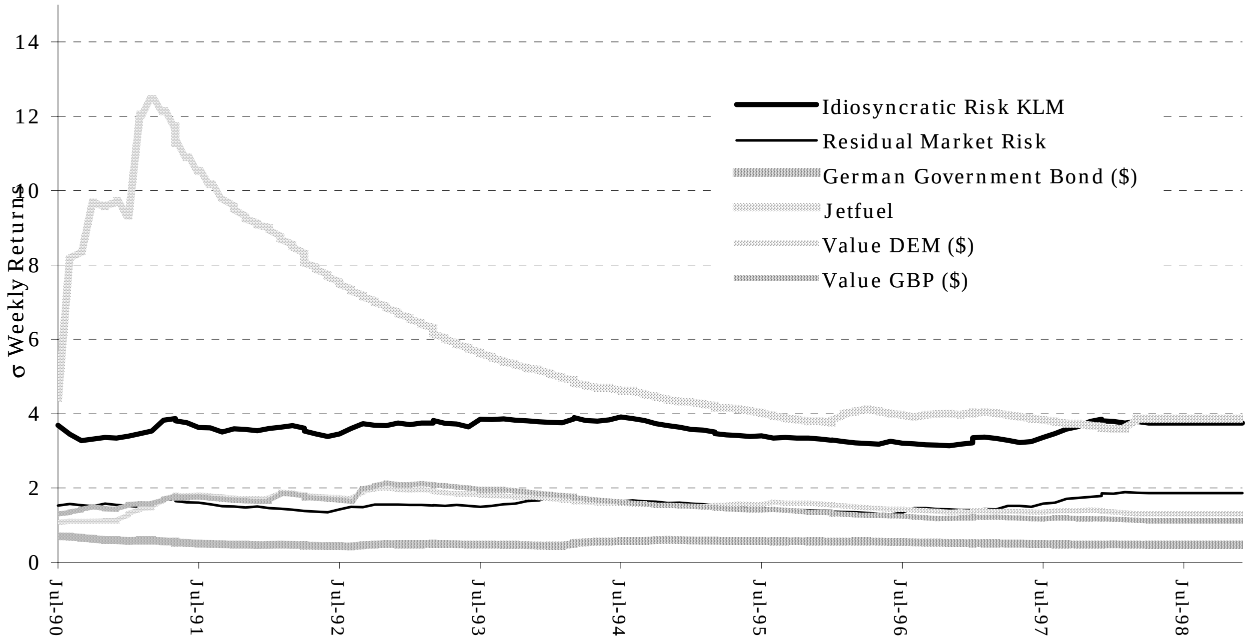
Mean	0.01
St. Dev.	1.08
Skewness	0.14
Kurtosis	3.11
Jarque-Bera	1.74
p-value	0.42

This figure illustrates the out of sample distribution of the airline shares. Estimates for mean and volatility are based on the observations until and including time t. The airline stock total return from t to t+1 is standardised according to these estimates. The empirical distribution of this out-of-sample standardised return is shown in the graphs. The distribution's mean, standard error, skewness and kurtosis can be found besides the graph.

The left-hand side shows returns standardised according to an exponentially weighted average mean and a RiskMetrics volatility estimate (λ=0.94).The right-hand side shows returns standardized according to a conditional mean and volatility based on the factor model.

Figure 3: Volatility Underlying Factors

λ(variance) = 0.94

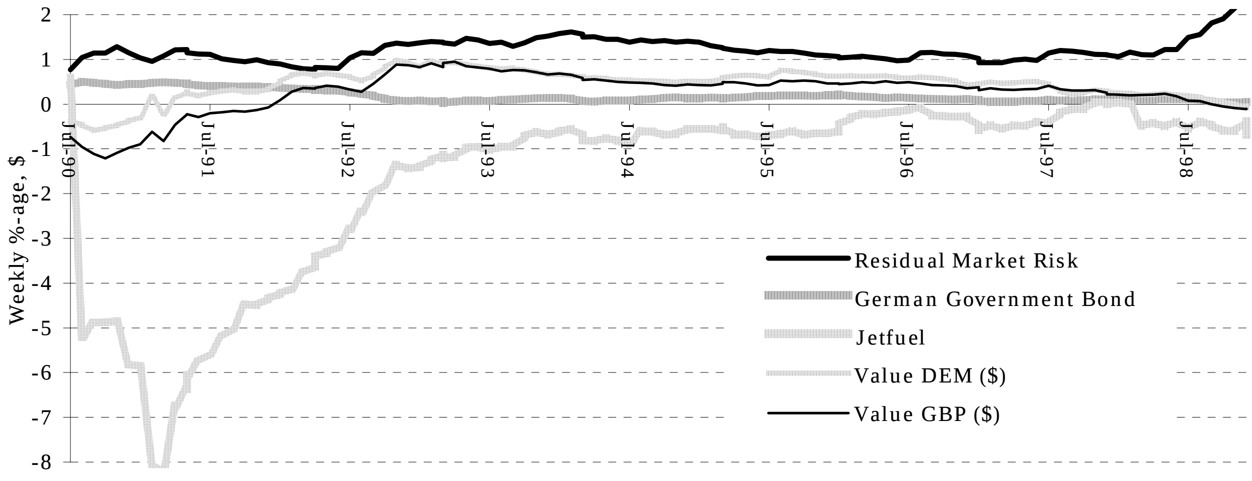


This figure shows return volatilities for the underlying factors. The covariance matrix is calculated using historical returns and applying exponential weights. The λ is equal to 0.94.

Figure 4: Marginal Value at Risk KLM Royal Dutch Airlines

λ(regression) = 0.99, λ(variance) = 0.94

VaR Confidence Level = 95%

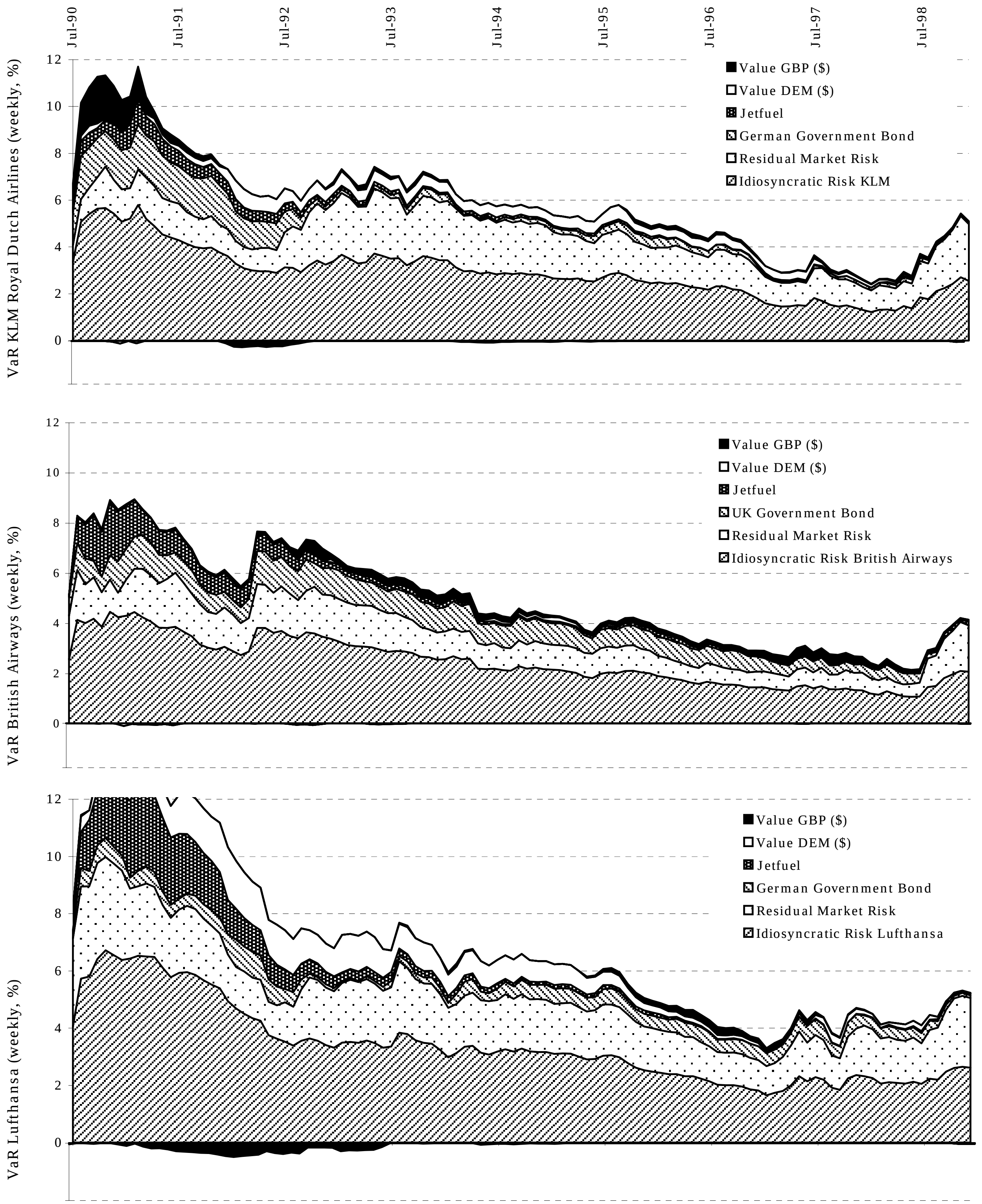


This figure shows the marginal Value at Risk for the KLM share in the period January 1, 1990 until January 1, 1999. The marginal VaR is calculated in a two step approach. First, the sensitivities of the KLM share for the explanatory factors are estimated. A rolling weighted least squares method is used, whereby recent observations are considered more valuable. An exponential scale is applied with λ equal to 0.99. Second, the marginal VaR technique is applied to find the marginal contribution of each factor to overall VaR. The VaR confidence level is set at 95%.

Figure 5a: Component Value at Risk European Airlines

λ(variance) = 0.94, λ(regression) = 0.99

VaR Confidence Level = 95%

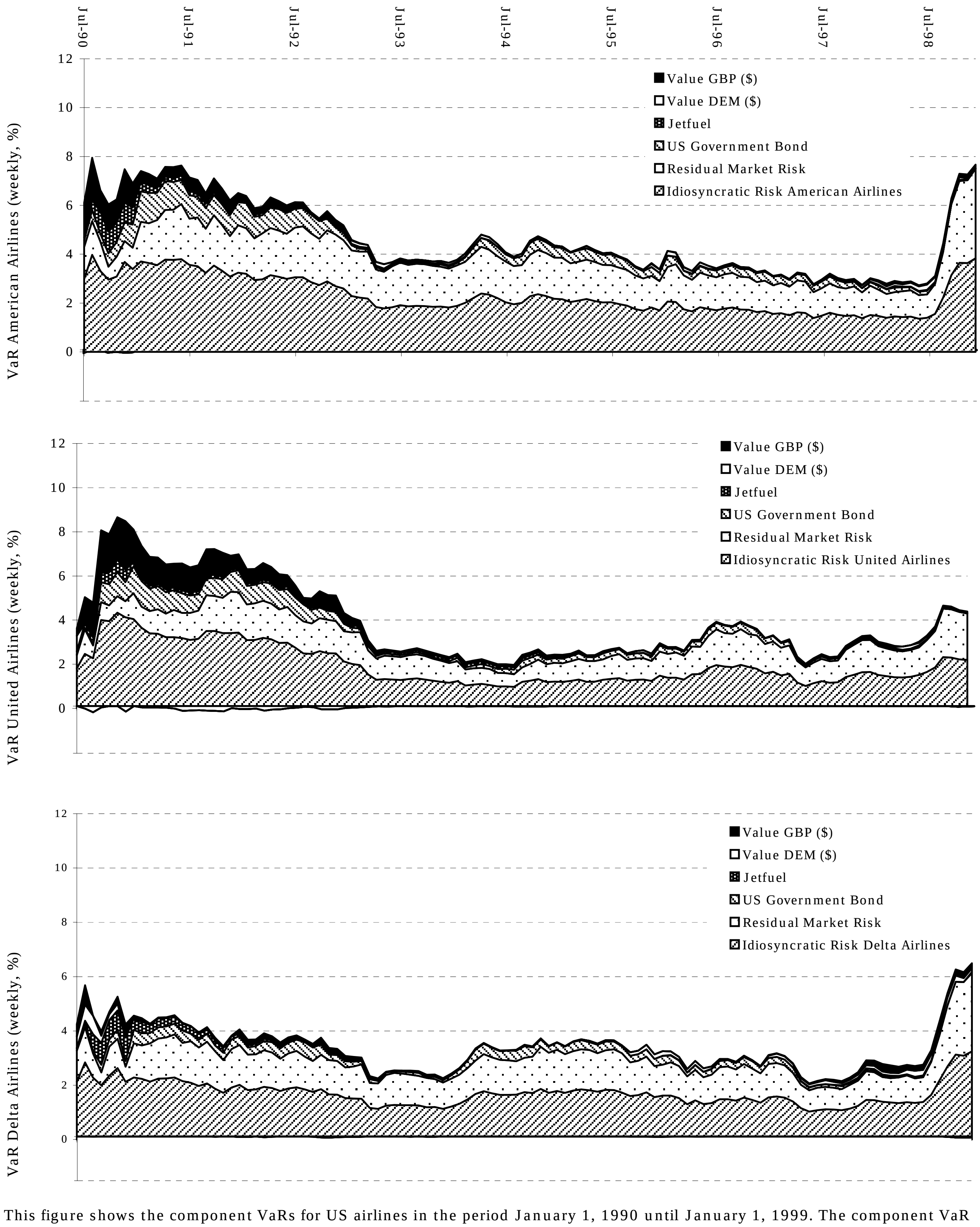


This figure shows the component VaRs for European airlines in the period January 1, 1990 until January 1, 1999. The component VaR is calculated in a two step approach. First, the sensitivities of the stock for the explanatory factors are estimated. A rolling weighted least squares method is used, whereby recent observations are considered more valuable. An exponential scale is applied with λ equal to 0.99. Second, the component VaR technique is applied to find the individual contribution of each factor to overall VaR. The VaR confidence level is set at 95%.

Figure 5b: Component Value at Risk US Airlines

λ(variance) = 0.94, λ(regression) = 0.99

VaR Confidence Level = 95%



This figure shows the component VaRs for US airlines in the period January 1, 1990 until January 1, 1999. The component VaR is calculated in a two step approach. First, the sensitivities of the stock for the explanatory factors are estimated. A rolling weighted least squares method is used, whereby recent observations are considered more valuable. An exponential scale is applied with λ equal to 0.99. Second, the component VaR technique is applied to find the individual contribution of each factor to overall VaR. The VaR confidence level is set at 95%.