

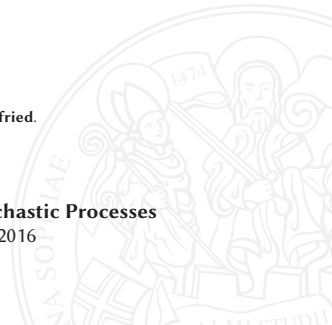
Backward Nonlinear Expectation Equations

Christoph Belak

Department IV – Mathematics
University of Trier
Germany

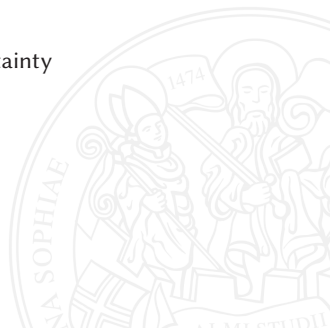
Joint work with **Thomas Seiferling** and **Frank Seifried**.

Colloquium on Mathematical Statistics and Stochastic Processes
University of Hamburg, November 29, 2016



Outline

- (1) Recursive and Stochastic Differential Utility
- (2) Nonlinear Expectations and Model Uncertainty
- (3) Backward Nonlinear Expectation Equations
- (4) Application to Recursive Utility under Model Uncertainty



Recursive and Stochastic Differential Utility



Ranking Consumption Plans

Let \mathcal{C} be a set of consumption plans (c, X) and assume that you have to choose today which plan you want to follow.

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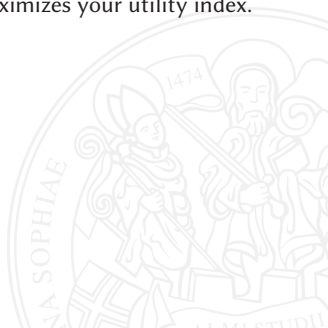


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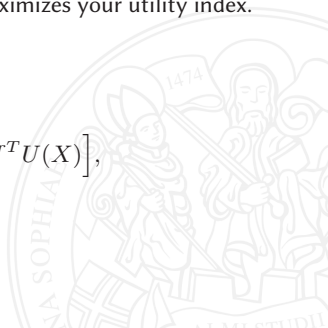
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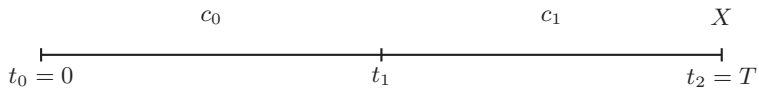
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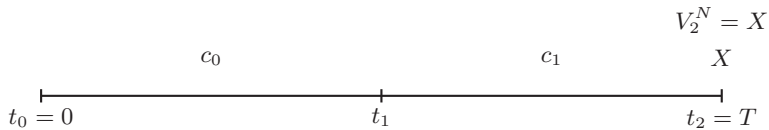
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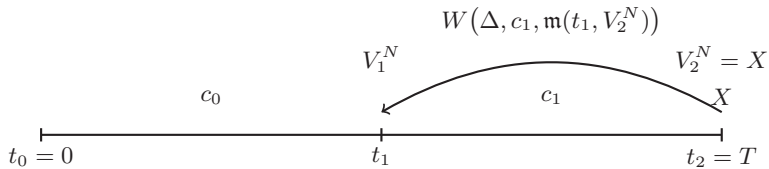
Recursive Utility (Kreps/Porteus 1978)



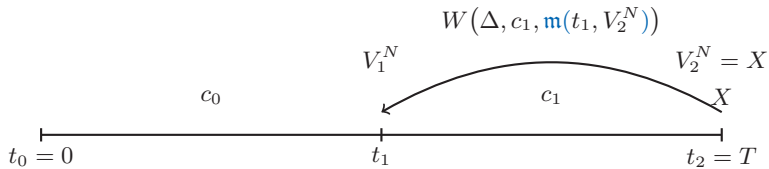
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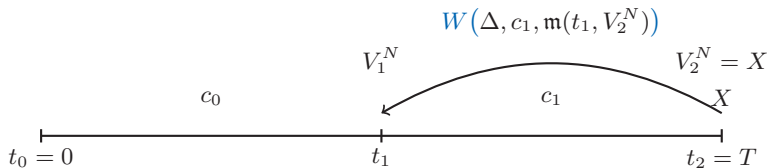
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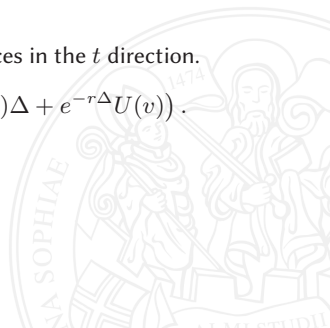


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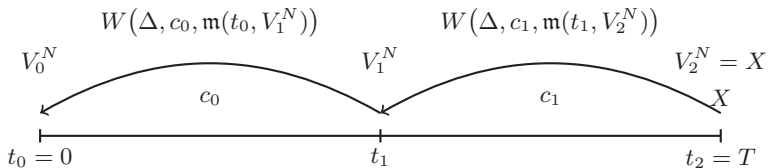
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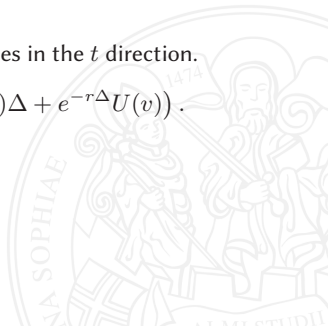


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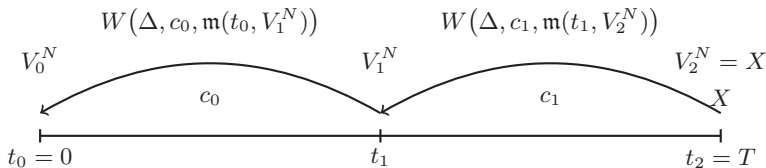
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$$\stackrel{\Delta \Rightarrow 1}{\Rightarrow} \mathbf{v}_N(c, X) \triangleq V_0^N = \dots = U^{-1}\left(\mathbb{E}\left[\sum_{n=0}^{N-1} e^{-rt_n} U(c_n) + e^{-rT} U(X)\right]\right) .$$

Stochastic Differential Utility (Duffie/Epstein 1992)

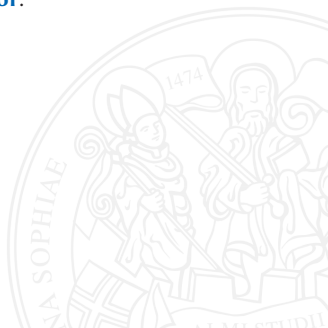
In a continuous-time setting, **stochastic differential utility** is defined axiomatically through

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where $V = (V_t)_{t \in [0, T]}$ is given as the solution of the **backward stochastic differential equation** (BSDE)

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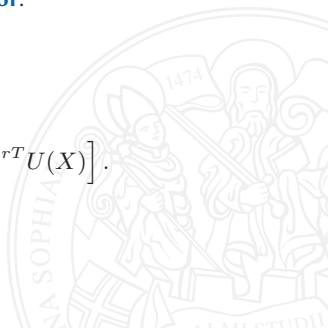
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Example: If $f(c, v) = U(c) - rv$, then

$$v(c, X) = V_0 = \mathbb{E} \left[\int_0^T e^{-rt} U(c_t) dt + e^{-rT} U(X) \right].$$



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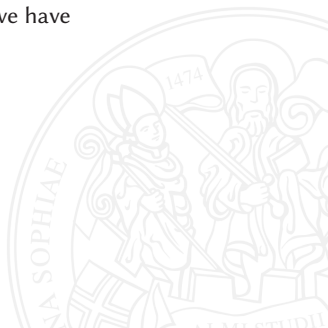
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$$W(\Delta, c, v) \approx v + \Delta f(c, v) \quad \text{and} \quad \mathfrak{m}(t, V) = \mathbb{E}_t[V].$$

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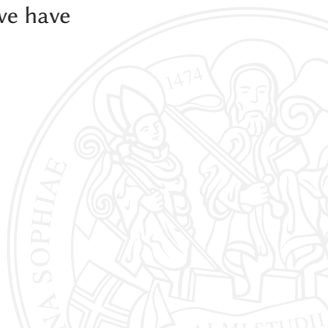
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In particular, $v_N(c, X) = V_0^N \rightarrow V_0 = v(c, X)$ and

$$f(c, v) = \frac{\partial}{\partial \Delta} W(\Delta, c, v)|_{\Delta=0}.$$



Research Question 1

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Research Question 2

Does the discrete-time recursive utility index still converge, if we replace the conditional expectation \mathbb{E}_t with a more general certainty equivalent m ?

Nonlinear Expectations and Model Uncertainty



Model Uncertainty

Aim: Generalize the results to certainty equivalents of the form

$$\mathcal{E}_t[\cdot] \triangleq \text{ess} \inf_{\mathbb{Q} \in \mathcal{Q}_t} \mathbb{E}_t^{\mathbb{Q}}[\cdot]$$



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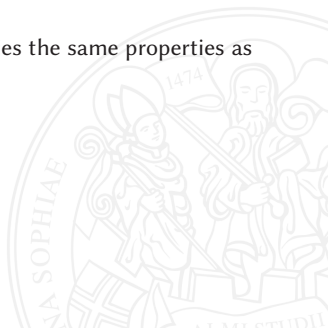
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Guess: The continuous-time object is of the form

$$V_t = \mathcal{E}_t \left[\int_t^T f(c_s, V_s) ds + U(X) \right], \quad t \in [0, T].$$

We call this a **backward nonlinear expectation equation** (BNEE).

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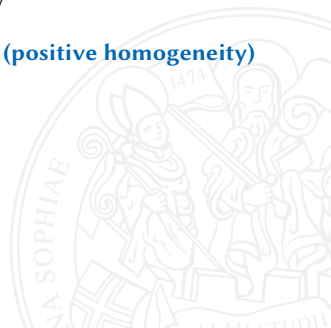
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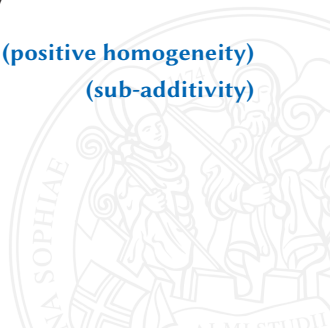
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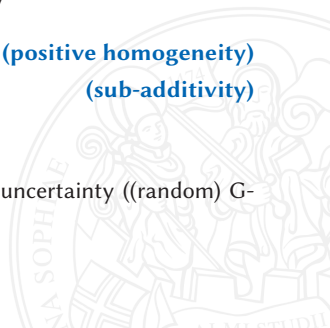
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Examples: drift uncertainty (g-Expectations), volatility uncertainty ((random) G-Expectations), dynamic risk measures, ...



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- (iv) There exists a sublinear expectation $\{\mathcal{E}_t^{\text{sub}}\}_{t \in [0, T]}$ such that

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Notice: There is no σ -field and no probability measure involved here!



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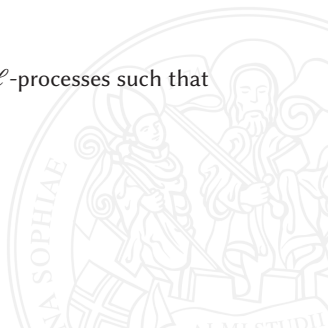
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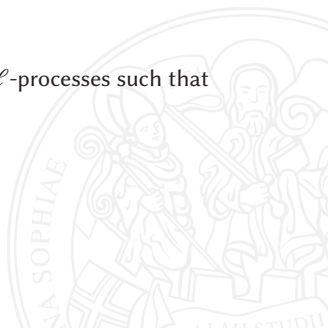
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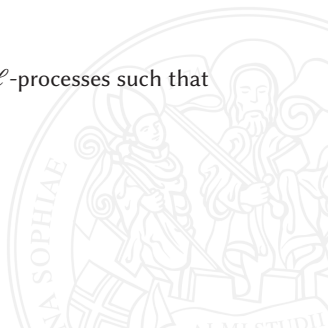
$$X : [0, T] \rightarrow L_T, \quad t \mapsto X_t = X(t)$$

which is $\mathfrak{B}([0, T])$ - $\mathfrak{B}(L_T)$ -measurable. It is called **adapted** if

$$X_t \in L_t \quad \text{for all } t \in [0, T].$$

We denote by $(D, \|\cdot\|_D)$ the Banach space of adapted \mathcal{L} -processes such that

- (i) X is càdlàg as a mapping $[0, T] \rightarrow L_T$ and
- (ii) $\|X\|_D \triangleq \sup_{t \in [0, T]} \|X_t\|_L < \infty$.



Backward Nonlinear Expectation Equations



Regularity of Nonlinear Expectations

For $\xi \in L_T$, consider the **simple BNEE**

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We say that the nonlinear expectation \mathcal{E}_t is **regular**, if the simple BNEE admits a solution $X \in D$ for every $\xi \in L_T$.

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Remark: g -Expectations, G -Expectations and **random G -Expectations** are regular nonlinear expectations!

Existence and Uniqueness of BNEEs

Let $\xi \in L_T$ and consider the **general BNEE**

$$X_t = \mathcal{E}_t \left[\int_t^T g(s, X_s) ds + \xi \right], \quad t \in [0, T].$$



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Existence and Uniqueness of BNEEs

If \mathcal{E}_t is **regular**, then the BNEE admits a unique solution in D .

Let \mathcal{E}_t be a **regular** nonlinear expectation and consider the BNEE

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Discretization of BNEEs

Let \mathcal{E}_t be a **regular** nonlinear expectation and consider the BNEE

$$X_t = \mathcal{E}_t \left[\int_t^T g(s, X_s) ds + \xi \right], \quad t \in [0, T],$$

as well as the **discrete-time backward aggregation** $X_N^N \triangleq \xi$,

$$X_k^N \triangleq \mathcal{E}_{t_k^N} \left[g(t_k^N, \mathcal{E}_{t_k^N} [X_{k+1}^N]) \Delta_{k+1}^N + X_{k+1}^N \right], \quad k = N-1, \dots, 0,$$

for a partition $\Delta^N : 0 = t_0^N < \dots < t_N^N = T$, $\Delta_k^N \triangleq t_k^N - t_{k-1}^N$. Assume that $(\Delta^N)_{N \in \mathbb{N}}$ is **infinitesimal**.



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Discrete-Time Approximation of BNEEs

If the mapping $t \mapsto g(t, \eta)$ is left-continuous for every $\eta \in L_T$, then

$$\max_{k=0, \dots, N} \|X_k^N - X_{t_k^N}\|_L \rightarrow 0 \quad \text{as } N \rightarrow \infty.$$

Recursive Utility under Model Uncertainty



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We fix a **consumption plan** (c, ξ) , where



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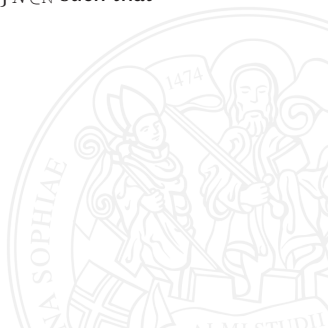


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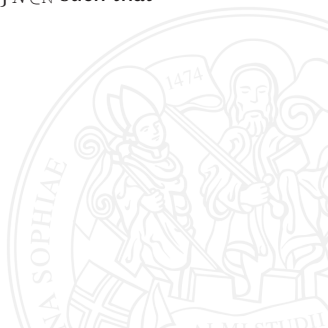
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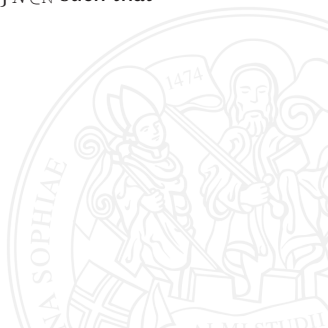
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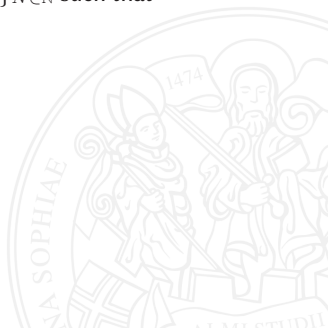
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Recursive and Stochastic Differential Utility under Uncertainty

We fix an **intertemporal aggregator**

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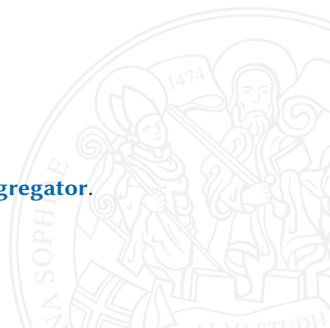
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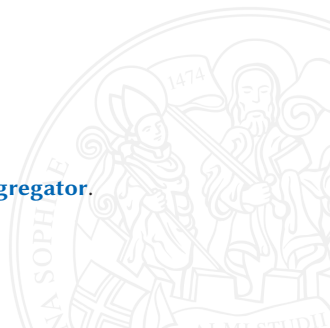
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- (v) $f(0, c, v) \in L_t$ whenever $c, v \in L_t$.

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Recursive Utility Process

The **recursive utility process** $V^N = \{V_k^N\}_{k \in \{0, \dots, N\}}$ is defined as

$$V_N^N \triangleq \xi,$$

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Stochastic Differential Utility Process

The **stochastic differential utility process** $V = \{V_t\}_{t \in [0, T]}$ is defined as the unique solution of the BNEE

$$V_t \triangleq \mathcal{E}_t \left[\int_t^T f(0, c_s, V_s) ds + \xi \right] \quad \text{for all } t \in [0, T].$$

The Convergence Result

Theorem

The recursive utility processes V^N converge to the stochastic differential utility process V in the sense that

$$\max_{k=0, \dots, N} \|V_k^N - V_{t_k^N}\|_L \rightarrow 0 \quad \text{as } N \rightarrow \infty.$$

In particular, the utility indices converge:

$$v_N(c^N, \xi) \triangleq V_0^N = V_0 \triangleq v(c, \xi).$$

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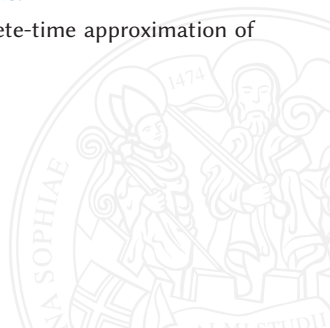
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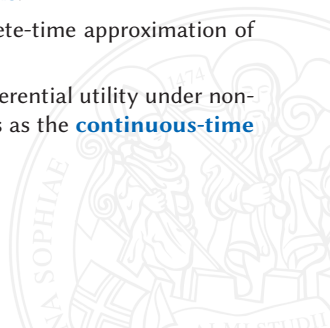
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- (4) We study existence, uniqueness, stability and discrete-time approximation of BNEEs.
- (5) We justify the axiomatic definition of stochastic differential utility under nonlinear expectations by identifying the utility process as the **continuous-time limit** of the discrete-time recursive utility process.



Thanks for your attention!

Belak, Seiferling, and Seifried (2016):
Backward Nonlinear Expectation Equations

Available at: www.belak.ch/publications/

