## Exploring recursive utility

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## Approximating processes

Follow Lombardo and Uhlig (IER, 2018) by considering the stochastic processes indexed by a q.

$$
X_{t+1}(\mathbf{q})=\psi\left[X_{t}(\mathbf{q}), \mathbf{q} W_{t+1}, \mathbf{q}\right]
$$

$\triangleright X$ is an $n$-dimensional stochastic process
$\triangleright W$ is an iid. normally distributed random vector with conditional mean 0 and conditional covariance $I$.
$\triangleright \mathrm{q}=1$ is the model of interest.

## A convenient approximation

Consider a local approximation of the form:

$$
X_{t} \approx X_{t}^{0}+\mathrm{q} X_{t}^{1}+\frac{\mathrm{q}^{2}}{2} X_{t}^{2}
$$

where the order zero process is invariant and satisfies:

$$
X_{t+1}^{0}=\psi\left(X_{t}^{0}, 0,0\right)
$$

## Order one

The first-derivative process obeys

$$
X_{t+1}^{1}=\left[\begin{array}{c}
\psi_{x^{\prime}}^{1} \\
\psi_{x^{\prime}}^{2} \\
\vdots \\
\psi_{x^{\prime}}^{n}
\end{array}\right] X_{t}^{1}+\left[\begin{array}{c}
\psi_{w^{\prime}}^{1} \\
\psi_{w^{\prime}}^{2} \\
\vdots \\
\psi_{w^{\prime}}^{n}
\end{array}\right] W_{t+1}+\left[\begin{array}{c}
\psi_{\mathrm{q}}^{1} \\
\psi_{\mathrm{q}}^{2} \\
\vdots \\
\psi_{\mathrm{q}}^{n}
\end{array}\right] .
$$

Write this compactly as a first-order vector autoregression t

$$
X_{t+1}^{1}=\psi_{x^{\prime}} X_{t}^{1}+\psi_{w^{\prime}} W_{t+1}+\psi_{\mathrm{q}}
$$

We assume that the matrix $\psi_{x}^{\prime}$ is stable in the sense that all of its eigenvalues are strictly less than one in modulus.

## Order two

$$
\begin{aligned}
X_{t+1}^{2}= & \psi_{x^{\prime}} X_{t}^{2}+\left[\begin{array}{c}
X_{t}^{1^{\prime}} \psi_{x x^{\prime}}^{1} X_{t}^{1} \\
X_{t}^{1^{\prime}} \psi_{x x^{\prime}}^{2} X_{t}^{1} \\
\vdots \\
X_{t}^{1^{\prime}} \\
\psi_{x x^{\prime}}^{n} X_{t}^{1}
\end{array}\right]+2\left[\begin{array}{c}
X_{t}^{1^{\prime}} \psi_{x w^{\prime}}^{1} W_{t+1} \\
X_{t}^{1^{\prime}} \psi_{x w^{\prime}}^{2} W_{t+1} \\
\vdots \\
X_{t}^{1^{\prime}} \psi_{x w^{\prime}}^{n} W_{t+1}
\end{array}\right]+\left[\begin{array}{c}
W_{t+1}^{\prime} \psi_{w w^{\prime}}^{1} W_{t+1} \\
W_{t+1}^{\prime} \psi_{w w^{\prime}}^{w^{\prime}} W_{t+1} \\
\vdots \\
W_{t+1}^{\prime} \psi_{w w^{\prime}}^{n} W_{t+1}
\end{array}\right] \\
& +2\left[\begin{array}{c}
\psi_{\mathrm{q} x^{\prime}}^{1} X_{t}^{1} \\
\psi_{\mathrm{q} x^{\prime}}^{2} X_{t}^{1} \\
\vdots \\
\psi_{\mathrm{qx}}{ }^{\prime} \\
X_{t}^{1}
\end{array}\right]+2\left[\begin{array}{c}
\psi_{\mathrm{q} w^{\prime}}^{1} W_{t+1} \\
\psi_{\mathrm{q} w^{\prime}}^{2} W_{t+1} \\
\vdots \\
\psi_{\mathrm{q} w^{\prime}}^{n} W_{t+1}
\end{array}\right]+\left[\begin{array}{c}
\psi_{\mathrm{qq}}^{1} \\
\psi_{\mathrm{qq}}^{2} \\
\vdots \\
\psi_{\mathrm{qq}}^{n}
\end{array}\right]
\end{aligned}
$$

## Growth-rate approximation

$$
\widehat{Y}_{t+1}-\widehat{Y}_{t}=\kappa\left(X_{t}, \mathbf{q} W_{t+1}, \mathbf{q}\right)
$$

Approximate this process by:

$$
\widehat{Y}_{t+1}-\widehat{Y}_{t} \approx \widehat{Y}_{t+1}^{0}-\widehat{Y}_{t}^{0}+\mathrm{q}\left(\widehat{Y}_{t+1}^{1}-\widehat{Y}_{t}^{1}\right)+\frac{\mathrm{q}^{2}}{2}\left(\widehat{Y}_{t+1}^{2}-\widehat{Y}_{t}^{2}\right)
$$

where

$$
\begin{aligned}
\widehat{Y}_{t+1}^{0}-\widehat{Y}_{t}^{0}= & \kappa\left(X_{t}^{0}, 0,0\right) \equiv \eta_{0}^{y} \\
\widehat{Y}_{t+1}^{1}-\widehat{Y}_{t}^{1}= & \kappa_{x^{\prime}} X_{t}^{1}+\kappa_{w^{\prime}} W_{t+1}+\kappa_{q} \\
\widehat{Y}_{t+1}^{2}-\widehat{Y}_{t}^{2}= & \kappa_{x^{\prime}} X_{t}^{2}+X_{t}^{1^{\prime}} \kappa_{x, x^{\prime}} X_{t}^{1}+2 X_{t}^{1^{\prime}} \kappa_{x w^{\prime}} W_{t+1}+W_{t+1}{ }^{\prime} \kappa_{w w^{\prime}} W_{t+1} \\
& +2 \kappa_{q, x^{\prime}} X_{t}^{1}+2 \kappa_{q w^{\prime}} W_{t+1}+\kappa_{q q} .
\end{aligned}
$$

## First-order approximation of cont values

$$
\begin{aligned}
& \widehat{R}_{t}^{1}-\widehat{C}_{t}^{1}=\left(\frac{1}{1-\gamma_{o}}\right) \log \mathbb{E}\left(\exp \left[\left(1-\gamma_{o}\right)\left(\widehat{V}_{t+1}^{1}-\widehat{C}_{t}^{1}\right)\right] \mid \mathfrak{A}_{t}\right) \\
& \widehat{V}_{t}^{1}-\widehat{C}_{t}^{1}=\left(\frac{\lambda}{1-\gamma_{o}}\right) \log \mathbb{E}\left(\exp \left[\left(1-\gamma_{o}\right)\left(\widehat{V}_{t+1}^{1}-\widehat{C}_{t}^{1}\right)\right] \mid \mathfrak{A}_{t}\right)
\end{aligned}
$$

where it is convenient to write

$$
\widehat{V}_{t+1}^{1}-\widehat{C}_{t}^{1}=\left(\widehat{V}_{t+1}^{1}-\widehat{C}_{t+1}^{1}\right)+\left(\widehat{C}_{t+1}^{1}-\widehat{C}_{t}^{1}\right) .
$$

and where: $\lambda=\beta \exp \left[(1-\rho) \eta_{c}^{0}\right]$.

## Uncertainty measure approximation

Measure

$$
N_{t+1}^{*} \stackrel{\text { def }}{=}\left(\frac{V_{t+1}}{R_{t}}\right)^{1-\gamma}
$$

Approximation

$$
N_{t+1}^{0}=\frac{\exp \left[\left(1-\gamma_{o}\right)\left(\widehat{V}_{t+1}^{1}-\widehat{C}_{t}^{1}\right)\right]}{\mathbb{E}\left(\exp \left[\left(1-\gamma_{o}\right)\left(\widehat{V}_{t+1}^{1}-\widehat{C}_{t}^{1}\right)\right] \mid \mathfrak{A}_{t}\right)}
$$

## Posterior histograms




Left figure: one period volatility and right figure martingale increment volatility for consumption

## Second-order approximation of cont values

$$
\begin{aligned}
& \widehat{R}_{t}^{2}-\widehat{C}_{t}^{2}=\mathbb{E} {\left[N_{t+1}^{0}\left(\widehat{V}_{t+1}^{2}-\widehat{C}_{t}^{2}\right) \mid \mathfrak{A}_{t}\right] } \\
& \widehat{V}_{t}^{2}-\widehat{C}_{t}^{2}=\lambda \mathbb{E}\left[N_{t+1}^{0}\left(\widehat{V}_{t+1}^{2}-\widehat{C}_{t}^{2}\right) \mid \mathfrak{A}_{t}\right) \\
&+(1-\rho)(1-\lambda) \lambda\left(\widehat{R}_{t}^{1}-\widehat{C}_{t}^{1}\right)^{2}
\end{aligned}
$$

## SDF approximation

$$
\frac{S_{t+1}}{S_{t}}=N_{t+1}^{*} \exp \left(\widehat{S}_{t+1}-\widehat{S}_{t}\right)
$$

where

$$
N_{t+1}^{*} \stackrel{\text { def }}{=}\left(\frac{V_{t+1}}{R_{t}}\right)^{1-\gamma}
$$

and

$$
\widehat{S}_{t+1}-\widehat{S}_{t} \stackrel{\text { def }}{=} \log \beta-\rho\left(\widehat{C}_{t+1}+\widehat{C}_{t}\right)+(\rho-1)\left(\widehat{V}_{t+1}-\widehat{R}_{t}\right)
$$

## SDF approx I

$\widehat{S}_{t+1}-\widehat{S}_{t}:$
$\log S_{t+1}-\log S_{t} \approx\left(1-\gamma_{o}\right)\left[\left(\widehat{V}_{t+1}^{1}-\widehat{R}_{t}^{1}\right)+\frac{1}{2}\left(\widehat{V}_{t+1}^{2}-\widehat{R}_{t}^{2}\right)\right]$

$$
+\left(\widehat{S}_{t+1}^{0}-\widehat{S}_{t}^{0}\right)+\left(\widehat{S}_{t+1}^{1}-\widehat{S}_{t}^{1}\right)+\frac{1}{2}\left(\widehat{S}_{t+1}^{2}-\widehat{S}_{t}^{2}\right)
$$

where $\log N_{t+1}^{*} \approx \log \widetilde{N}_{t+1}$ and

$$
\widetilde{N}_{t+1} \stackrel{\text { def }}{=} \exp \left[\left(1-\gamma_{o}\right)\left[\left(\widehat{V}_{t+1}^{1}-\widehat{R}_{t}^{1}\right)+\frac{1}{2}\left(\widehat{V}_{t+1}^{2}-\widehat{R}_{t}^{2}\right)\right]\right]
$$

Observation:
$\triangleright$ approximation $\widetilde{N}_{t+1}$ does not have a conditional expectation that is equal to one

## SDF approx II

$$
\log \widetilde{N}_{t+1}=\frac{\exp \left[\left(1-\gamma_{o}\right)\left[\left(\widehat{V}_{t+1}^{1}-\widehat{R}_{t}^{1}\right)+\frac{1}{2}\left(\widehat{V}_{t+1}^{2}-\widehat{R}_{t}^{2}\right)\right]\right]}{\mathbb{E}\left(\left.\exp \left[\left(1-\gamma_{o}\right)\left[\left(\widehat{V}_{t+1}^{1}-\widehat{R}_{t}^{1}\right)+\frac{1}{2}\left(\widehat{V}_{t+1}^{2}-\widehat{R}_{t}^{2}\right)\right]\right] \right\rvert\, \mathfrak{A}_{t}\right)} .
$$

Observation:
$\triangleright$ approximation $\widetilde{N}_{t+1}$ has a conditional expectation that is equal to one
$\triangleright$ induces a change in probability measure for $W_{t+1}$ with a conditional mean that is affine in $X_{t}^{1}$ and an altered state independent covariance matrix

## Model solution

$$
\mathbb{E}\left[N_{t+1}^{*} Q_{t+1}^{*} \psi_{1}\left(X_{t}, J_{t}, X_{t+1}, J_{t+1}\right) \mid \mathfrak{A}_{t}\right]+\psi_{2}\left(X_{t}, J_{t}\right)=0
$$

where $X_{t}$ is a state vector, $J_{t}$ is jump vector and

D

$$
N_{t+1}^{*} \stackrel{\text { def }}{=}\left(\frac{V_{t+1}}{R_{t}}\right)^{1-\gamma}
$$

$\triangleright$

$$
Q_{t+1}^{*} \stackrel{\text { def }}{=}\left(\frac{V_{t+1}}{R_{t}}\right)^{\rho-1}
$$

$\triangleright \beta\left(\frac{C_{t+1}}{C_{t}}\right)^{-\rho}$ is absorbed in $\psi_{1}$.

## Model solution

Schmidtt-Grohe and Lombardo and Uhlig treat the case in which

$$
\mathbb{E}\left[\psi_{1}\left(X_{t}, J_{t}, X_{t+1}, J_{t+1}\right) \mid \mathfrak{A}_{t}\right]+\psi_{2}\left(X_{t}, J_{t}\right)=0
$$

combined with the state evolution. $m+n$ equations where $n$ is the number of states and $m$ is the number of jump variables.
$\triangleright$ First order - affine difference equation in $\left(X_{t}^{1}, J_{t}^{1}\right) . n+m$ equations and $n$ initial conditions for the state. Find $J_{t}^{1}$ as an affine function of $X_{t}^{1}$ so that the combined system is stochastically stable.
$\triangleright$ Second order - affine difference equation in $\left(X_{t}^{2}, J_{t}^{2}\right)$ and linear-quadratic in $\left(X_{t}^{1}, J_{t}^{1}\right)$. Find $J_{t}^{2}$ as an affine function of $X_{t}^{2}$ and linear-quadratic function of $X_{t}^{1}$ so that the combined system is stochastically stable

## Incorporating recursive utility

Iterate to convergence
$\triangleright$ Take guesses for $N_{t+1}^{*}$ and $Q_{t+1}^{*}$ and use the guess for $N_{t+1}^{*}$ as a change in probability. Compute first and second order approximations for states and jumps
$\triangleright$ Given approximate state dynamics deduce a new guess for $N_{t+1}^{*}$ and $Q_{t+1}^{*}$ by applying the approximation formulas

