

# Using SWIM for sensitivity analysis: a brief illustration

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This document is meant as a follow-up to the presentation to CALM on 25 November 2019, by Andreas Tsanakas. Here we aim to illustrate some basic functionalities of the SWIM R package, on an simplified example of an insurance portfolio. The code is written to be easily applicable to a user's own simulated scenarios and is also provided separately. For more on SWIM, see <https://cran.r-project.org/web/packages/SWIM/index.html>. A longer user guide for the package, illustrating a wider range of functionalities is in preparation.

First make sure to install and load the SWIM package. To produce matrices of plots, the gridExtra package is also useful.

```
### install and load package
# install.packages("SWIM")
library(SWIM)
### load table of simulations, that was saved as a csv file
dat <- read.csv("example_data.csv",header=T)
### let's have a look a the first few rows
head(dat)

##           Y           X1           X2           X3           X4
## 1 326.9935 147.9126 159.7889 1.062697 0.0021683060
## 2 408.7388 212.8642 223.0332 1.004764 0.0254834838
```

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```
## 3 345.1352 139.9741 189.5972 1.047225 0.0007566604
## 4 356.2930 139.7702 196.8030 1.058590 0.0003710395
## 5 418.3190 210.5270 209.4139 1.035085 0.4548199785
## 6 372.1750 142.0501 225.5039 1.012572 0.0148598422
```

In the example we are considering, we have loaded a table of 1 million, simulations of 5 variables. The first column (variable  $Y$ ) corresponds to total portfolio loss, while columns 2-5 (variables  $X_1$  to  $X_4$ ) are risk factors. In particular,  $X_1$  and  $X_2$  are gross claims from two lines of business,  $X_3$  is a common risk driver, and  $X_4$  is the percentage of reinsurance recovery lost because of RI credit risk.

We start by performing a reverse stress test. We produce a stressed model, such that the 90% VaR of the portfolio loss is increased by 10% while the 90% TVaR (or “Expected Shortfall”) is increased by 13%. Then we show statistics for all variables under the baseline and stressed models.

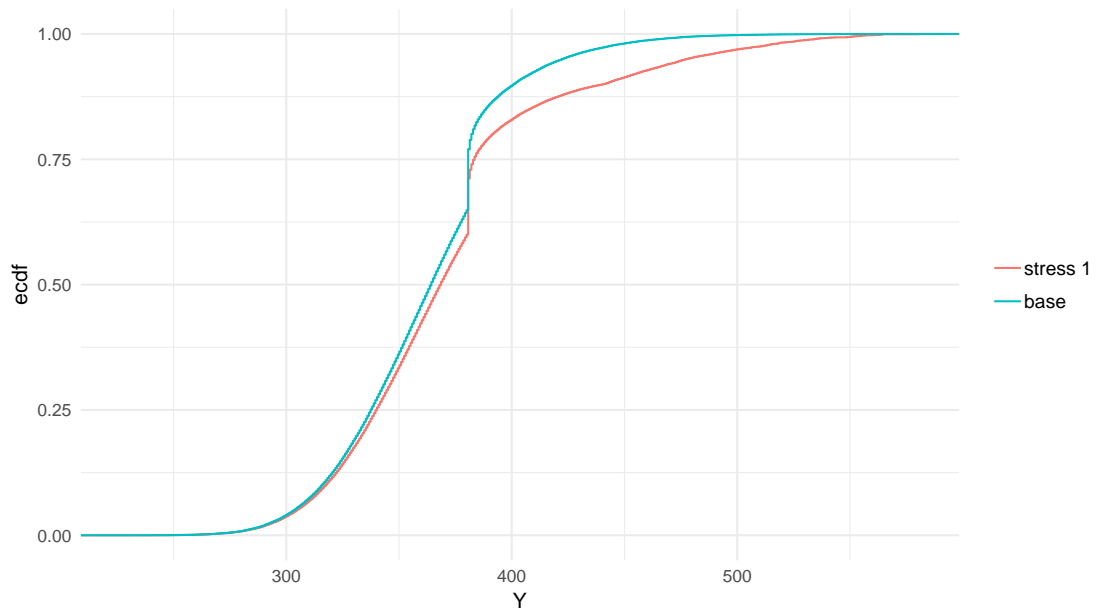
```
### perform stress using the stress_VaR_ES function
### the outcome of this stress is stored in the object str1
str1 <- stress_VaR_ES(x = dat, alpha = 0.9, q_ratio = 1.1, s_ratio = 1.13, k = 1)
### the summary of the object str1 gives statistics for all variables
summary(str1, base = TRUE)
```

## \$base	Y	X1	X2	X3	X4
## mean	361.493311	149.6701119	199.92240611	1.04992000	9.927799e-02
## sd	36.094535	34.5272146	20.05549626	0.01988193	1.988826e-01
## skewness	0.365937	0.6297829	0.20496335	0.02624693	2.472193e+00
## ex kurtosis	1.264028	0.4866342	0.08842275	-0.05804328	5.598707e+00
## 1st Qu.	337.274275	124.9760376	185.94730276	1.03646282	1.211057e-05
## Median	363.825856	145.8406103	199.29600013	1.04977616	3.278576e-03
## 3rd Qu.	380.284354	170.3898348	212.98973575	1.06325987	8.423168e-02
##					
## \$`stress 1`	Y	X1	X2	X3	X4
## mean	371.34463	157.2183398	201.78170715	1.05053140	1.430086e-01
## sd	49.77232	43.1406744	21.10639323	0.01998464	2.571302e-01
## skewness	1.16707	0.9284355	0.26179025	0.02953619	1.943946e+00
## ex kurtosis	2.05468	0.6848267	0.08091403	-0.06806144	2.616560e+00

```
## 1st Qu.      339.63483 126.7429017 187.06325967  1.03702518 2.254619e-05
## Median       368.02305 149.2328843 200.82062226  1.05036968 6.093783e-03
## 3rd Qu.      382.92536 178.5004508 215.30738600  1.06391778 1.478615e-01
```

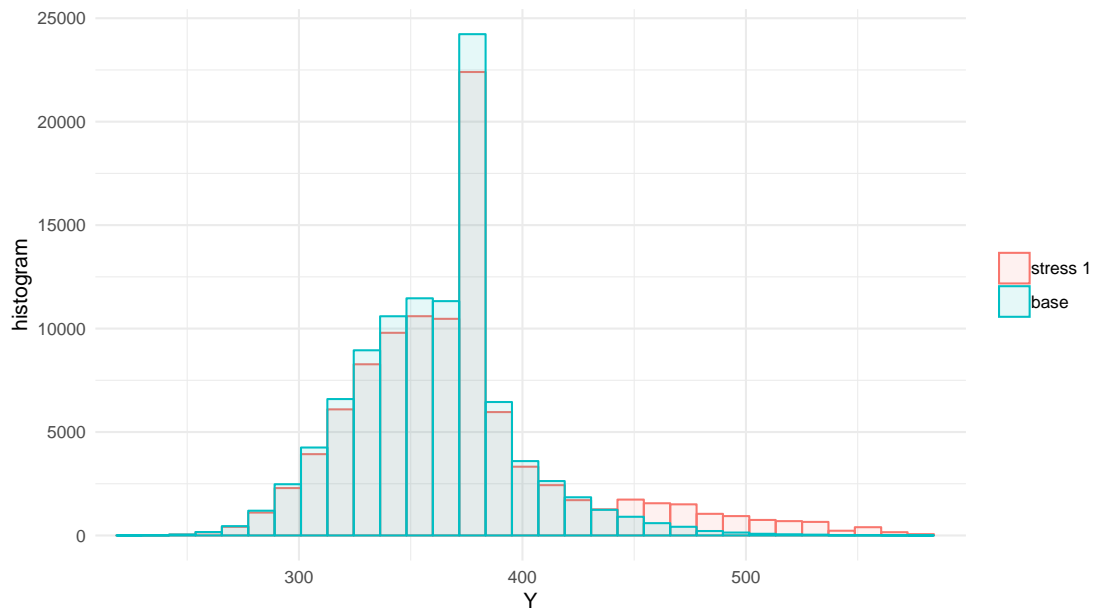
Furthermore, the distribution of the portfolio loss  $Y$  under the baseline and stressed models can be easily plotted.

```
### plot distributions under the baseline and stressed models
plot_cdf(str1, xCol = 1, base = TRUE)
```



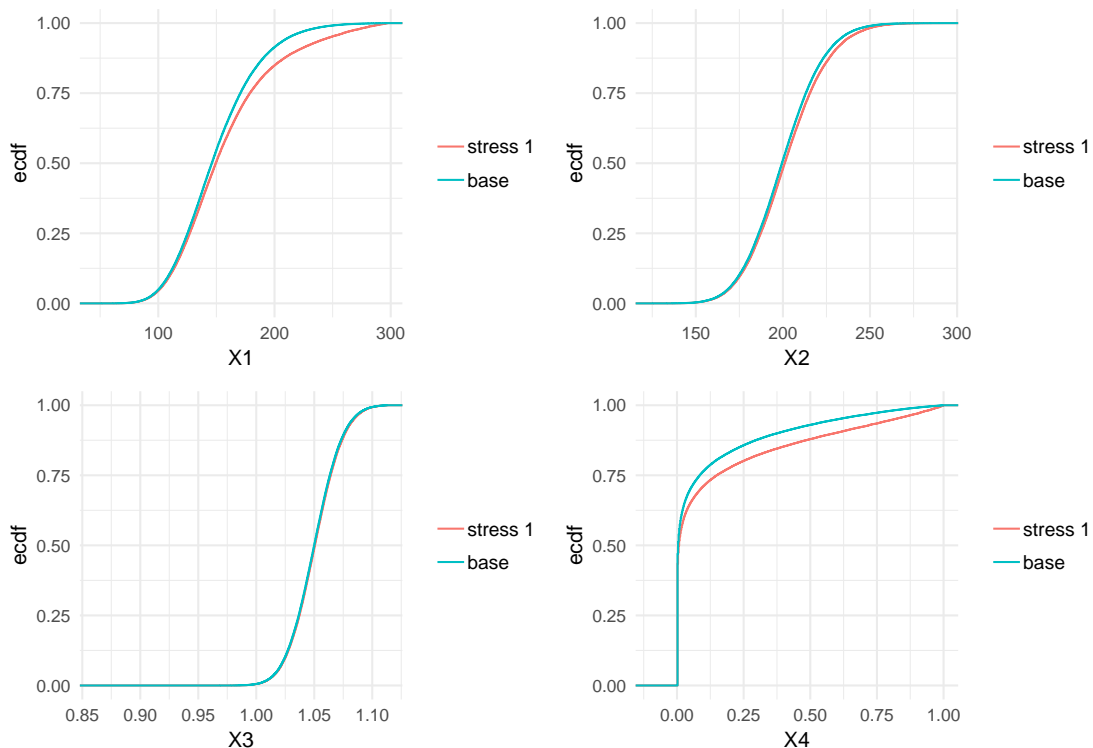
The cdf under the stressed model is lower, which indicates an increase in risk, particularly in the tail. The respective histograms give a consistent picture:

```
plot_hist(str1, xCol = 1, base = TRUE)
```



As part of reverse stress testing, one can monitor how the distributions of different risk factors change, when the portfolio loss is stressed. For this we plot the cumulative distribution functions of all four risk factors.

```
# install.packages("gridExtra")
library(gridExtra)
### to arrange plots nicely, first store them as objects...
pX1 <- plot_cdf(str1, xCol = 2, base = TRUE)
pX2 <- plot_cdf(str1, xCol = 3, base = TRUE)
pX3 <- plot_cdf(str1, xCol = 4, base = TRUE)
pX4 <- plot_cdf(str1, xCol = 5, base = TRUE)
### ...and then use grid.arrange to display them
grid.arrange(pX1,pX2,pX3,pX4,ncol=2,nrow=2)
```



We see that the distributions of claims from the 1st LoB ( $X_1$ ) and of reinsurance credit risk ( $X_4$ ) are the most heavily impacted. This indicates that, under the reverse stress test conducted, these are the most influential variables.

It is notable that the common risk driver  $X_3$  does not appear very impactful. This is explained by its very low volatility. But the risk driver could still have a substantial impact, e.g. if assumptions around its mean are revised. To see such an impact, we carry out a different stress to the model, now increasing the mean of  $X_3$  by 5%.

```
### first work out the mean under the baseline model...
meanX3.base <- mean(dat$X3)
### ... and its stressed value
meanX3.new <- 1.05 * meanX3.base
### Use the stress_mean function to change the mean of X3
### Note that k=4 means that we are selecting the 4th column in our data for stressing
str2 <- stress_mean(x = dat, k = 4, new_means = meanX3.new)
```

We can now consider the impact of the shift in the risk driver on the portfolio. For this we will compare VaR values for the portfolio loss before and after the stress.

```

### baseline VaRs at 95%, 99%, 99.5% levels, using standard R
quantile(x = dat$Y, probs = c(0.95, 0.99, 0.995))

##      95%      99%      99.5%
## 422.1639 465.6980 480.5237

### stressed VaRs using SWIM
quantile_stressed(str2, xCol=1, probs = c(0.95, 0.99, 0.995))

##           Y
## 95%    442.3064
## 99%    491.4105
## 99.5% 503.1711

```

Hence, we see that a change in the mean of the risk driver can have a very substantial effect on the tail of the portfolio loss.