

# Optimal Revealed Utilities and Convex Pricing kernels:

A Forward Point of view of convexity propagation

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# Regular utility function $u$ and its conjugate

A regular utility function  $u$  is a

- ▶ (concave, increasing, positive) function on  $[0, \infty)$ , with  $u(0) = 0$ .
- ▶ Inada condition on its derivative  $u_z$ :  $u_z(+\infty) = 0$ ,  $u_z(0) = \infty$ .
- ▶ power utility  $u(z) = \frac{z^{1-\alpha}}{1-\alpha}$ ,  $\alpha < 1$ , with conjugate  $-\tilde{u}_y(y) = y^{-1/\alpha}$

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The convex decreasing conjugate utility  $\tilde{u}$  and Legendre inequalities

- ▶  $\tilde{u}(y) = \sup_{x>0} (u(x) - xy)$ , with  $u'_x(x^*) = y$ ,
- ▶  $\tilde{u}(y) = u(-\tilde{u}_y(y)) + y\tilde{u}_y(y)$ ,  $u(x) = x u_x(x) - \tilde{u}(u_x(x))$
- ▶ Legendre inequality:  $\tilde{u}(y) - u(x) - xy \geq 0 \forall (x, y) > 0$

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A dynamic utility on  $(\Omega, \mathbb{P}, (\mathcal{F}_t))$

- ▶ is a family of optional random field  $U = \{U(t, z), z \in \mathbb{R}^+\}$
- ▶ such that  $\forall t, (z \rightarrow U(t, z))$  is a standard utility function.
- ▶ Its conjugate is the field  $\tilde{U} = \{\tilde{U}(t, y), y \in \mathbb{R}^+\}$

## Definition Gap function (G.Charlier)

- ▶ Let  $(u, \tilde{u})$  be a pair of conjugate utility functions ( $\bar{R}^+ \rightarrow \bar{R}^+$ )
- ▶ The bivariate Gap function,  $G_u(x, y) = \tilde{u}(y) - u(x) + xy \geq 0$
- ▶ Fenchel:  $G_u(x, u_x(x)) = 0, \forall x > 0$
- ▶ Convex in each argument  $(x, y)$  (separately), with  $x$ -derivative  $-u_x(x) + y$ .

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## Integral Gap function and minimization

- ▶ Let  $\mu$  be a probability measure and  $Z \geq 0$  a r.v. with finite mean (or barycentre)  $b_\mu = \mathbb{E}_\mu(Z) < +\infty$ .
- ▶  $\mathbb{E}_\mu(G_u(Z, y)) = G_u(b_\mu, y) + \mathbb{E}_\mu(u(Z)) - u(\mathbb{E}_\mu(Z))$
- ▶ The maximum in  $y$  is  $\mathbb{E}_\mu(u(Z)) - u(\mathbb{E}_\mu(z))$ , attained at  $u_x(b_\mu)$ .

## Decision making under uncertainty

- ▶ Most of decision making focuses on the selection of optimal sequence of actions given **preferences** criterium
  - ▶ In economy and finance the preferences are based on **expected utility (concave criterium)** of some terminal value, or its robust extension.
  - ▶ **Backward point of view**
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## Decision making in e-commerce

- ▶ Learning based on observed data, over the time.
- ▶ Preferences of the agent are "estimated" in view to propose an optimal offer
- ▶ **Forward point of view**

## Samuelson (1930) C.P. Chambers

- ▶ Samuelson (1930) "Theory of revealed preference"
- ▶ Chambers : *"We can never see a utility function, but what we might be able to see are demand observations at a finite list of prices."*

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## Forward stochastic utilities(2002-2009) Musiela, Zariphopoulou

- ▶ Preferences are defined in **isolation** to the investment universe
- ▶ How use intertemporal **diversification**, (short, medium, long term strategies). With which utility function ?
- ▶ At the optimum the investor should become **indifferent** to the investment horizon.

## A backward toy model with conjugacy

- ▶ **Data:** utility concave function  $u$ , its conjugate  $\tilde{u}$ , a horizon  $T$ ,  $\mathcal{X}$  a convex family of r.v.  $X_T$ ,
- ▶  $\{Y_t \geq 0\}$  a state price process with  $\mathbb{E}(X_T Y_T) \leq X_0 Y_0, \forall X_T \in \mathcal{X}$ .
- ▶ **Optimization problem**  $\max\{\mathbb{E}(u(X_T)) | X_T \in \mathcal{X}\}$ , with budget constraint  $\mathbb{E}(Y_T X_T) \leq x$ .

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## Solution of the problem via Lagrange multiplier and conjugate

- ▶ Equivalent Pb:  $\max\{\mathbb{E}(u(X_T) + y(x - Y_T X_T)) | X_T \in \mathcal{X}\} = U_0(x, y)$
- ▶ If  $-\tilde{u}_y(y Y_T) \in \mathcal{X}$ , then optimum is  $X_T^* = -\tilde{u}_y(y Y_T)$
- ▶  $y$  is selected by  $\mathbb{E}[-\tilde{u}_y(y Y_T) Y_T] = x$
- ▶  $\tilde{U}_0(y) = \mathbb{E}[\tilde{u}(y Y_T)]$  decreasing convex conjugate utility in  $y$ .
- ▶ Its conjugate at 0,  $U_0(x)$  is an increasing concave function.

# Forward recovery bi-revealed utility problem

without optimization and control problem

# Observed process and Choice of an adjoint process

To recover  $\{U(t, z)\}$ , the observable also must depend on  $z$

## The data

- ▶ An initial condition  $U(0, z) = u(z)$  a given utility function
- ▶ An observed (data) positive adapted random field,  $X = \{X_t(x)\}$ ,
- ▶ The optimal adequation between  $\{U(t, z)\}$  and  $\{X_t(x)\}$  is the requirement that  $\{U(t, X_t(x))\}$  is a martingale for any  $x$ .

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To limit the size of family of dynamic utilities coherent with the data  $X$ , we add constraints on the conjugate utility  $\{\tilde{u}(t, y)\}$  via an other family.

- ▶  $Y = \{Y_t(y)\}$  of positive adjoint process,
- ▶ Orthogonal to  $\{X_t(x)\}$  s.t  $X_t(x)Y_t(y)$  is a supermartingale  $\forall(x, y)$
- ▶ Coherent-optimal to  $\tilde{u}(t, y)$ , that is  $\tilde{u}(t, Y_t(y))$  is a martingale.



# Examples of bi-revealed problems

The constant case  $X_t(x) = x$

- ▶  $\{U(t, x)\}$  is a revealed utility "if and only" if
- ▶ its marginal utility  $\{U_z(t, x)\}$  is a martingale.
- ▶ Then,  $U$  is bi-revealed, by two constant process

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Linear characteristic process  $X_t(x) := xX_t(1) = x X_t$

- ▶ Use  $X_t$  as numeraire and define  $U^X(t, z) = U(t, zX_t)$ , a martingale with characteristic process  $x$
- ▶ Then "  $U_z^X(t, z) = X_t U_z(t, zX_t) = X_t Y_t(u_z(z))$  is a martingale"
- ▶  $U$  is a bi-revealed utility

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Power utility:  $u(z) = z^{1-\alpha}/(1-\alpha)$

- ▶ Then,  $U'_z(t, z) = Y_t(u_z(z/X_t))$ , and if  $u$  is a **power utility**, then  $U$  is a power utility, if and only if  $Y$  is **linear**

## Bi-revealed utility problem

How to express on  $(X_t(x), Y_t(y))$  and the previous (sur)-martingales conditions, that  $\tilde{u}$  is the conjugate of  $U$ .

$$\tilde{u}(y) - u(x) + xy \geq 0, \text{ with equality for } y = u_x(x)$$

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## Pathwise First order condition

- ▶ A system is bi-revealed system, iff
  - A Pathwise first order condition holds  $Y_t(u_x(x)) = U_z(t, X_t(x))$
  - $\{X_t(x)Y_t(u_x(x))\}$  is a martingale
- ▶ Sketch of the proof: Thanks to martingale-surmartingales conditions, and Legendre inequalities
  - $0 \leq \mathbb{E}[\tilde{u}(\tau, Y_\tau(y)) - U(\tau, X_\tau(x) + Y_\tau(y)X_\tau(x))] \leq \tilde{u}(y) - u(x) + xy$
  - For  $y = u_x(x)$ , by Fenchel, the left and right sides are 0, as the non negative function on the expectation are 0
  - By strict monotony, first order condition:  $Y_t(u_x(x)) = U_z(t, X_t(x))$

The utility  $U$  is bi-revealed by the triplet  $(u, X, Y)$  iff (approx)

- ▶  $\forall(x, y), \{X_t(x)Y_t(y)\}$  is a **supermartingale**
- ▶  $\{X_t(x)Y_t(u_z(x))\}$  is a **martingale**
- ▶ First order  $U_x(X_t(x)) = Y_t(u_x)$

Asymptotic behavior and intrinsic behavior

▶ **Limit Conditions**

- $\lim_{x \rightarrow 0} \frac{X_t(x)}{x} = \Lambda_t^X > 0$  and  $\lim_{y \rightarrow \infty} \frac{Y_t(y)}{y} = H_t^Y > 0$ ,
- $L_t^{\text{int}} = \Lambda_t^X H_t^Y$ ,  $L_0^{\text{int}} = 1$  is a  $\mathbb{P}$ -martingale.

▶ **The intrinsic universe:**

- Change of proba :  $d\mathbb{Q}^{\text{int}} = L_T^{\text{int}} \cdot d\mathbb{P}$ ,
- Change of numeraire  $X_t^{\text{int}}(x) = X_t(x)/\Lambda_t^X$ ,  $Y_t^{\text{int}}(y) = Y_t(y)/H_t^Y$

▶  **$\mathbb{Q}^{\text{int}}$ - Supermartingale properties**

- $\{X_t^{\text{int}}(x)\}, \{Y_t^{\text{int}}(y)\}, \{X_t^{\text{int}}(x)Y_t^{\text{int}}(y)\}$  are  $\mathbb{Q}^{\text{int}}$ -supermartingales.
- Preference for the present with  $\{U(t, z)\}$   $\mathbb{Q}^{\text{int}}$ -supermartingale

## Pathwise Utility construction

Hyp  $x \rightarrow X_t(x)$  is strictly increasing in  $x$  with range  $[0, \infty)$ ,

- ▶  $U_z(t, z) = Y_t(u_z(X_t^{-1}(z)))$ ,  $U(t, x) = \int_0^x Y_t(u_z(X_t^{-1}(z))) dz$
- ▶ Why  $U(t, X_t(x)) = \int_0^x Y_t(u_z(z)) d_z X_t(z)$  is a "martingale" ?
  - This last integral is a Stieljes integral, with explosion near to  $z = 0$
  - One to one algebraic bijection between  $(u, X, U)$  and  $(u, X, Y)$

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## Exemple of Differentiable characteristic process

- ▶ Assume  $x \mapsto X_t(x)$  to be  $x$ -differentiable with differential  $X_x(t, x)$ .
- ▶  $U(t, X_t(x))$  is given by  $U(t, X_t(x)) = \int_{(0, x]} Y_t(u_x(z)) X_x(t, z) dz$
- ▶ Under some "regularity", the  $U$ -martingale condition is equivalent to  $\{Y_t(u_x(x))X_x(t, x)\}$  is martingale
- ▶ In the bi-revealed case,  $\{Y_t(u_x(x))X_x(t, x)\}, \{Y_t(u_x(x))X_t(x)\}$  are martingales

In the general case, similar argument from Darboux sums

## Application to Itô's framework

$(\Omega, (\mathcal{F}_t), \mathbb{P})$  is equipped with a  $d$ -dimensional Brownian motion  $(W_t)$

Random field SDEs  $(\mu_t(z), \sigma_t(z))$ ,

$$\text{SDE form: } dX_t(x) = \mu_t^X(X_t(x))dt + \sigma_t^X(X_t(x)).dW_t, \quad X_0 = x$$

$$\text{Random Field } dX_t(x) = \beta^X(t, x)dt + \gamma^X(t, x).dW_t, \quad X_0 = x$$

$$\text{Parameter/Coeff } \gamma^X(t, x) = \sigma_t(X_t(x)) \quad \beta^X(t, x) = \mu_t(X_t(x))$$

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## Comments

- ▶ The SDE point of view is better suited for problem related to comparison
- ▶ RF Point of view is better suited to differentiability issues.
- ▶ All results are based on a strong differential regularity of coefficients or parameters, detailed in SIAM paper(2013)

## Itô Ventzel Formula for semimartingale $Z$

- ▶ A  $\mathcal{K}_{loc}^2$ -Itô semimartingale RF  $F(t, z)$ ,  $(\beta^F, \gamma^F)$ .
- ▶  $dF(t, Z_t) = \beta^F(t, Z_t)dt + \gamma^F(t, Z_t).dW_t$
- ▶  $+F_z(t, Z_t)dZ_t + \frac{1}{2}F_{zz}(t, Z_t)\langle dZ_t \rangle + \langle \gamma_z^F(t, Z_t).dW_t, dZ_t \rangle$

## Second formulation

- ▶  $dF(t, z) = \beta^F(t, z)dt + \gamma^F(t, z).dW_t = d_t F(t, z)|_{z=Z_t}$   
 $dF_z(t, z) = \beta_z^F(t, z)dt + \gamma_z^F(t, z).dW_t$ .
- ▶ Then,  $dF(t, Z_t) =$   
 $d_t F(t, z)|_{z=Z_t} - \frac{1}{2}F_{zz}(t, Z_t)\langle dZ_t \rangle + d(F_z(t, Z_t)Z_t) - Z_t dF_z(t, Z_t)$

## Bi-revealed utilities

- ▶  $dU(t, X_t(x)) = \gamma^U(t, X_t(x)).dW_t + d(U_z(t, X_t(x))X_t(x))$
- ▶  $+ \beta^U(t, X_t(x))dt - \frac{1}{2}U_{zz}(t, X_t(x)\langle dX_t(x) \rangle - X_t(x)dY_t(u_z(x))$

- ▶  $X$  regular solution of SDE  $(\mu^X, \sigma^X)$  with inverse flow  $\{\xi(t, z)\}$
- ▶  $Y$  regular solution of SDE  $(\mu^Y, \sigma^Y)$  decoupled of  $X$
- ▶ **suborthogonality** :  $z\mu_t^Y(y) + y\mu_t^X(x) + \langle \sigma_t^X(x), \sigma_t^Y(y) \rangle \leq 0$ ,

## $U$ differential coefficients

$$\gamma_z^U(t, z) = \sigma_t^Y(U_z(t, z)) - U_{zz}(t, z)\sigma_t^X(z).$$

$$\beta^U(t, z) = \frac{1}{2}U_{zz}(t, z)\|\sigma_t^X(z)\|^2 + z\mu_t^Y(U_z(t, z)) \quad \text{or}$$

$$\beta^U(t, z) + \langle \gamma_z^U(t, z), \sigma_t^X(z) \rangle = -\left[\frac{1}{2}U_{zz}(t, z)\|\sigma_t^X(z)\|^2 + U_z(t, z)\mu_t^X(z)\right].$$

In the intrinsic case,  $\mu_t^Y(y) \leq 0$ ,  $\beta^U(t, z) \leq 0$  and  $U(t, z)$  is a supermartingale



Generally utility criteria are associated with optimization problem;

General utility of test process:  $dZ_t = \phi_t^Z dt + \psi_t^Z \cdot dW_t$

- ▶  $dU(t, Z_t) =$   
 $\frac{1}{2} U_{zz}(t, Z_t) \|\sigma_t^X(Z_t) - \psi_t^Z\|^2 dt + \gamma^U(t, Z_t) + U_z(t, Z_t) \psi_t^Z \cdot dW_t$   
 $+ [Z_t \mu_t^Y(U_z(t, Z_t)) + U_z(t, Z_t) \phi_t^Z + \langle \sigma_t^Y(U_z(t, Z_t)), \psi_t^Z \rangle] dt$
- ▶ The last term is the drift of the product  $\{Z_t Y_t(y)\}$  taken at  $y = U_z(t, Z_t)$ , negatif for  $\{Z_t Y_t(y)\}$  supermartingale

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## Controlled processes

- ▶ A controlled process  $Z$  is suborthogonal to  $\{Y_t(y), \forall y\}$ , that is  $Z_t Y_t(y)$  is supermartingale (ex  $X_t(x)$ )
- ▶ A controlled process  $Z$  is **suboptimal**
  - $U(t, Z_t)$  is a supermartingale.
  - $U(t, Z_t)$  is a martingale iff  $Z$  is a solution of the SDE( $\mu, \sigma$ ).

# Applications to convex pricing forward dynamics

Work in progress

## Stephane Comment

- ▶ OK, it is interesting, but utility framework is not so useful in practice, in mathematical finance
- ▶ Pricing problems are more challenging, even the more classical with convex pay-off  $h$ .
- ▶ In particular, given a price derivative today how simulate coherent price in the future

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- ▶ Very similar to utility problem where concave is replaced by convex
  - ▶ But, only if the price today of convex derivative is a convex function.

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A old question studied with S.Shreve and M.Jeanblanc in 1995

## Classical BS Formula

- ▶  $X_t(x)$  = Geometric Brownian motion =  $xX_t(1)$
- ▶ Option pay-off = Target =  $h(T, X_T(x))$
- ▶  $h$  convex option, positive, (nondecreasing)
- ▶ Intrinsic universe:  $(\Omega, (\mathcal{F}_t), \mathbb{Q})$

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## BS Formula

- ▶ By change of numeraire, and probability measure,  $X_t(x)$  can be assumed to be  $\mathbb{Q}$  martingale
- ▶  $X_t = x \exp(\sigma W_t^{\mathbb{Q}} - \frac{1}{2}\sigma^2 t) = xL_T$
- ▶ The pricing rule is risk-neutral, that is
$$BS(h)(x, T) = \mathbb{E}_{\mathbb{Q}}(h(xL_T)) = \Phi_h(0, x) = \Phi_h(x)$$
- ▶  $BS(h)(x)$  is a convex function  $\Phi_h(x)$  with  $\Phi_h(T, x) = h(x)$

## Model with local volatility in risk neutral universe

- ▶  $dX_t = X_t(\sigma(t, X_t)dW_t^Q), \quad X_0 = x$
- ▶  $\gamma(t, x) = x\sigma(t, x)$
- ▶  $\sigma(t, x)$  continuous and bounded above
- ▶  $\partial_x \gamma(t, x)$  is continuous in  $(t, x)$  and Lipschitz continuous and bounded in  $x$  uniformly in  $t$

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**Theorem** The European price  $\Phi_h(0, x) = \mathbb{E}_Q(h(X_T(x)))$  is a convex function, with bounded derivatives

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Then, it is possible to adapt the “machinery” of concave utility.

Que Sau, God of health and longevity



Te garde sous son regard bienveillant  
**Merci pour tout, Denis...**