# What are the risks of food price changes? A time series analysis 

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## Background

- It is a widely held belief (IPCC) that climate change brings more risks to the world
- Since the start of MACSUR, TradeM has had risk on the agenda, but few results have so far come out. It has been claimed though, that there is no evidence for more risk in the global wheat market (Steen and Gjølberg 2014) (TradeM workshop at Hurdalssjøen)
- I have myself had the ambition of creating a dynamic stochastic model of the food system in which risk would be an integral part, but time has been too short
- I have also pointed to methods from finance to reveal insights, and that is the road to be followed here, guided by Bølviken Benth (2000)


## A concept of financial risk

- Let $p_{0}$ and $p_{t}$ be prices of a commodity currently and at time $t$, and consider the return

$$
r_{t}=\log \left(p_{t} / p_{0}\right) \approx \frac{p_{t}-p_{0}}{p_{0}}
$$

measuring an approximate rate of return in selling one unit of the commodity at time $t$ instead of now

- Since $r_{t}$ is a stochastic variable, we have to specify from past experience how $r_{t}$ may turn out - its probability distribution
- That knowledge can be expressed as value at risk

$$
\operatorname{VaR}\left(r_{t} ; q\right)=\mathbb{E} r_{t}-Q\left(r_{t}, q\right)
$$

where $\mathbb{E} r_{t}$ is the expected return and $Q\left(r_{t}, q\right)$ is the $q$-quantif of the distribution of $r_{t}$. In the proportion of $q$ cases the return will be larger than $\operatorname{VaR}\left(r_{t} ; q\right)$, while in the proportioNIBIO of $1-q$ cases it will be smaller

## The relevance of value at risk

- When $p_{t}$ follows the standard stock-price model

$$
\operatorname{VaR}\left(() r_{t} ; q\right)=Q(q) \sigma \sqrt{t}
$$

where $Q(q)$ is the quantile of the standard normal distribution, and $\sigma$ is the constant volatility

- In more general cases:
- $\operatorname{VaR}\left(r_{t} ; 0.025\right)$ is usually a positive number - if too small, sell now. What "too small" means depend on risk preferences and portfolio
- $\operatorname{VaR}\left(r_{t} ; 0.5\right)$ may be positive or negative. If positive, the return will be positive in half of cases, encouraging sale at $t$
- $\operatorname{VaR}\left(r_{t} ; 0.975\right)$ is usually a negative number. Its negative is relevant for the agent who is short in the commodity. Should a unit be bought at $t$ instead of now? Is $-\operatorname{VaR}\left(r_{t} ; 0.975\right)$ a "too small" number, buy now?
- Largely, lower tail of distribution relevant for sellers, upper tailBIO relevant for buyers


## Some commodity prices



Figure: Nominal monthly prices. Source: "Data Extract From Global Economic Monitor (GEM) Commodities", 1960/1-2016/8, World Bank

Something happened in the year of oil crisis, 1972. Price changeşons.iskngmur for turned much more freauent

## Commodity returns, 1 month



## Commodity returns, 11 months



## Q-Q plots of 1 month commodity returns



The nlots show, "fat tails" of all return distributions

## Partial auto-correlation plots of 1 month commodity returns

Series d11\$wheat


Series d11\$rice


Lag


Series d11\$sugar


Lag

Series d11\$maize


Series d11\$croil



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## Stochastic volatility model

- Well known from finance that volatility tend to change over time. A stochastic volatility model is fitted
- A flexible model of $r_{t}$ is that of Normal-Inverse-Gaussian distributions with both skewness and fat-tail parameters in addition to mean and variance, $\mathcal{N} \mathcal{I} \mathcal{G}$. Following (Martino et al. 2011):

$$
\begin{gathered}
\frac{r_{t}}{\sigma_{t}} \sim \mathcal{N} \mathcal{I} \mathcal{G}(0,1, \beta, \gamma, \delta) \\
\sigma_{t}-\rho \sigma_{t-1} \sim \mathcal{N}(0,1 /(1-\rho))
\end{gathered}
$$

- In effect, volatility of returns, $r_{t}$, is allowed to change over time
- Bayesian estimation following Rue et al. (2009)


## Volatilities of 1 month commodity returns, starting 1960



Figure: Models for maize and oil have poor fit. Clearer pictures are obtained by excluding years 1960-1972

## Volatilities of 1 month commodity returns, starting 1973



## Volatilities of 11 months commodity returns, starting 1973



## Conclusions (1)

- There are actually signs of increasing volatility for wheat and barley, while the opposite is the case for rice and sugar
- Steen \& Gjølberg (2015) state comparable results for wheat, maize and oil but for a shorter time interval, 1996-2014, which make eventual long term trends less pronounced
- The presumption that climate change should show up as increasing volatility in all agricultural markets is obviously wrong. Inspection of curves suggests that causes for change may be found in the interplay between different markets, between markets and nature, and between markets and institutions. In order to isolate the causal effects of changing nature, one would need a larger model


## What about 1 month price risks?

Blue lines $=-\operatorname{VaR}(0.975)$, buyers's risk. Red lines $=\operatorname{VaR}(0.025)$, seller's risk, black lines $=\operatorname{VaR}(0.5)$


## What about 11 months price risks?

Blue lines $=-\operatorname{VaR}(0.975)$, buyers's risk. Rede lines $=\operatorname{VaR}(0.025)$, seller's risk, black lines $=\operatorname{VaR}(0.5)$


## Conclusions (2)

- Buyer's risk larger than seller's risk - due to asymmetric distribution of returns. Large price jumps are more likely than equally sized price falls.
- Long term positions much more risky than short term ones as expected
- Agricultural commodities much less risky than crude oil
- Price risk are related to volatility, and their changes over time will have similar causal explanations
- Risks of producers and consumers of agricultural commodities will to some extent be related to the price risk, and also to their portfolios and the co-variance between returns


## References

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The End

