

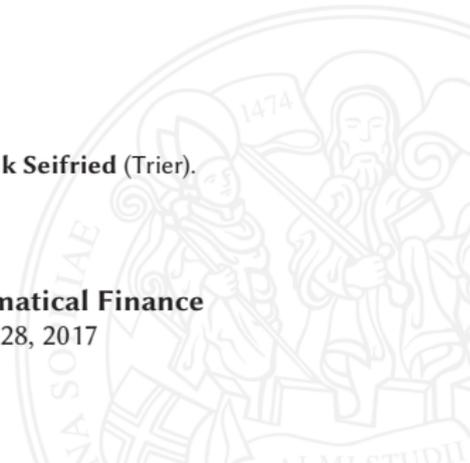
Non-Smooth Verification for Impulse Control Problems

Christoph Belak

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University of Trier
Germany

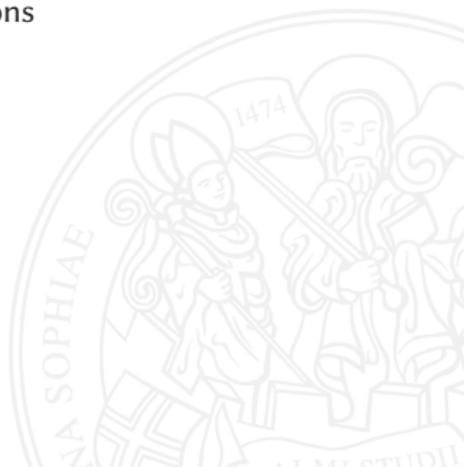
Joint work with **Sören Christensen** (Hamburg) and **Frank Seifried** (Trier).

Byrne Young Researcher Workshop on Mathematical Finance
University of Michigan, Ann Arbor, March 28, 2017



Outline

- (1) Motivation: Portfolio Optimization with Proportional and Constant Costs
- (2) The General Impulse Control Problem
- (3) Non-Smooth Verification via Superharmonic Functions
- (4) Application to the Transaction Cost Problem



Portfolio Optimization with Transaction Costs



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- τ_k denotes the **time** of the k th transaction (stopping time),
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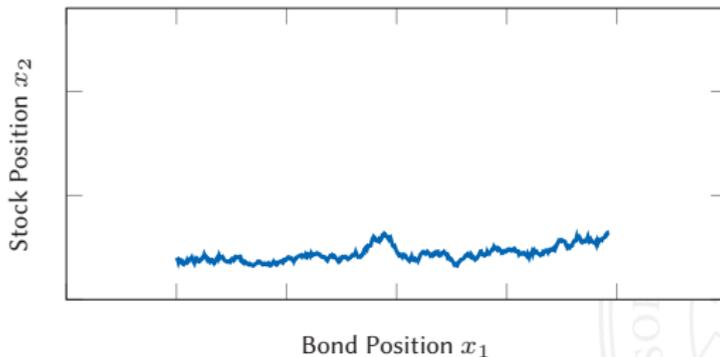


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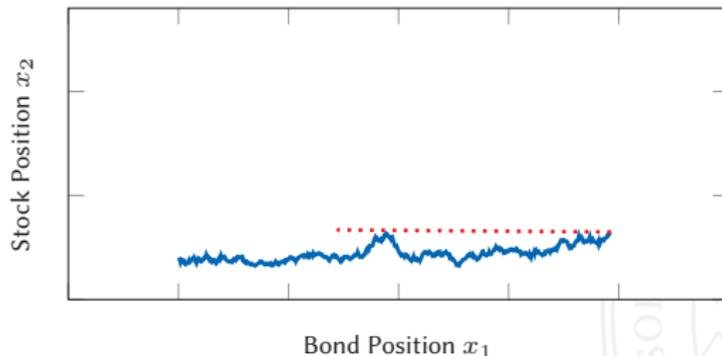


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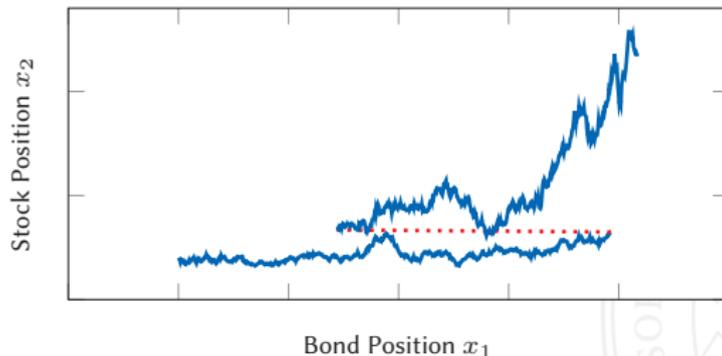


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Related Literature

The case of **purely proportional costs** is very well understood:
Davis and Norman (1990), Shreve and Soner (1994), Kallsen and Muhle-Karbe (2010),
Czichowsky and Schachermayer (2015, 2016), ...



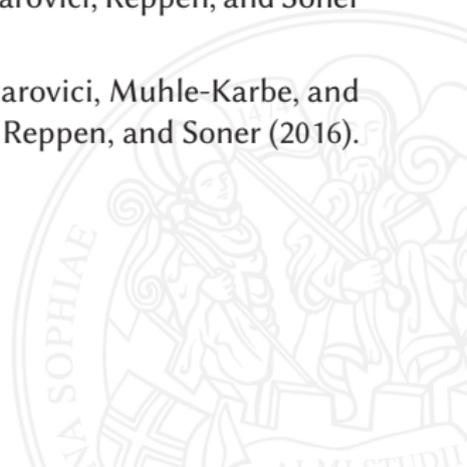
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Existing literature involving **constant costs**:

- **Classical verification**: Eastham and Hastings (1988), Korn (1998), Bielecki and Pliska (2000), Liu (2004).
- **Viscosity solutions**: Øksendal and Sulem (2002), Altarovici, Reppen, and Soner (2016).
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To the best of our knowledge, existence of optimal controls is **unknown** — even in a Black-Scholes setting with log- or power utility.

The General Impulse Control Problem



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Consider an \mathbb{R}^n -valued **system** $X = X^\Lambda$ controlled by an **impulse control** $\Lambda = \{(\tau_k, \Delta_k)\}_{k \in \mathbb{N}}$ as follows:

$$\begin{aligned}dX(t) &= \mu(X(t))dt + \sigma(X(t)) dW(t), & t \in [\tau_k, \tau_{k+1}), \\X(\tau_k) &= \Gamma(X(\tau_k^-), \Delta_k),\end{aligned}$$



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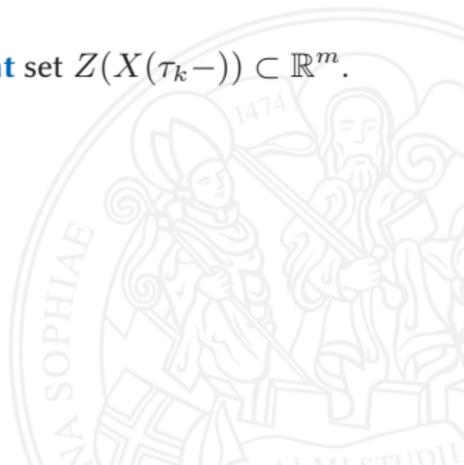
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- the stopping times τ_k are **increasing** and **do not accumulate** in that

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The **objective** is to find a maximizer of

$$\mathcal{V}(t, x) = \sup_{\Lambda \in \mathcal{A}(t, x)} \mathbb{E} \left[\sum_{k \in \mathbb{N}} K(X_{t,x}^\Lambda(\tau_k-), \Delta_k) \mathbf{1}_{\{\tau_k \leq T\}} + g(X_{t,x}^\Lambda(T)) \right].$$

The Quasi-Variational Inequalities

The martingale optimality principle of stochastic control suggests that the value function \mathcal{V} can be linked to the **quasi-variational inequalities** (QVIs)

$$\begin{aligned} \min\{-\partial_t \mathcal{V} - \mathcal{L}\mathcal{V}, \mathcal{V} - \mathcal{M}\mathcal{V}\} &= 0 && \text{on } [0, T) \times \mathbb{R}^n, \\ \mathcal{V}(T, \cdot) &= g && \text{on } \mathbb{R}^n, \end{aligned}$$



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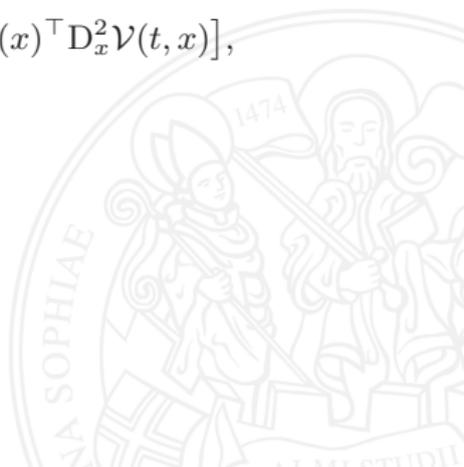
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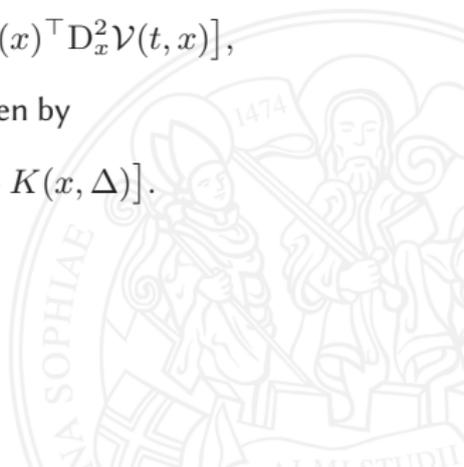
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- and the operator \mathcal{M} is the **maximum operator** given by

$$\mathcal{M}\mathcal{V}(t, x) \triangleq \sup_{\Delta \in Z(x)} [\mathcal{V}(t, \Gamma(x, \Delta)) + K(x, \Delta)].$$



A Candidate Optimal Control

Observe that

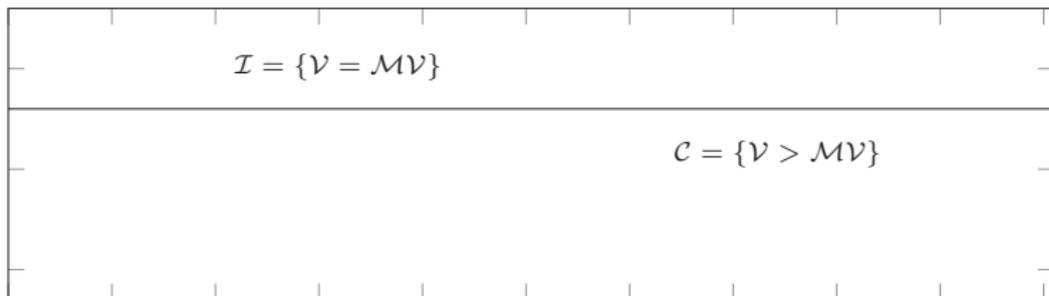
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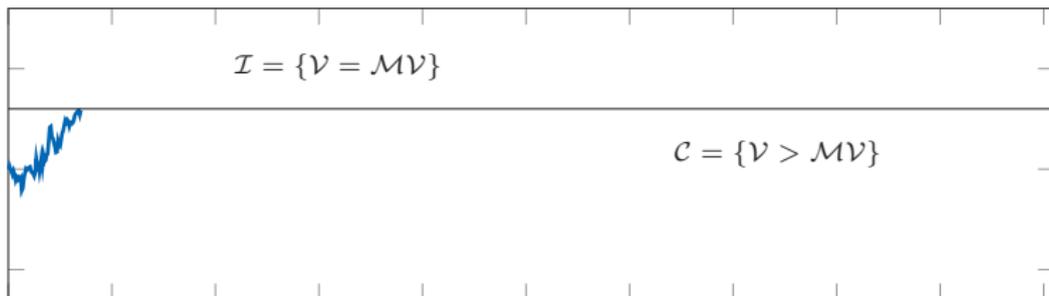
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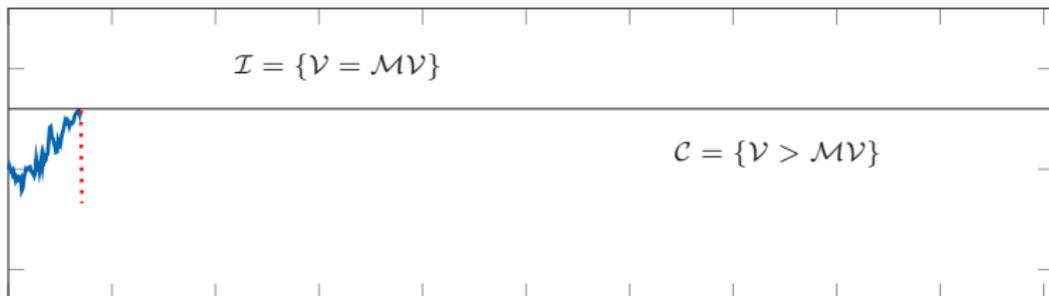
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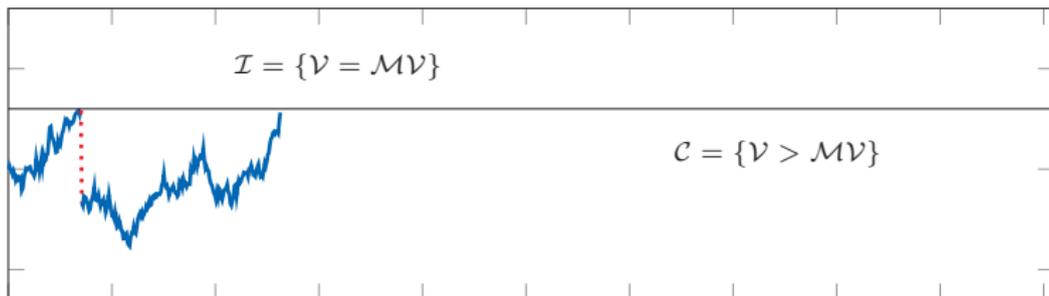
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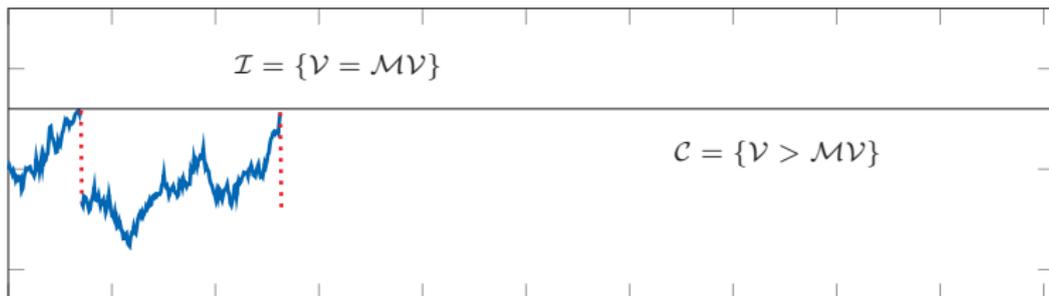
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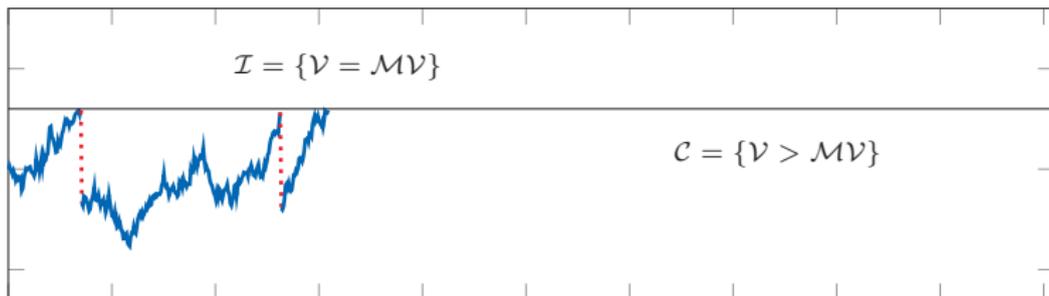
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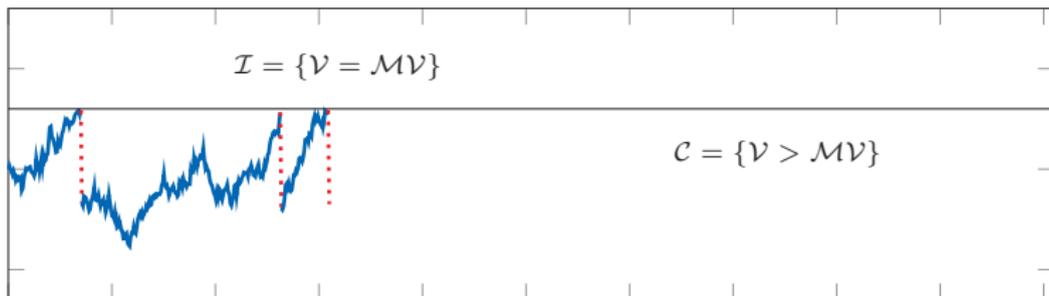
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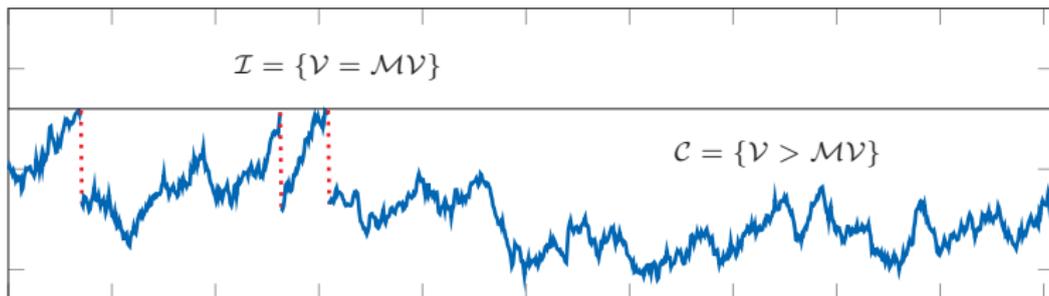
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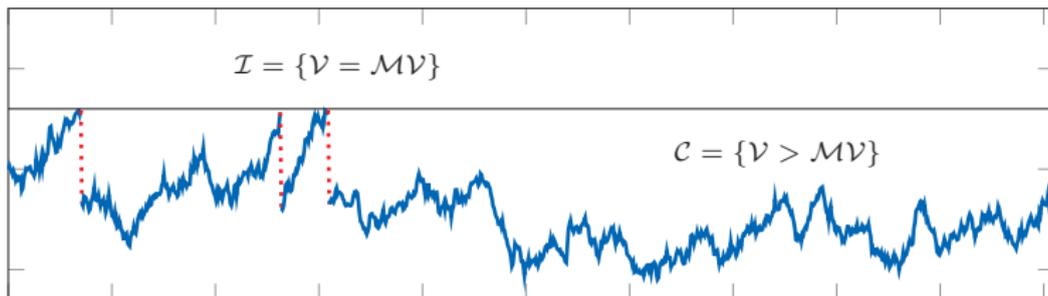
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Problem: Verification requires a solution of the QVIs which is sufficiently smooth to apply Itô's formula.

Non-Smooth Verification via Superharmonic Functions



A Formal Optimal Stopping Problem

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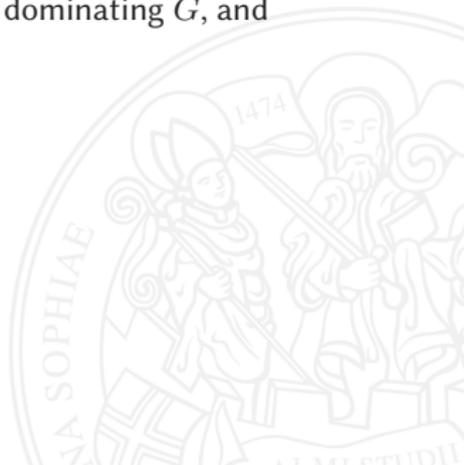
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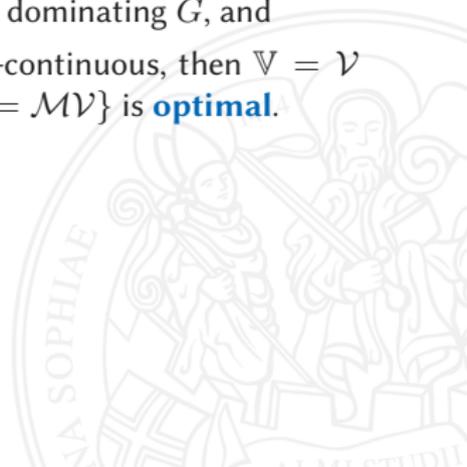
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Remark: Under standard assumptions, $G = \mathcal{M}\mathbb{V}$ is upper semi-continuous if \mathbb{V} is upper semi-continuous. That is, to verify optimality, continuity of \mathbb{V} should suffice!

The Verification Theorem

Let \mathbb{H} be the set of **upper semi-continuous** functions $h : [0, T] \times \mathbb{R}^n \rightarrow \mathbb{R}$ with

(H1) h is **superharmonic** with respect to the uncontrolled state process,

(H2) h **dominates the reward**, i.e. $h \geq \mathcal{M}h$,

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Note: If \mathcal{V} is known to be continuous, then $\mathcal{V} \in \mathbb{H}$ and things become easy.

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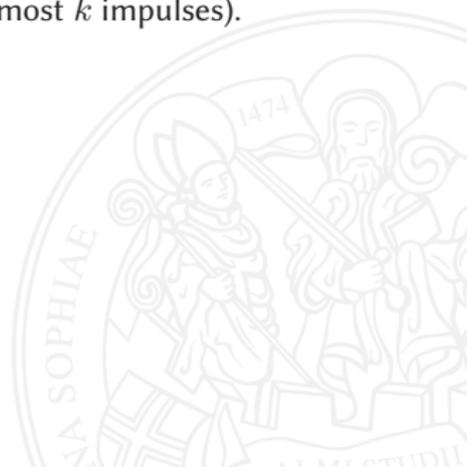


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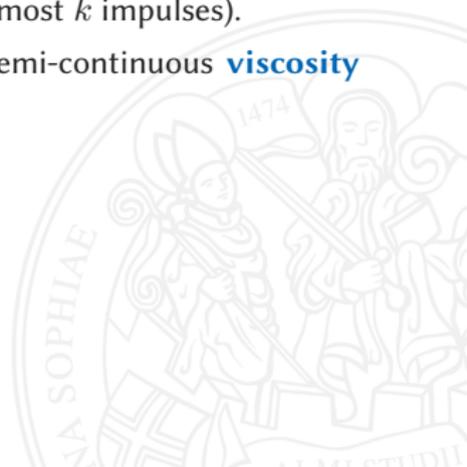


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- (3) Show that the limit $\mathfrak{V} \triangleq \lim_{k \rightarrow \infty} v_k$ is a lower semi-continuous **viscosity supersolution** of the QVIs.



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How can we prove the continuity of \mathcal{V} ?

We adapt the **Stochastic Perron Method** of Bayraktar and Sirbu:

- (1) Show that \mathbb{V} is an upper semi-continuous **viscosity subsolution** of the QVIs.
- (2) Approximate \mathcal{V} from below by a sequence $\{v_k\}_{k \in \mathbb{N}}$ of **iterated optimal stopping problems** (by restricting to the problem to at most k impulses).
- (3) Show that the limit $\mathfrak{V} \triangleq \lim_{k \rightarrow \infty} v_k$ is a lower semi-continuous **viscosity supersolution** of the QVIs.
- (4) Then $\mathfrak{V} \leq \mathcal{V} \leq \mathbb{V}$. Now apply viscosity comparison so that $\mathfrak{V} \geq \mathbb{V}$ and hence

$$\mathcal{V} = \mathbb{V} = \mathfrak{V}$$

is **continuous** and the **unique viscosity solution** of the QVIs.

Sufficient Conditions

Our procedure is based on **three ingredients**:

- Superharmonic function techniques in optimal stopping
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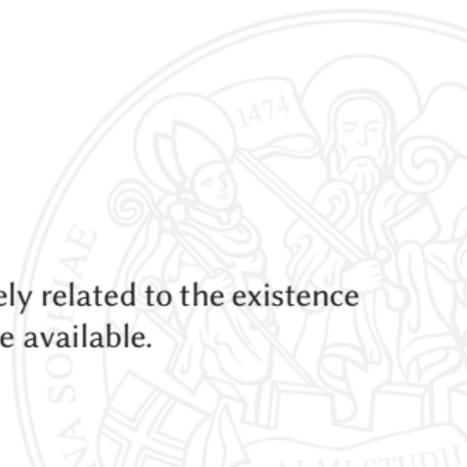
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Note: The existence of Ψ and viscosity comparison is closely related to the existence of a strict supersolution of the QVIs. Candidates for Ψ are available.



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- Proving **admissibility** can be difficult and has to be done case-by-case.
- **Advantage** over the classical approach: The candidate optimal control is defined in terms of the value function, making it easier to verify admissibility (at least in principle).



Solving the Transaction Cost Problem



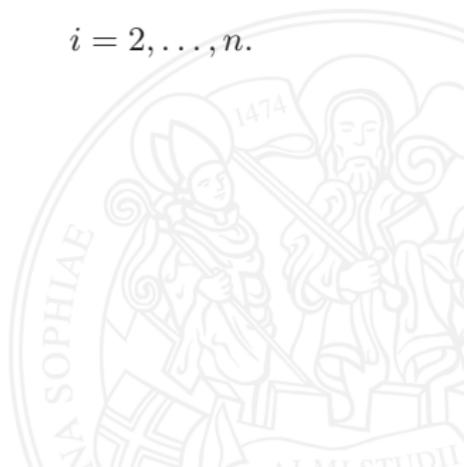
The Market Model

We assume that the portfolio $X = \{X(t)\}_{t \in [0, T]}$ evolves as

$$\begin{aligned}dY(t) &= \alpha(Y(t))dt + \beta(Y(t))dW(t), & t \in [0, T], \\dX(t) &= \text{diag}(X(t))[\mu(Y(t))dt + \sigma(Y(t))dW(t)], & t \in [\tau^k, \tau^{k+1}), \\X(\tau^k) &= \Gamma(X(\tau^k -), \Delta^k),\end{aligned}$$

where $\Gamma(x, \Delta) = \xi$ with

$$\begin{aligned}\xi_1 &= x_1 - \sum_{j=2}^n [\Delta_j + \gamma_j |\Delta_j| + K_j] \mathbb{1}_{\{\Delta_j \neq 0\}}, \\ \xi_i &= x_i + \Delta_i, & i = 2, \dots, n.\end{aligned}$$



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A portfolio $x \in \mathbb{R}^n$ is **solvent** if it has a **positive liquidation** value $L(x)$, i.e.,

$$L(x) \triangleq x_1 + \sum_{j=2}^n [x_j - \gamma_j |x_j| - K_j] > 0.$$

The set $\mathcal{S} \subset \mathbb{R}^n$ of solvent portfolios is called the **solvency region**.

The Optimization Criterion

Now fix a **utility function** $U : \mathbb{R}_+ \rightarrow \mathbb{R}$ such that

- U is strictly increasing and continuous (not necessarily concave),
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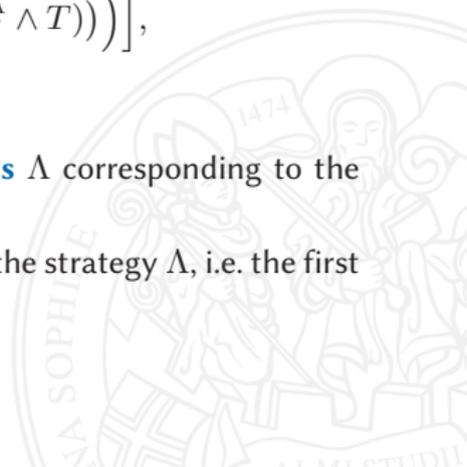
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The objective is to **maximize utility of terminal wealth**, i.e.

$$\mathcal{V}(t, x, y) = \sup_{\Lambda \in \mathcal{A}(t, x, y)} \mathbb{E} \left[U \left(L(X_{t,x,y}^\Lambda(\tau_S^\Lambda \wedge T)) \right) \right],$$

where

- $\mathcal{A}(t, x, y)$ denotes the set of **admissible strategies** Λ corresponding to the initial state (t, x, y) .
- τ_S^Λ denotes the **bankruptcy time** corresponding to the strategy Λ , i.e. the first exit time of $X_{t,x,y}^\Lambda$ from the solvency region \mathcal{S} .



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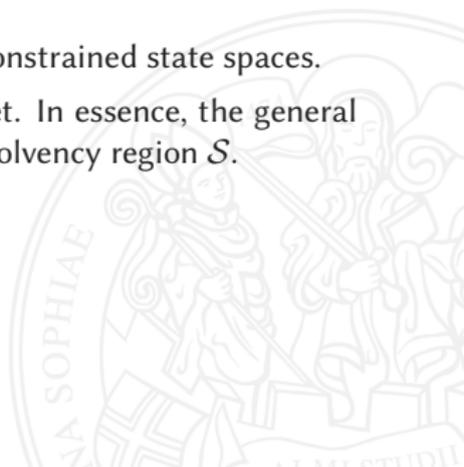
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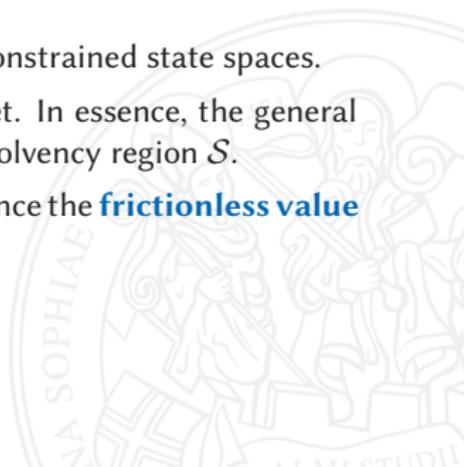
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- Admissibility of the candidate optimal strategy can be verified. **Idea**: The investor goes bankrupt before the trading times accumulate.

Conclusion and Outlook



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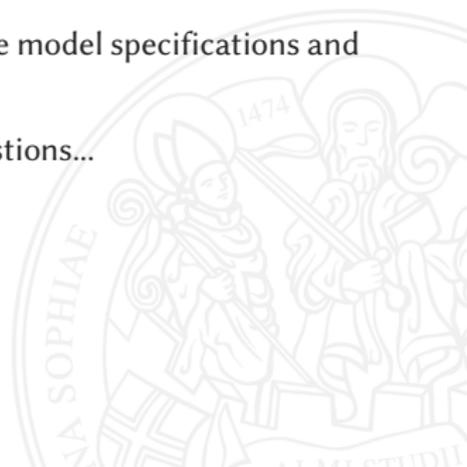
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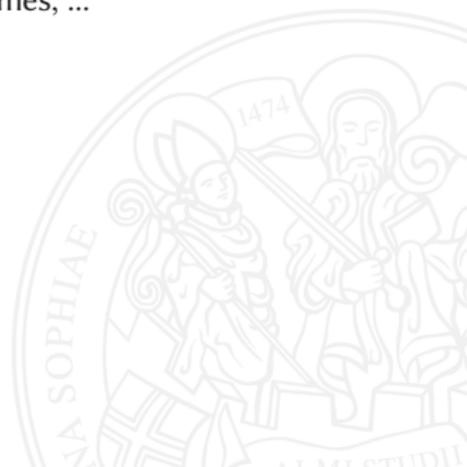
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Thanks for your attention!

