Food inflation at risk

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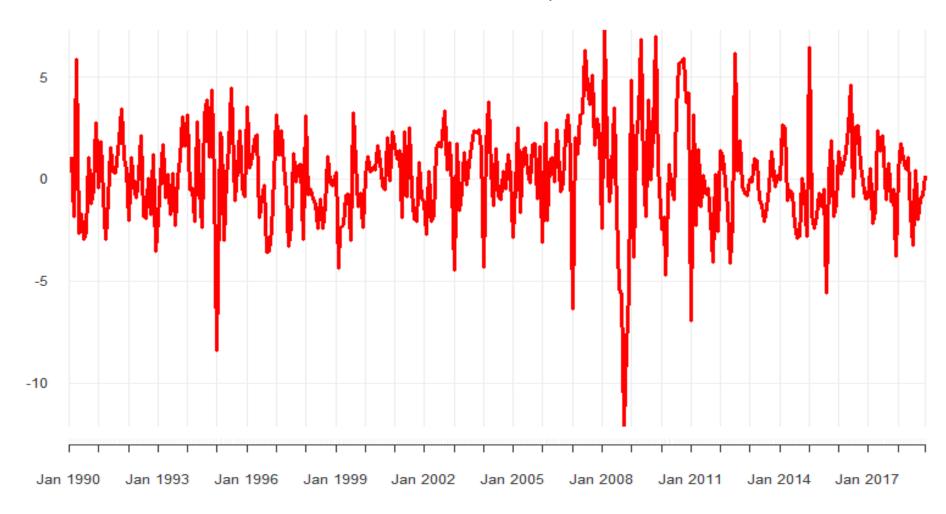
Motivation

FFPI - International food price index



Source: Food and Agriculture Organization of the United Nations (FAO)

Inflation rate of the FAO food price index



In this paper, we:

Study the risk associated with the inflation rate of food price

Atribute the total food inflation risk to the underlying food items

Propose some implications for Food Stability Policies



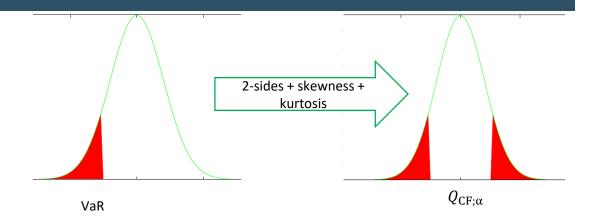
the risk that the actual food inflation rate will be different with the expected inflation rate

Important for:
 Central banks
 Consumers
 Producers

Risk measures?

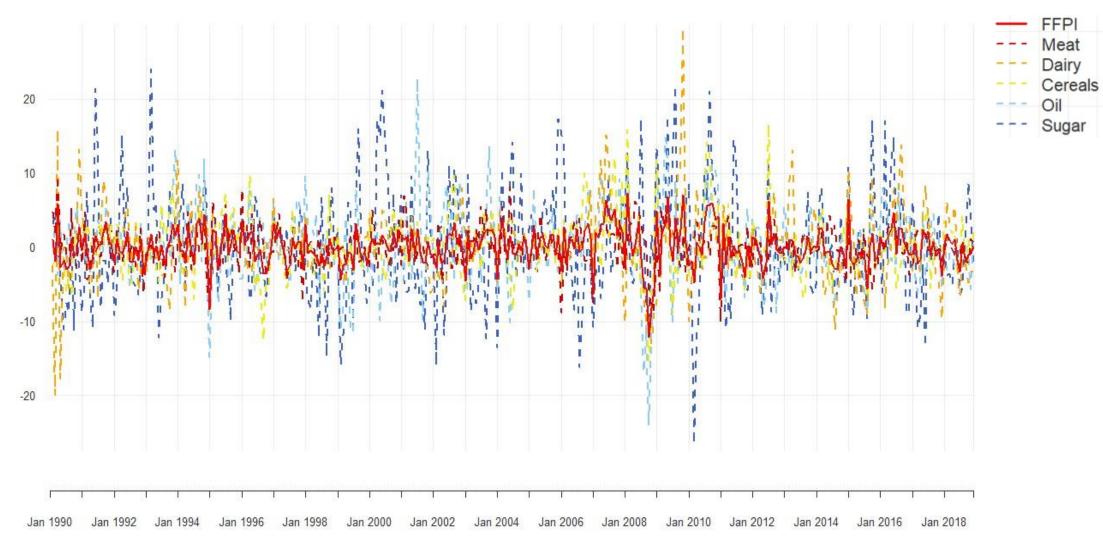
Volatility or standard deviation:
the lower the volatility is, the more
stable the inflation rate is

Alpha quantile risk measure: determine 5% and 95% quantiles of the inflation distribution



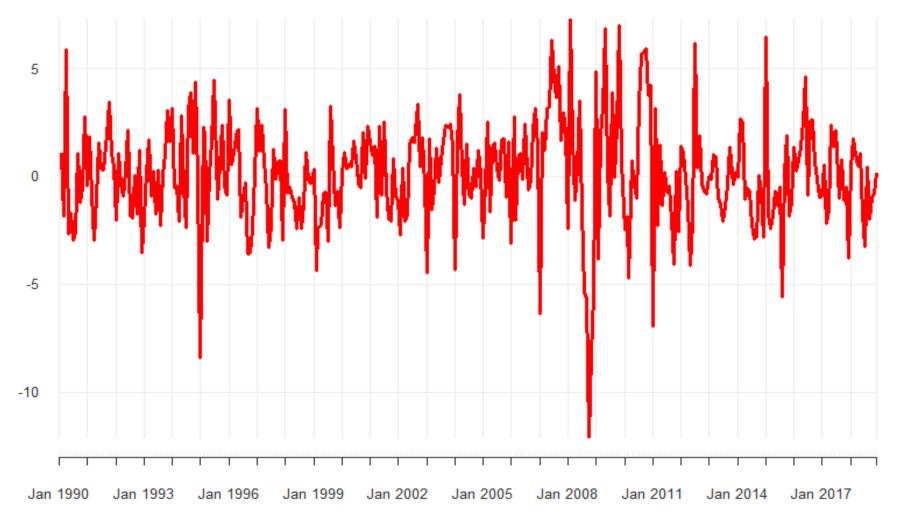
Data

Inflation rates of food and 5 components



Analysis

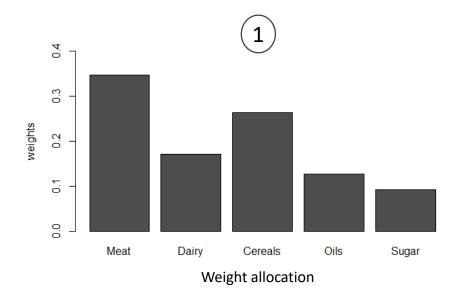


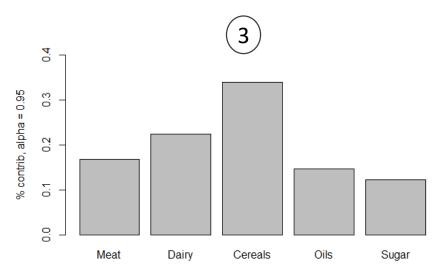


Volatility = 2.45%

5% quantile = -4.1%

95% quantile = 3.8%

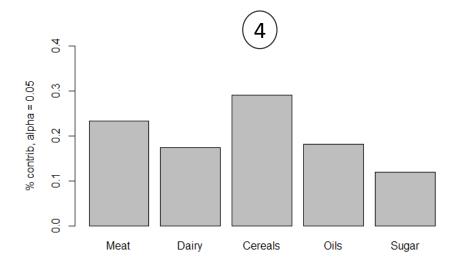




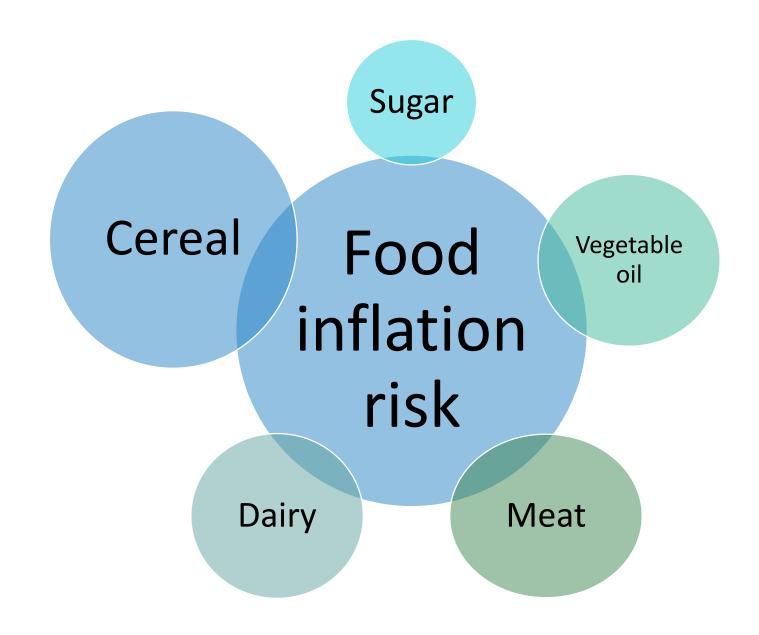
Contributions of components in unconditional 5% quantile



Contributions of components in unconditional food volatility



Contributions of components in unconditional 95% quantile



Inflation rates of food and 5 components

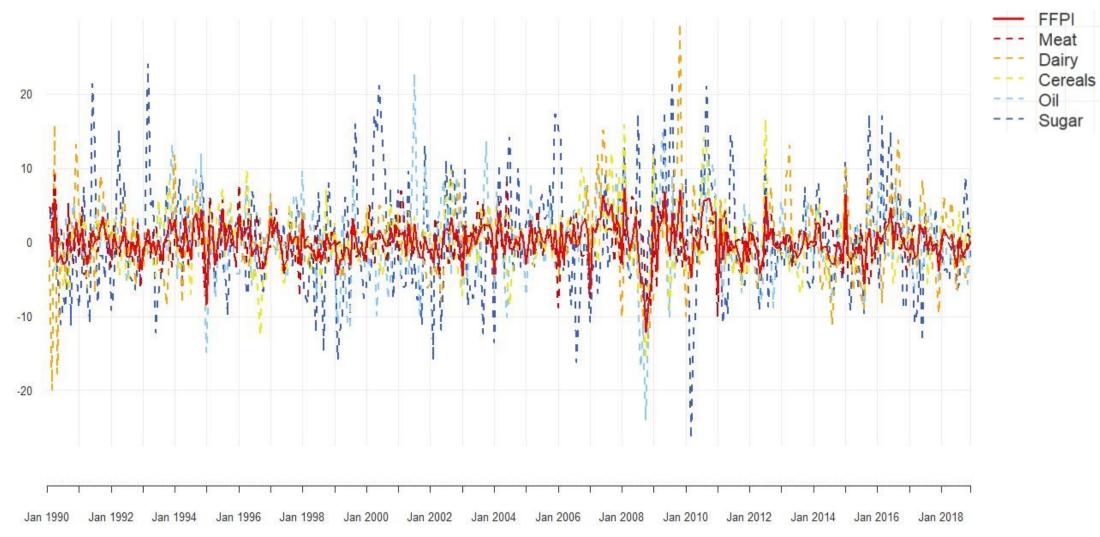


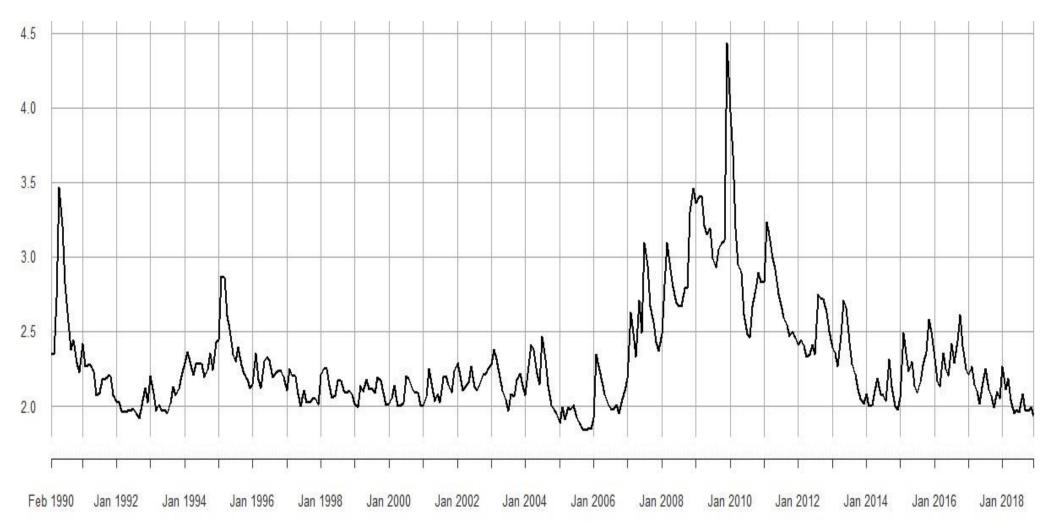
Table 1: Unconditional correlation between food inflation and component inflations

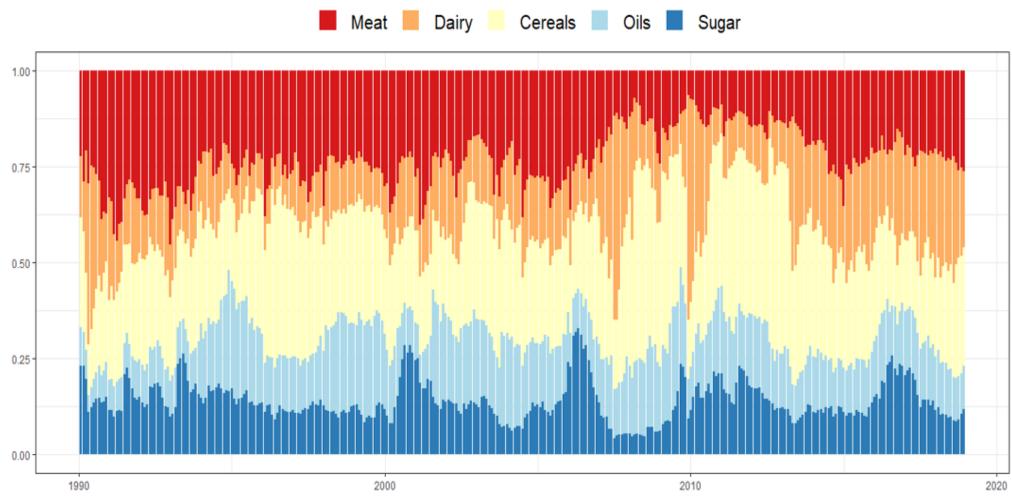
Correlation	Meat	Dairy	Cereals	Oils	Sugar
Food	0.53	0.57	0.71	0.63	0.43

Table 2: Unconditional weight shares of component inflations

Meat	Dairy	Cereals	Oils	Sugar
0.35	0.17	0.26	0.13	0.09

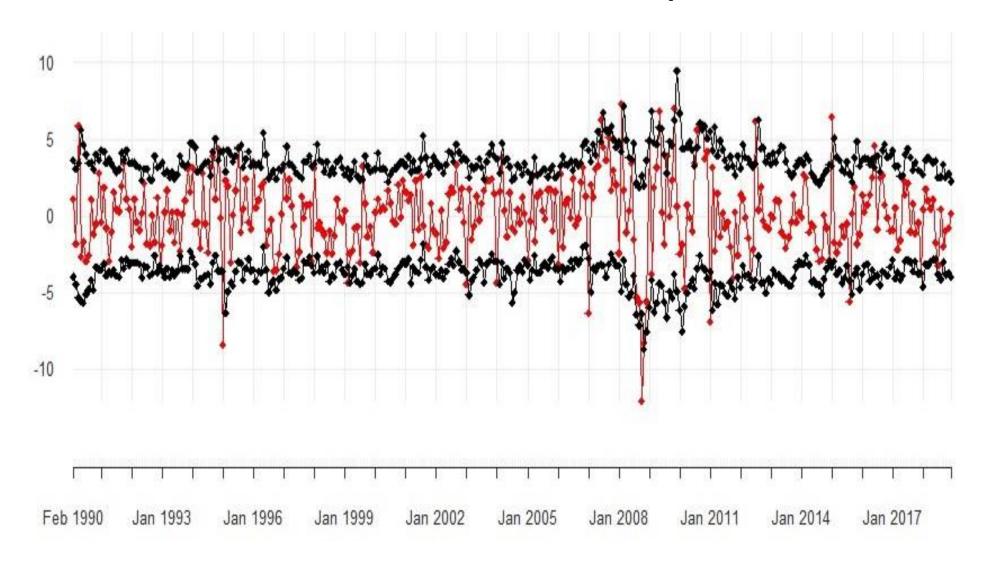
Conditional volatility of food inflation

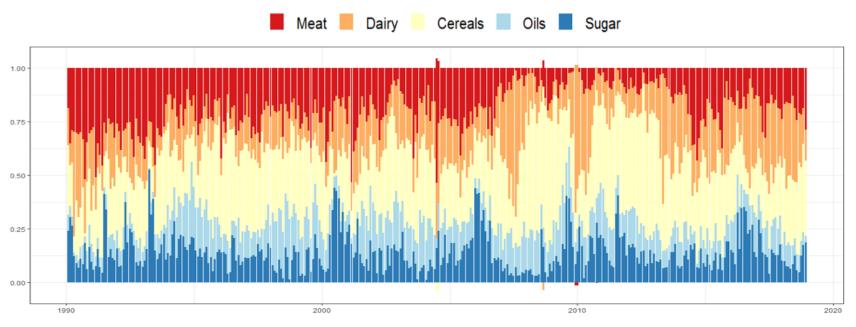




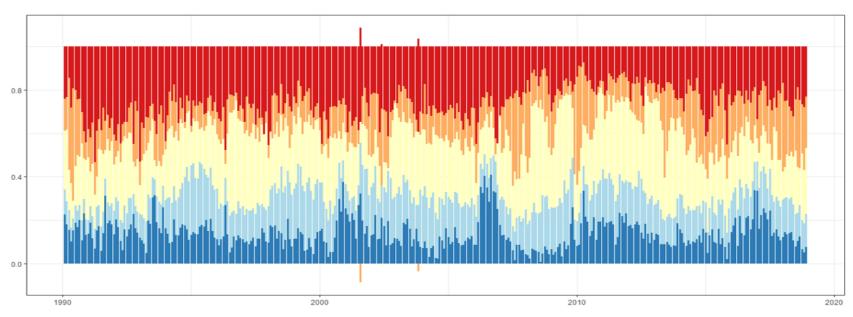
Conditional contribution of 5 components in food volatility

Food inflation and its conditional 5% and 95% quantiles





Conditional contributions of 5 components in the upside limit



Conditional contributions of 5 components in the downside limit

Implications

Food volatility is too high

Applying price stabilization to a few key components







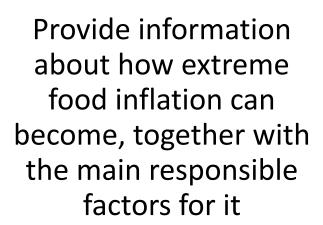


Analyze components' risk contribution

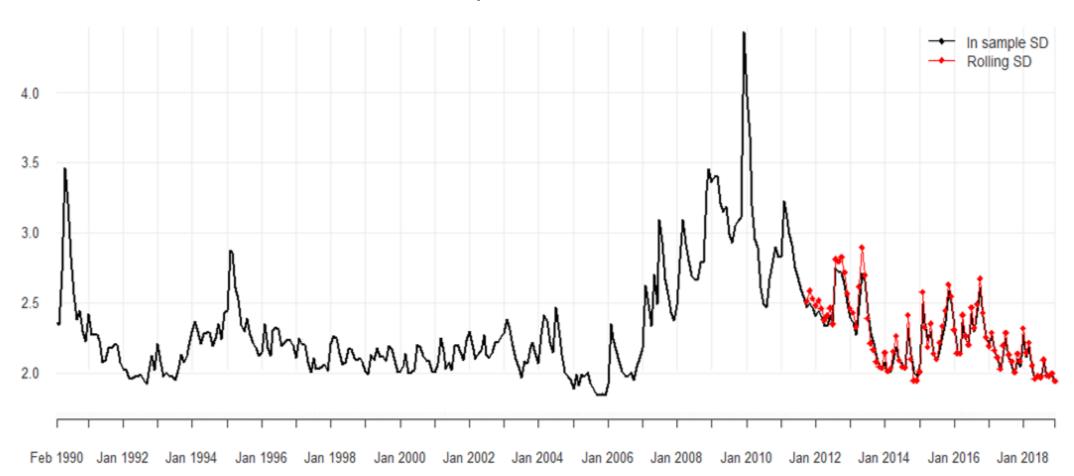
Impact the overall inflation

Quantile risk measures and risk decomposition

Apply hedging policies on the food components which carry high hidden risks.

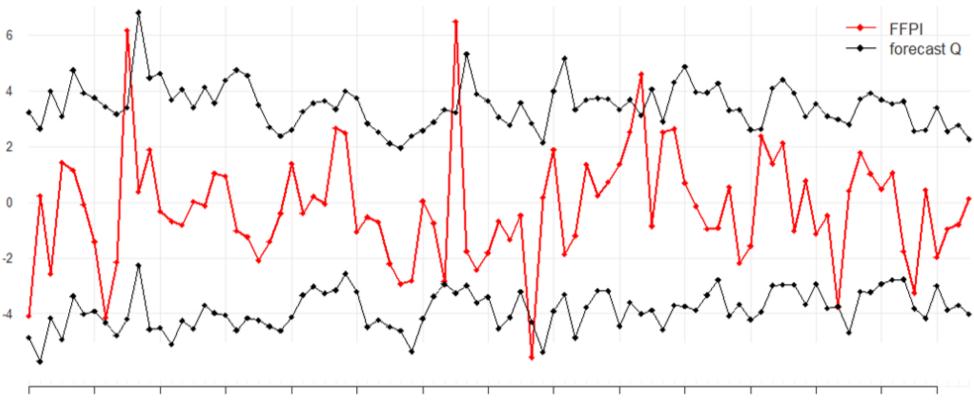


One-step-ahead forecast - SD



One-step-ahead forecast – Q

2011-10-01 / 2018-12-01



Oct 2011 Apr 2012 Oct 2012 Apr 2013 Oct 2013 Apr 2014 Oct 2014 Apr 2015 Oct 2015 Apr 2016 Oct 2016 Apr 2017 Oct 2017 Apr 2018

How?

Load packages library(PerformanceAnalytics) library(rugarch) library(rmgarch)

Load data

inflation <- read.csv("inflation.csv")
w1 <- read.csv("w1.csv")</pre>

*	Meat ‡	Dairy [‡]	Cereals [‡]	Oils [‡]	Sugar ‡
Feb 1990	4.78816285	-2.49616816	-2.31723870	-0.69228596	3.16501075
Mar 1990	1.61375197	-19.96406917	-1.79652605	2.85958173	4.85007943
Apr 1990	9.57189712	15.83894501	2.98160501	-3.73443983	-0.78121301
May 1990	-0.38597873	-17.82729805	0.17666111	3.64942529	-4.19927467
Jun 1990	1.70804998	0.00000000	-2.15538356	-3.71499861	-11.16756326
Jul 1990	-1.11180221	0.00000000	-6.07790127	-0.11517420	-7.55298867
Aug 1990	-0.95919491	-5.64480472	-3.39019190	3.63217065	-8.84333111
Sep 1990	5.30284988	3.45204624	-6.70933569	-1.36300417	1.28418391

^	wMeat ‡	wDairy 🕏	wCereals [‡]	wOils [‡]	wSugar ‡
Feb 1990	0.3594778	0.1500138	0.2663300	0.09071275	0.13346574
Mar 1990	0.3726313	0.1446931	0.2573552	0.08911408	0.13620631
Apr 1990	0.3857196	0.1179703	0.2574541	0.09337509	0.14548089
May 1990	0.3992225	0.1290837	0.2504399	0.08490749	0.13634647
Jun 1990	0.4086067	0.1089856	0.2577746	0.09042384	0.13420934
Jul 1990	0.4227403	0.1108618	0.2565606	0.08856344	0.12127386
Aug 1990	0.4307719	0.1142381	0.2483058	0.09115557	0.11552854
Sep 1990	0.4379856	0.1106561	0.2462671	0.09697865	0.10811254

Conduct a multivariate model on component inflations

Mean = VAR(1).

Variance = DCC-sGARCH.

Skew-student distribution.

Calculate attributes

Food inflation's moments and their partial derivatives.

Estimate total risks and contributions of components

Standard deviation/ Volatility.

Alpha quantile risk measures.

+ Weight allocation of components

```
###### Define a DCC-GARCH model to describe component inflations:
### univariate GARCH(1,1) for each series
uspec <- ugarchspec(mean.model = list(armaOrder = c(0,0)), variance.model = list(garchOrder = c(1,1),
          model = "sGARCH", variance.targeting = TRUE), distribution.model = "sstd")
### replicate the specification for 5 components:
muspec <- multispec(replicate(5,uspec))</pre>
### DCC specification
spec1 <- dccspec(uspec= muspec, VAR=TRUE, lag=1, dccOrder = c(1,1), distribution = "mvt")
### DCC-GARCH model
fit1 <- dccfit(spec1, data = inflation, fit.control = list(eval.se=T))
```

```
###### Unconditional risk measures
### Model attributes:
w <- matrix(colMeans(w1),ncol=1)
mu <- matrix(colMeans(inflation),ncol=1)
sigma <- cov(inflation)
z <- fit1@mfit$stdresid
stdm3 < -M3.MM(z)
stdm4 <- M4.MM(z)
```

```
###### Calculate volatility
vol budget <- PerformanceAnalytics:::Portsd(w=w, sigma = sigma)</pre>
Sdfood<- vol budget$StdDev
Sdcomponent <- vol budget$pct contrib StdDev
####### Alpha quantile risk measures:
### Lower limit and components' contributions
out05 <- CFVaR(p=0.05, w=w, mu=mu, sigma= sigma, M3 = stdm3, M4= m4)
05food<- out05$MVaR
05component<- out05$contribution
```

Upper limit and components' contributions

out95 <- CFVaR(p=0.95, w=w, mu=mu, sigma= sigma, M3 = stdm3, M4= stdm4) 95food<- out95\$MVaR 95component<- out95\$contribution

```
### modified version of VaR in PerformanceAnalytics package
CFVaR <- function (p, w, mu, sigma, M3, M4)
alpha = p
 z = qnorm(alpha)
 location = sum(w * mu)
 pm2 = PerformanceAnalytics:::portm2(w, sigma)
 dpm2 = as.vector( PerformanceAnalytics:::derportm2(w, sigma))
 pm3 = PerformanceAnalytics:::portm3(w, M3)
 dpm3 = as.vector( PerformanceAnalytics:::derportm3(w, M3))
 pm4 = PerformanceAnalytics:::portm4(w, M4)
 dpm4 = as.vector( PerformanceAnalytics:::derportm4(w, M4))
 ww = sum(w^2)
 skew = pm3/(ww^{3/2})
 exkurt = (pm4/(ww^2))-3
 derskew = ((ww^{(3/2)})*dpm3 - 3*pm3*(ww^{(1/2)})*w)/(ww^{3})
 derexkurt = (ww*dpm4 - 4*pm4*w)/(ww^3)
 h = z + (1/6) * (z^2 - 1) * skew
 h = h + (1/24) * (z^3 - 3 * z) * exkurt - (1/36) * (2 * z^3 - 5 * z) * skew^2
```

```
MVaR = -location - h * sqrt(pm2)
derh = (z^2 - 1) * derskew/6 + (z^3 - 3 * z) * derexkurt/24 - (2 * z^3 - 5 * z) * skew * derskew/18
derMVaR = -as.vector(mu) - h * as.vector(dpm2)/(2 * sqrt(pm2)) - sqrt(pm2) * derh
contrib = as.vector(w) * as.vector(derMVaR)
pct_contrib = contrib/MVaR
names(contrib) <- names(w)
names(pct_contrib) <- names(w)
ret = (list(-MVaR, -contrib, pct_contrib)) #-1
names(ret) = c("MVaR", "contribution", "pct_contrib_MVaR")
return(ret)
}
```

Conditional risk measures

Run a for loop

Change to time-varying attributes

```
sigma <- as.matrix(as.data.frame(fit1@mfit$H[,,i]))</pre>
```

mu <- as.numeric(fit1@model\$mu[i,])</pre>

w <- as.numeric(w1[i,])

One-step-ahead forecasts

Rolling estimation using expanding window

Reestimate the model

Make forecast of sigma, mu, and w

Function: dccforecast

References

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Thank you