

Martingale Representation Theorem for the G -expectation

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Abstract

This paper considers the nonlinear theory of G -martingales as introduced by Peng in [14, 15]. A martingale representation theorem for this theory is proved by using the techniques and the results established in [18] for the second order stochastic target problems and the second order backward stochastic differential equations. In particular, this representation provides a hedging strategy in a market with an uncertain volatility.

Key words: G -expectation, G -martingale, nonlinear expectation, stochastic target problem, singular measure, BSDE, 2BSDE, duality.

AMS 2000 subject classifications: 60H10, 60H30.

1 Introduction

The notion of a G -expectation as recently introduced by Peng [14, 15] has several motivations and applications. One of them is the study of financial problems with uncertainty about the volatility. This important problem was also considered earlier by Denis & Martini [3]. Motivated by this application, Denis & Martini developed an almost pathwise theory of stochastic calculus. In this second approach, probabilistic statements are required to hold *quasi surely*: namely \mathbb{P} -almost surely for all probability measures \mathbb{P} from a large class of mutually singular measures \mathcal{P} . Denis & Martini employ functional analytic techniques while Peng's approach utilizes the theory of viscosity solutions of parabolic partial differential equations.

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Indeed, the G -expectation is defined by Peng using the nonlinear heat equation,

$$-\partial_t u - G(D^2 u) = 0 \quad \text{on } [0, 1),$$

where the time maturity is taken to be $T = 1$ and for given symmetric matrices $\bar{a} > 0$ and $0 \leq \underline{a} \leq \bar{a}$, the nonlinearity G is defined by,

$$G(\gamma) := \frac{1}{2} \sup\{\operatorname{tr}[\gamma a] \mid \underline{a} \leq a \leq \bar{a}\}. \quad (1.1)$$

Then for ‘‘Markov-like’’ random variables, the G -expectation and conditional expectations are defined through the solution of the above equation with this random variable as its terminal condition at time $T = 1$. A G -martingale is then defined easily as a process which satisfies the martingale property by this conditional expectation. A brief introduction to this theory is provided in Section 2 below.

Denis & Martini [3] also construct a similar structure of quasi-sure stochastic analysis. However, they use a quite different approach which utilizes the set \mathcal{P} of all probability measures \mathbb{P} so that the canonical map in the Wiener space is a martingale under \mathbb{P} and the quadratic variation of this martingale lies between $\underline{a} \leq \bar{a}$. Although the constructions of the quasi sure analysis and the G -expectations are substantially different, these theories are very closely related as proved recently by Denis, Hu & Peng [4]. The paper [4] also provides a dual representation of the G -expectation as the supremum of expectations over \mathcal{P} .

A probabilistic construction similar to quasi-sure stochastic analysis and G -expectations, is the theory of second order backward stochastic differential equations (2BSDE). This theory is developed in [1, 2, 16] as a generalization of BSDEs as initially introduced in [6, 12]. In particular, 2BSDEs provide a stochastic representation for fully nonlinear partial differential equations. Since the G -expectation is defined through such a nonlinear equation, one expects that the G -expectations are naturally connected to the 2BSDEs. Equivalently, 2BSDEs can be viewed as the extension of G -expectations to more general nonlinearities. Indeed, recently the authors developed such a generalization and a duality theory for 2BSDEs using probabilistic constructions similar to quasi-sure analysis [17, 18, 19].

In this paper, we investigate the question of representing an arbitrary G -martingale in terms of stochastic integrals and other processes. Specifically, we fix a finite horizon say $T = 1$. Since all martingales can be seen as the conditional expectation, we also fix the final value ξ . We then would like to construct stochastic processes H and K so that

$$Y_t := \mathbb{E}_t^G[\xi] = \xi - \int_t^1 H_s dB_s + K_1 - K_t = \mathbb{E}^G[\xi] + \int_0^t H_s dB_s - K_t,$$

where \mathbb{E}_t^G is the G -conditional expectation and the process $M := -K$ is a non-increasing G -martingale. The stochastic integral that appears in the above is the regular Itô one. But it is also defined quasi-surely. More precisely, the above statement holds almost-surely for all

probability measures in \mathcal{P} . Equivalently, the above equation holds quasi-surely in the sense of Denis & Martini. In particular, all the above processes as well as the stochastic integral are defined on the support of all measures in the set \mathcal{P} . This is an important property of this martingale representation as \mathcal{P} contains measures which are mutually singular. Moreover, there is no measure that dominates all measures in \mathcal{P} . Hence the above processes are defined on a large subset of our probability space.

A partial answer to this question was already provided by Xu and Zhang [20] for the class of *symmetric G -martingales*, i.e. a process N which is both itself and $-N$ are G -martingales. Since the G -expectation is not linear, the class of symmetric martingales is a strict subset of all G -martingales. In particular, the representation of symmetric martingales are obtained using only the stochastic integrals. We obtain the martingale representation in Theorem 5.1 for almost all square-integrable martingales. This result essentially provides a complete answer to the question of representation for the integrable classes defined in [15]. We also show that the non-increasing martingale $M := -K$ does not admit any further structure as illustrated in Example 6.4.

Our analysis utilizes the already mentioned duality result of Denis, Hu and Peng [4]. Similar to [4], we also provide a dual characterization of G -martingales as an immediate consequence of the results in [4, 15]. This observation is one of the key-ingredients of our representation proof. Moreover, it can be used to extend the definition of G -martingales to a class larger than the integrability class \mathcal{L}_G^1 of Peng. Indeed, the above martingale representation result could also be proved for a larger class of random variables. But this development also requires the extension of G -expectations and conditional expectations to this larger class. These types of results are not pursued here. But in an example, Example 6.3 below, we show that the integrability class \mathcal{L}_G^1 does not include all bounded random variables. Thus it is desirable to extend the theory to a larger class of random variables using the equivalent definitions that do not refer to partial differential equations. Indeed such a theory is developed by the authors in [17, 18, 19].

The paper is organized as follows. In Section 2, we review the theory of G -expectations and G -martingales. Section 3 defines the quasi-sure analysis of Denis & Martini and also provides the dual formulation. The main ingredients for our approach, such as the norms and spaces, are collected in Section 4. The main result is then stated and proved in Section 5. In the Appendix, we provide an approximation argument for the solutions of the partial differential equation. Then the connection between the integrability class of Peng and the spaces utilized in this paper is given in the subsection 6.2.

1.1 Notation and spaces

We collect all the spaces and the notation used in the paper with a reference to their definitions. We always assume that $\bar{a} > 0$, $0 \leq \underline{a} \leq \bar{a}$.

- $\mathbb{F} = \{\mathcal{F}_t^B, t \geq 0\}$ is the filtration generated by the canonical process B .
- \mathbb{E}^G is the G -expectation, defined in [15] and in subsection 2.1.
- \mathbb{E}_t^G is the conditional G -expectation.
- \mathcal{L}_{ip} is the space of random variables of the form $\varphi(B_{t_1}, \dots, B_{t_n})$ with a bounded, Lipschitz deterministic function φ and time points $0 \leq t_1 \leq \dots \leq t_n \leq 1$.
- \mathcal{L}_G^p is the integrability class defined in subsection 2.1 as the closure of \mathcal{L}_{ip} .
- $\mathcal{H}_G^{p,0}$ is the space of piecewise constant G -stochastic integrands, see subsection 2.2.
- \mathcal{H}_G^p is the integrability class defined in subsection 2.2 as the closure of $\mathcal{H}_G^{p,0}$.
- $\mathcal{P} = \overline{\mathcal{P}}_{[\underline{a}, \bar{a}]}^W$ measures under which the canonical process is a martingale and satisfies (3.1).
- $\mathcal{P}(t, \mathbb{P})$ is defined in (3.2).
- $\mathbb{L}_{\mathcal{P}}^p$ is the set of all p -integrable random variables; see (4.1).
- $\mathcal{L}_{\mathcal{P}}^p$ is the the closure of \mathcal{L}_{ip} under the norm $\mathbb{L}_{\mathcal{P}}^p$; see (4.1).
- $\mathbb{H}_{\mathcal{P}}^p$ is the set of all p -integrable, \mathbb{R}^d -valued stochastic integrands; see (4.2).
- $\mathcal{H}_{\mathcal{P}}^p$ is the closure of $\mathcal{H}_G^{p,0}$ under the norm $\|\cdot\|_{\mathbb{H}_{\mathcal{P}}^p}$; see Definition 4.2
- $\mathbb{S}_{\mathcal{P}}^p$ is the set of all p -integrable, *continuous* processes; see Definition 4.2.
- $\mathbb{I}_{\mathcal{P}}^p$ is the subset of $\mathbb{S}_{\mathcal{P}}^p$ that are *non-decreasing* with initial value 0; see Definition 4.2.
- \mathbb{S}_d is the set of all $d \times d$ symmetric matrices with the usual ordering and identity I_d .
- For $\nu, \eta \in \mathbb{R}^d$, $A := \nu \otimes \eta \in \mathbb{S}_d$ is defined by $Ax = (\eta \cdot x)\nu$ for any $x \in \mathbb{R}^d$.
- For $A \in \mathbb{S}_d$, $\nu_k \in \mathbb{R}^d$ are its orthonormal eigenvectors and λ_k are the corresponding eigenvalues so that

$$A = \sum_k \lambda_k [\nu_k \otimes \nu_k].$$

- For $A \in \mathbb{S}_d$, and a real number, $A \vee cI_d \in \mathbb{S}_d$ is defined by

$$A \vee cI_d := \sum_k (\lambda_k \vee c) [\nu_k \otimes \nu_k].$$

2 G -stochastic analysis of Peng [14, 15]

We fix the time horizon $T = 1$. Let $\Omega := \{\omega \in C([0, 1], \mathbb{R}^d) : \omega(0) = 0\}$ be the canonical space, B the canonical process, and \mathbb{P}_0 the Wiener measure. $\mathbb{F} = \{\mathcal{F}_t^B, t \in [0, 1]\}$ is the filtration generated by B . We note that $\mathcal{F}_{t-}^B = \mathcal{F}_t^B \neq \mathcal{F}_{t+}^B$. In what follows, we always use the space Ω together with the filtration \mathbb{F} .

2.1 G -expectation and G -martingale

Following Peng [14], let $\bar{a} > 0$, $0 \leq \underline{a} \leq \bar{a}$ and G be as in (1.1). For a bounded uniformly Lipschitz continuous function φ on \mathbb{R}^d , let u be the unique bounded viscosity solution of the following parabolic equation,

$$-\partial_t u - G(D^2 u) = 0 \quad \text{on } [0, 1), \quad \text{and} \quad u(1, x) = \varphi(x). \quad (2.1)$$

Here, ∂_t and D^2 denote, respectively, the partial derivative with respect to t , and the partial Hessian with respect to the space variable x . Then, the conditional G -expectation of the random variable $\varphi(B_1)$ at time t is defined by

$$\mathbb{E}_t^G[\varphi(B_1)] := u(t, B_t).$$

In particular, the G -expectation of $\varphi(B_1)$ is given by

$$\mathbb{E}^G[\varphi(B_1)] := \mathbb{E}_0^G[\varphi(B_1)] = u(0, 0).$$

Next consider the random variables of the form $\xi := \varphi(B_{t_1}, \dots, B_{t_{n-1}}, B_{t_n})$ for some bounded uniformly Lipschitz continuous function φ on $\mathbb{R}^{d \times n}$ and $0 \leq t_1 < \dots < t_n = 1$. For $t_{i-1} \leq t < t_i$, let

$$\mathbb{E}_t^G[\xi] = \mathbb{E}_t^G[\varphi(B_{t_1}, \dots, B_{t_n})] := v_i(t, B_{t_1}, \dots, B_{t_{i-1}}, B_t),$$

where $\{v_i\}_{i=1, \dots, n-1}$ is the unique, bounded, Lipschitz viscosity solution of the following equation,

$$\begin{aligned} -\partial_t v_i - G(D^2 v_i) &= 0, & t_{i-1} \leq t < t_i & \quad \text{and} & & (2.2) \\ v_i(t_i, x_1, \dots, x_{i-1}, x) &= v_{i+1}(t_i, x_1, \dots, x_{i-1}, x, x), \end{aligned}$$

and v_n solves the above equation with final data $v_n(1, x_1, \dots, x_{n-1}, x) = \varphi(x_1, \dots, x_{n-1}, x)$. Moreover, if we set $u_i(x_1, \dots, x_i) = v_{i+1}(t_i, x_1, \dots, x_i, x_i)$, then for $t_{i-1} \leq t < t_i$ we have the following additional identity,

$$\mathbb{E}_t^G[\varphi(B_{t_1}, \dots, B_{t_n})] = v_i(t, B_{t_1}, \dots, B_{t_{i-1}}, B_t) = \mathbb{E}_t^G[u_i(B_{t_1}, \dots, B_{t_i})].$$

Let \mathcal{L}_{ip} denote the space of such random variables $\varphi(B_{t_1}, \dots, B_{t_n})$ with a bounded and Lipschitz φ . For $p \geq 1$, \mathcal{L}_G^p is the closure of \mathcal{L}_{ip} under the norm

$$\|\xi\|_{\mathcal{L}_G^p}^p := \mathbb{E}^G[|\xi|^p].$$

We may then extend the definitions of the G -expectation and the conditional G -expectation to all $\xi \in \mathcal{L}_G^1$. A characterization of this space, in particular a Lusin type theorem, is obtained in [4]. However, since these integrability classes are defined through the closure of a rather smooth space \mathcal{L}_{ip} , they require substantial ‘‘smoothness’’. Indeed, in the Appendix, we construct a bounded random variable which is not in \mathcal{L}_G^1 (see Example 6.3).

We now can define G -martingales.

Definition 2.1 A adapted \mathcal{L}_G^1 -valued process M is called a G -martingale iff for any $0 \leq s < t$, $M_s = \mathbb{E}_s^G[M_t]$.

M is called a symmetric G -martingale, if both M and $-M$ are G -martingales.

A G -stochastic integral (as will be defined in the next subsection) is an example of a symmetric G -martingale. But not all martingales are stochastic integrals and not all are symmetric.

2.2 Stochastic integral and quadratic variation

For $p \in [1, \infty)$, we let $\mathcal{H}_G^{p,0}$ be the space of \mathbb{F} -adapted, \mathbb{R}^d -valued piecewise constant processes $H = \sum_{i \geq 0} H_{t_i} \mathbf{1}_{[t_i, t_{i+1})}$ such that $H_{t_i} \in \mathcal{L}_G^p$. For $H \in \mathcal{H}_G^{p,0}$, the G -stochastic integral is easily defined by

$$\int_0^t H_s d_G B_s := \sum_{i \geq 0} H_{t_i} [B_{t \wedge t_{i+1}} - B_{t \wedge t_i}].$$

Notice that this definition is completely universal in the sense that it is pointwise and independent of G . Let \mathcal{H}_G^p be the closure of $\mathcal{H}_G^{p,0}$ under the norm:

$$\|H\|_{\mathcal{H}_G^p}^p := \int_0^1 \mathbb{E}^G[|H_t|^p] dt.$$

By a closure argument the stochastic integral is defined for all $H \in \mathcal{H}_G^p$.

It is clear that the set of G -martingales does not form a linear space. However, for any $H \in \mathcal{H}_G^{p,0}$, one may directly verify that the stochastic integral process $M := \int_0^\cdot H_s d_G B_s$ is a G -martingale and so is $-M$. Hence, any G -stochastic integral is a symmetric G -martingale.

This notion of the stochastic integral can be used to define the quadratic variation process $\langle B \rangle_t^G$ as well. Indeed, the \mathbb{S}_d -valued process is defined by the identity

$$\langle B \rangle_t^G := \frac{1}{2} B_t \otimes B_t - \int_0^t B_s \otimes d_G B_s, \quad \forall 0 \leq t \leq 1, \quad (2.3)$$

where the tensor product \otimes is as in the Notations 1.1. We can directly check that the integrand B_t is in the integration class \mathcal{H}_G^p . Therefore, $\langle B \rangle_t^G$ is well defined.

3 Quasi-sure stochastic analysis of Denis & Martini [3]

Let \mathbb{P} be a measure on (Ω, \mathbb{F}) so that the canonical process B is a martingale. Then, the quadratic variation process $\langle B \rangle_t$ of B under \mathbb{P} exists. We consider the subset $\mathcal{P} := \overline{\mathcal{P}}_{[a, \bar{a}]}$ of such measures \mathbb{P} so that $\langle B \rangle_t$ satisfies the following for some deterministic constant $c = c(\mathbb{P}) > 0$,

$$0 < [cI_d \vee a] \leq \frac{d\langle B \rangle_t}{dt} \leq \bar{a}, \quad \forall t \in [0, 1], \quad \mathbb{P} - \text{a.s.}, \quad (3.1)$$

where I_d is the identity matrix in \mathbb{S}_d . Notice that when \underline{a} is positive definite, as required in Denis and Martini [3], we do not need cI_d in the lower bound. Also, the constant $c = c(\mathbb{P})$ may be different for each measure. Denis and Martini [3] define the following.

Definition 3.1 *We say that a property holds \mathcal{P} -quasi-surely, abbreviated as *q.s.*, if it holds \mathbb{P} -almost surely for all $\mathbb{P} \in \mathcal{P}$.*

Remark 3.2 All the results in this paper will also hold true if we set $\mathcal{P} := \overline{\mathcal{P}}_{[\underline{a}, \overline{a}]}^S$ as the collection of all probability measures \mathbb{P}^α given by

$$\mathbb{P}^\alpha := \mathbb{P}_0 \circ (X^\alpha)^{-1} \quad \text{where} \quad X_t^\alpha := \int_0^t \alpha_s^{1/2} dB_s, t \in [0, 1], \mathbb{P}_0 - \text{a.s.}$$

for some \mathbb{F} -adapted process α taking values in \mathbb{S}_d and satisfying

$$[c(\alpha)I_d \vee \underline{a}] \leq a_t \leq \overline{a}, \quad \forall t \in [0, 1], \mathbb{P}_0 - \text{a.s.},$$

where the constant $c(\alpha) > 0$ may depend on α . We note that $\overline{\mathcal{P}}_{[\underline{a}, \overline{a}]}^S$ is a strict subset of $\overline{\mathcal{P}}_{[\underline{a}, \overline{a}]}^W$ and each $\mathbb{P} \in \overline{\mathcal{P}}_{[\underline{a}, \overline{a}]}^S$ satisfies the Blumenthal zero-one law and the martingale representation property. We remark that Denis and Martini [3] uses the space $\overline{\mathcal{P}}_{[\underline{a}, \overline{a}]}^W$. But Denis, Hu and Peng [4] and our subsequent work [19] essentially use $\overline{\mathcal{P}}_{[\underline{a}, \overline{a}]}^S$. \square

The following are immediate consequences of the definition of G -expectations.

Proposition 3.3 *Let $H \in \mathcal{H}_G^2$. Then, H is Itô-integrable for every $\mathbb{P} \in \mathcal{P}$. Moreover,*

$$\int H_s d_G B_s = \int H_s dB_s, \quad \text{q.s.},$$

where the right hand side is the usual Itô integral. Consequently, the quadratic variation process $\langle B \rangle^G$ defined in (2.3) agrees with the usual quadratic variation process quasi surely.

Proof. The above statement clearly holds for the integrands $H \in \mathcal{H}_G^{2,0}$ (i.e. the piece-wise constant processes). For any fix $\mathbb{P} \in \mathcal{P}$, the $\mathbb{L}^2(\mathbb{P})$ norm is clearly weaker than the \mathcal{L}_G^2 norm. Therefore, the quasi-sure equality also holds in the \mathcal{L}_G^2 closure of $\mathcal{H}_G^{2,0}$. The statement about the quadratic variation follows from the general statement about the stochastic integrals and the formula (2.3). \square

Next we recall a dual characterization of the G -expectation as proved in [4]. We will then generalize that characterization to the G -conditional expectations. Like the previous result, this generalization is also an immediate consequence of the previous results. We need the following notation, for $t \in [0, 1]$ and $\mathbb{P} \in \mathcal{P}$,

$$\mathcal{P}(t, \mathbb{P}) := \{\mathbb{P}' \in \mathcal{P} : \mathbb{P}' = \mathbb{P} \text{ on } \mathcal{F}_t\}. \quad (3.2)$$

Notice that for any $\mathbb{P}' \in \mathcal{P}(t, \mathbb{P})$ and $\xi \in \mathcal{L}_G^1$, the random variable $\mathbb{E}^{\mathbb{P}'}[\xi | \mathcal{F}_t]$ is defined both \mathbb{P} and \mathbb{P}' almost surely. Also recall that $\text{ess sup} = \text{ess sup}^{\mathbb{P}}$ is the essential supremum of a class of \mathbb{P} almost surely defined random variables. Clearly, it is also defined \mathbb{P} almost surely (see Definition A.1 on page 323 in [9]). In particular, for $t \in [0, 1]$, we may define

$$\text{ess sup}_{\mathbb{P}' \in \mathcal{P}(t, \mathbb{P})} \mathbb{E}^{\mathbb{P}'}[\xi | \mathcal{F}_t] \quad (3.3)$$

as a \mathbb{P} almost sure random variable.

We now have the following characterization of the G -conditional expectation.

Proposition 3.4 *For any $\xi \in \mathcal{L}_G^1$, $t \in [0, 1]$, and $\mathbb{P} \in \mathcal{P}$,*

$$\mathbb{E}_t^G[\xi] = \text{ess sup}_{\mathbb{P}' \in \mathcal{P}(t, \mathbb{P})} \mathbb{E}^{\mathbb{P}'}[\xi | \mathcal{F}_t], \quad \mathbb{P} - a.s..$$

Moreover, an adapted \mathcal{L}_G^1 valued process M is a G -martingale if and only if it satisfies the following dynamic programming principle for all $0 \leq s \leq t \leq 1$ and $\mathbb{P} \in \mathcal{P}$,

$$M_s = \text{ess sup}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}^{\mathbb{P}'}[M_t | \mathcal{F}_s], \quad \mathbb{P} - a.s.. \quad (3.4)$$

Proof. The characterization of the conditional expectation follows directly from [4] for $\xi \in \mathcal{L}_{ip}$. Then, a closure argument proves the equality for all $\xi \in \mathcal{L}_G^1$. The martingale property is a direct consequence of the tower property of the G -conditional expectation as proved in [14] and the above formula for the conditional expectation. \square

Remark 3.5 In their classical paper [7], El Karoui & Jeanblanc consider a very general stochastic optimal control problem. Their results in our context imply that

$$M_s^{\mathbb{P}} := \text{ess sup}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}^{\mathbb{P}'}[M_t | \mathcal{F}_s]$$

is a \mathbb{P} -super-martingale for all $\mathbb{P} \in \mathcal{P}$. Moreover \mathbb{P}^* is the maximizer if and only if $M^{\mathbb{P}^*}$ is \mathbb{P}^* -martingale. While this result provides a characterization of the optimal measure \mathbb{P}^* , it does not provide a “universal” hedge. More precisely their approach provides an optimal control which is defined only for the optimal measure and on its support. Indeed, the super-martingale property of $M^{\mathbb{P}}$ imply that there are an increasing function $K^{\mathbb{P}}$ and an integrand $H^{\mathbb{P}}$ so that

$$M_t^{\mathbb{P}} = \int_0^t H_s^{\mathbb{P}} dB_s - K_t^{\mathbb{P}}.$$

However, aggregating these processes into one universally defined K and H is not immediate. In the standard Markovian context, this problem can be solved directly. However, it is exactly the non-Markovian generalization that motivates this paper and [3, 15, 14]. This interesting question of aggregation is further discussed in the Remark 4.3. \square

4 Spaces and Norms

The particular case of $t = 0$ in (3.4) gives the following dual characterization proved in [4],

$$\mathbb{E}^G[\xi] = \sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}}[\xi].$$

The above results enable us to extend the definition of G -expectation and G -martingales to a possibly larger class of random variables. In particular, this extension has the advantage of not referring to the partial differential equation (2.1). We will not develop this theory here. However, in view of the results and the norms used in the theory of BSDEs, we introduce the following function spaces.

For $p \geq 1$, and a \mathcal{F}_1 -measurable, non-negative map ξ , we set

$$\|\xi\|_{\mathbb{L}_{\mathcal{P}}^p}^p := \sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}} \left[\operatorname{ess\,sup}_{t \in [0,1]} \left(M_t^{\mathbb{P}}(\xi) \right)^p \right], \quad \text{where } M_t^{\mathbb{P}}(\xi) := \operatorname{ess\,sup}_{\mathbb{P}' \in \mathcal{P}(t, \mathbb{P})} \mathbb{E}^{\mathbb{P}'}[\xi | \mathcal{F}_t].$$

In fact the process $M_t^{\mathbb{P}}(\xi)$ a \mathbb{P} -supermartingale. Therefore it admits a càdlàg version and thus the term $\sup_{t \in [0,1]} \left(M_t^{\mathbb{P}}(\xi) \right)^p$ is measurable. However, in this paper we do not wish to prove the supermartingale property and that is the reason for defining the above norm through the random variable $\operatorname{ess\,sup}_{t \in [0,1]} \left(M_t^{\mathbb{P}}(\xi) \right)$ which is by definition measurable.

We next define

$$\begin{aligned} \mathbb{L}_{\mathcal{P}}^p &:= \left\{ \xi : \|\xi\|_{\mathbb{L}_{\mathcal{P}}^p} := \|\xi\|_{\mathbb{L}_{\mathcal{P}}^p} < \infty \right\}, \\ \mathcal{L}_{\mathcal{P}}^p &:= \text{closure of } \mathcal{L}_{ip} \text{ under the norm } \mathbb{L}_{\mathcal{P}}^p. \end{aligned} \quad (4.1)$$

Notice that if $\xi \in \mathcal{L}_G^1$, then $M_t^{\mathbb{P}}(\xi) = \mathbb{E}_t^G[\xi]$ for every $\mathbb{P} \in \mathcal{P}$. Moreover, $\|\xi\|_{\mathbb{L}_{\mathcal{P}}^p} = \|\xi^*\|_{\mathcal{L}_G^p}$ whenever $\xi^* := \sup_{t \in [0,1]} \mathbb{E}_t^G[|\xi|]$ is in the class \mathcal{L}_G^p .

In the Appendix, we compare the integrability classes defined by Peng [15] and the above spaces. The connection is related to the Doob maximal inequalities in the setting of G -expectations. In particular, we prove the following.

Lemma 4.1 $\cup_{p>2} \mathcal{L}_G^p \subset \mathcal{L}_{\mathcal{P}}^2 \subset \mathbb{L}_{\mathcal{P}}^2 \cap \mathcal{L}_G^2 \subset \mathbb{L}_{\mathcal{P}}^2$. Moreover, the final inclusion is strict.

We also define the following norms for the processes. As usual $1 \leq p < \infty$. For an \mathbb{F} -adapted integrand H and a stochastic process Y , we set

$$\|H\|_{\mathbb{H}_{\mathcal{P}}^p}^p := \sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}} \left[\left(\int_0^1 (d\langle B \rangle_t H_t \cdot H_t) \right)^{\frac{p}{2}} \right], \quad (4.2)$$

$$\|Y\|_{\mathbb{S}_{\mathcal{P}}^p}^p := \sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}} \left[\operatorname{ess\,sup}_{0 \leq t \leq 1} |Y_t|^p \right]. \quad (4.3)$$

If $Y_t = \mathbb{E}_t^G[|\xi|]$ for some $\xi \in \mathcal{L}_G^1$, then $\|Y\|_{\mathbb{S}_{\mathcal{P}}^p}^p = \|\xi\|_{\mathbb{L}_{\mathcal{P}}^p}^p$. This identity also motivates the definition of the norm $\mathbb{L}_{\mathcal{P}}^p$. Moreover, when the lower bound \underline{a} in (3.1) is non-degenerate, then the $\mathbb{H}_{\mathcal{P}}^p$ norm is equivalent to the norm used in [4, 14]:

$$\sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}} \left[\left(\int_0^1 |H_t|^2 dt \right)^{\frac{p}{2}} \right].$$

In analogy with the standard notation in stochastic calculus, we define the following spaces.

Definition 4.2 Let $p \in [1, \infty)$ and \mathcal{P} be as in Section 3.

- $\mathbb{H}_{\mathcal{P}}^p$ is the set of all integrands with a finite $\|\cdot\|_{\mathbb{H}_{\mathcal{P}}^p}$ -norm,
- $\mathcal{H}_{\mathcal{P}}^p$ is the closure of $\mathcal{H}_G^{p,0}$ under the norm $\|\cdot\|_{\mathbb{H}_{\mathcal{P}}^p}$,
- $\mathbb{S}_{\mathcal{P}}^p$ is the set of all *continuous* processes with finite $\|\cdot\|_{\mathbb{S}_{\mathcal{P}}^p}$ -norm,
- $\mathbb{I}_{\mathcal{P}}^p$ is the subset of $\mathbb{S}_{\mathcal{P}}^p$ of *non-decreasing* processes with $X_0 = 0$. □

Clearly all of the above spaces are complete and therefore Banach spaces. Notice that $\|H\|_{\mathbb{H}_{\mathcal{P}}^p} \leq \|H\|_{\mathcal{H}_G^p}$ for $H \in \mathcal{H}_G^{p,0}$, then it is clear that $\mathcal{H}_G^p \subset \mathcal{H}_{\mathcal{P}}^p$ and thus $\mathcal{H}_{\mathcal{P}}^p$ is the closure of \mathcal{H}_G^p under the norm $\|\cdot\|_{\mathbb{H}_{\mathcal{P}}^p}$.

Remark 4.3 Given $\xi \in \mathbb{L}_{\mathcal{P}}^1$ (but not necessarily in \mathcal{L}_G^1) and a stopping time τ , it is not straightforward to define the conditional $G_{\mathcal{P}}$ -expectation $\mathbb{E}_{\tau}^{\mathcal{P}}[\xi]$ as in (3.3). Indeed, set

$$M_{\tau}^{\mathbb{P}} := \operatorname{ess\,sup}_{\mathbb{P}' \in \mathcal{P}(\tau, \mathbb{P})} \mathbb{E}_{\tau}^{\mathbb{P}'}[\xi], \quad \mathbb{P} - \text{a.s.}$$

Then, to define the conditional expectation, we need to aggregate this family of random variables $\{M_{\tau}^{\mathbb{P}}, \mathbb{P} \in \mathcal{P}\}$ into one “universally” defined random variable. A similar problem arises in the definition of a stochastic integral for a given integrand $H \in \mathbb{H}_{\mathcal{P}}^2$. Again, for $\mathbb{P} \in \mathcal{P}$, we set $M_t^{\mathbb{P}} := \int_0^t H_s dB_s$. Then, to define the G -stochastic integral of H we need to aggregate this family of stochastic processes.

The issue of aggregation is an interesting technical question. Generally, solution is given by imposing regularity on the random variables. Indeed, for all random variables which are in \mathcal{L}_G^p , one can define the universal version through a closure argument. However, there are other alternatives and a comprehensive study of this question is given in our accompanying paper [17].

Finally we recall that, when the integrand H has the additional regularity that it is a càdlàg process, then Karandikar [8] defines the stochastic integral $M_t^{\mathbb{P}} := \int_0^t H_s dB_s$ point wise. This definition can then be used as the aggregating process. □

5 The martingale representation theorem

To motivate the main result of this paper, we first consider the case $\xi = \varphi(B_1)$ for some smooth, bounded function φ . In this case, as in Peng [13, 14], a formal construction can be derived by simply using the Itô's formula. Now suppose that the solution $u(t, x)$ of the (2.1) is smooth. Indeed, we can approximate the equation (2.1) so that the approximating equation admits smooth solutions as proved by [10]. This is done in the Appendix. Then, we set $Y_t := u(t, B_t) = \mathbb{E}_t^G[\xi]$, $H_t := \nabla u(t, B_t)$ and

$$K_t := \int_0^t \left(G(D^2 u(s, B_s)) - \frac{1}{2} \text{tr} [\hat{a}_s D^2 u(s, B_s)] \right) ds, \quad \hat{a}_t := \frac{d\langle B \rangle_t}{dt}, \quad q.s..$$

Using (2.1), (3.1) and the definition of the nonlinearity G , one may directly check that

$$dY_t = -dK_t + H_t dB_t, \quad \text{and} \quad dK_t \geq 0 \quad q.s..$$

Also, the characterization of G -martingales in Proposition 3.4 and the definition of the nonlinearity G imply that $-K$ is a G -martingale. Hence for the random variable $\xi = \varphi(B_1)$, we have the martingale representation. More importantly, this example also shows that in general a non-decreasing process K is always present in this representation. The above construction is also the basic step in our construction. Indeed essentially for almost all random variables in \mathcal{L}_{ip} the above construction proves the result. We then prove that stochastic integrals and non-decreasing martingales are closed subsets under the appropriate norms as defined in the preceding section. Finally, these results allow us to prove the result by a closure argument.

5.1 Main results

We first state the main result. Recall that function spaces are defined in Definition 4.2.

Theorem 5.1 *For every $\xi \in \mathcal{L}_{\mathcal{P}}^2$, the conditional G -expectation process $Y_t := \mathbb{E}_t^G[\xi]$ is in $\mathbb{S}_{\mathcal{P}}^2$, and there exist unique $H \in \mathcal{H}_{\mathcal{P}}^2$, $K \in \mathbb{L}_{\mathcal{P}}^2$ so that $N := -K$ is a G -martingale and for every $t \in [0, T]$,*

$$Y_t = \xi - \int_t^1 H_s dB_s + K_1 - K_t = \mathbb{E}^G[\xi] + \int_0^t H_s dB_s - K_t, \quad q.s.. \quad (5.1)$$

In particular, the stochastic integrals are defined both as G -stochastic integrals and also quasi surely. Moreover the following estimate is also satisfied with a universal constant C^ ,*

$$\|Y\|_{\mathbb{S}_{\mathcal{P}}^2} + \|H\|_{\mathbb{H}_{\mathcal{P}}^2} + \|K\|_{\mathbb{L}_{\mathcal{P}}^2} \leq C^* \|\xi\|_{\mathbb{L}_{\mathcal{P}}^2}. \quad (5.2)$$

The proof of the above theorem will be completed in several lemmas below.

In the above theorem the integrand H is not only in the class $\mathbb{H}_{\mathcal{P}}^2$ but also in the closure of $\mathcal{H}_G^{2,0}$ under the norm $\|\cdot\|_{\mathbb{H}_{\mathcal{P}}^2}$. Indeed this fact implies that stochastic integral is well defined quasi surely as it is shown in the next subsection.

The following is an immediate corollary of the above martingale representation.

Corollary 5.2 *A G -martingale is symmetric if and only if the process K in the representation (5.1) is identically equal to zero.*

In addition to the estimate (5.2) an estimate of the differences of the solutions is known to be an important tool. Let $\xi_1, \xi_2 \in \mathcal{L}_{\mathcal{P}}^2$ and (Y^i, H^i, K^i) be the processes in the martingale representation. We set $\delta\xi := \xi^1 - \xi^2$, $\delta Y := Y^1 - Y^2$, $\delta Z := Z^1 - Z^2$ and $\delta K := K^1 - K^2$.

Theorem 5.3 *There exists a universal constant C^* so that,*

$$\begin{aligned} \|\delta Y\|_{\mathbb{S}_{\mathcal{P}}^2} &\leq \|\delta\xi\|_{\mathbb{L}_{\mathcal{P}}^2}, \\ \|\delta H\|_{\mathbb{H}_{\mathcal{P}}^2} + \|\delta K\|_{\mathbb{S}_{\mathcal{P}}^2} &\leq C^* \left[\|\delta\xi\|_{\mathbb{L}_{\mathcal{P}}^2} + \left(\|\xi^1\|_{\mathbb{L}_{\mathcal{P}}^2}^{\frac{1}{2}} \wedge \|\xi^2\|_{\mathbb{L}_{\mathcal{P}}^2}^{\frac{1}{2}} \right) \|\delta\xi\|_{\mathbb{L}_{\mathcal{P}}^2}^{\frac{1}{2}} \right]. \end{aligned}$$

5.2 Stochastic Integral and Symmetric G -martingales

As discussed in Remark 4.3, for an integrand $H \in \mathbb{H}_{\mathcal{P}}^2$ it is not immediate to define the stochastic integral $\int_0^\cdot H_s dB_s$ quasi surely. However, the stochastic integral is defined in [15] for integrands $H \in \mathcal{H}_G^{2,0}$. Then, for integrands in $\mathcal{H}_{\mathcal{P}}^2$ a closure argument can be used to construct the stochastic integral quasi-surely. (Recall that $\mathcal{H}_{\mathcal{P}}^2$ is the closure of \mathcal{H}_G^2 under the norm $\|\cdot\|_{\mathbb{H}_{\mathcal{P}}^2}$.)

Theorem 5.4 *For any $H \in \mathcal{H}_{\mathcal{P}}^2$, the stochastic integral $\int_0^\cdot H_s dB_s$ exists quasi surely. Moreover, the stochastic integral satisfies the Burkholder-Davis-Gundy inequality*

$$\|H\|_{\mathbb{H}_{\mathcal{P}}^2} \leq \left\| \int_0^\cdot H_s dB_s \right\|_{\mathbb{S}_{\mathcal{P}}^2} \leq 2\|H\|_{\mathbb{H}_{\mathcal{P}}^2}. \quad (5.3)$$

Proof. Let $H \in \mathcal{H}_{\mathcal{P}}^2$. Then, there is a sequence $\{H^n\}_n \subset \mathcal{H}_G^2$ so that $\|H^n - H\|_{\mathbb{H}_{\mathcal{P}}^2}$ converges to zero as n tends to infinity. By relabeling the sequence we may assume that $\|H^n - H\|_{\mathbb{H}_{\mathcal{P}}^2} \leq 2^{-n}$ for every n . Moreover, since $H \in \mathbb{H}_{\mathcal{P}}^2$, for every $\mathbb{P} \in \mathcal{P}$,

$$M_t^{\mathbb{P}} := \int_0^t H_s dB_s, \quad t \in [0, 1],$$

is \mathbb{P} -almost surely well-defined. Also since $H^n \in \mathcal{H}_G^2$, the G -stochastic integral

$$M_t^n := \int_0^t H_s^n dB_s, \quad t \in [0, 1],$$

is also quasi-surely defined.

We now have to prove that the family $\{M^{\mathbb{P}}, P \in \mathcal{P}\}$ can be aggregated into a universal process. For this, we define

$$\overline{M}_t := \overline{\lim}_{n \rightarrow \infty} M_t^n, \quad t \in [0, 1].$$

Notice that \overline{M} is quasi-surely defined. We continue by showing that $\overline{M} = M^{\mathbb{P}}$, \mathbb{P} -almost surely, for every $\mathbb{P} \in \mathcal{P}$. Indeed for any $\mathbb{P} \in \mathcal{P}$, we use the Burkholder-Davis-Gundy inequality to obtain

$$\begin{aligned} \mathbb{E}^{\mathbb{P}} \left[\sup_{0 \leq t \leq 1} |M_t^n - M_t^{\mathbb{P}}|^2 \right] &= \mathbb{E}^{\mathbb{P}} \left[\sup_{0 \leq t \leq 1} \left| \int_0^t (H_s^n - H_s) dB_s \right|^2 \right] \\ &\leq 4 \mathbb{E}^{\mathbb{P}} \left[\left| \int_0^1 (H_s^n - H_s) dB_s \right|^2 \right] \\ &= 4 \mathbb{E}^{\mathbb{P}} \left[\int_0^1 |\hat{a}_s^{1/2} (H_s^n - H_s)|^2 ds \right] \\ &\leq 4 \|H^n - H\|_{\mathbb{H}_{\mathbb{P}}^2}^2 \leq 2^{2-2n}. \end{aligned}$$

We then directly estimate that

$$\sum_{n=1}^{\infty} \mathbb{P} \left[\sup_{0 \leq t \leq 1} |M_t^n - M_t^{\mathbb{P}}| \geq n^{-2} \right] \leq \sum_{n=1}^{\infty} n^2 \mathbb{E}^{\mathbb{P}} \left[\sup_{0 \leq t \leq 1} |M_t^n - M_t^{\mathbb{P}}|^2 \right]^{\frac{1}{2}} < \infty.$$

By the Borel-Cantelli Lemma,

$$\lim_{n \rightarrow \infty} \sup_{0 \leq t \leq T} |M_t^n - M_t^{\mathbb{P}}| = 0, \quad \mathbb{P} - \text{a.s. .}$$

This implies that $M^{\mathbb{P}} = \overline{M}$, $dt \times d\mathbb{P}$ -almost surely. Since this holds for every $\mathbb{P} \in \mathcal{P}$, we conclude that the process \overline{M} is an aggregating process. Hence the stochastic integral is defined.

The Burkholder-Davis-Gundy inequalities follow directly from the definitions. \square

We close this subsection by stating the following result for symmetric G -martingales, which is an immediate consequence of the main results.

Theorem 5.5 *The following are equivalent:*

- (i) M is a \mathbb{P} -martingale for every $\mathbb{P} \in \mathcal{P}$,
- (ii) M is a symmetric G -martingale,
- (iii) For any G -martingale N , both $N + M$ and $N - M$ are also G -martingales,
- (iv) M is a G -martingale satisfying $\mathbb{E}^G \{-M_t\} = -\mathbb{E}^G \{M_t\}$ for any $t \geq 0$,
- (v) There exists $H \in \mathcal{H}_{\mathcal{P}}^2$ so that $M_t := M_0 + \int_0^t H_s dB_s$.

Recall that $\mathbb{I}_{\mathcal{P}}^2$ is defined in Definition 4.2 as the set of all non-decreasing, continuous processes with finite $\|\cdot\|_{\mathbb{S}_{\mathcal{P}}^2}$. For $(H, K) \in \mathcal{H}_{\mathcal{P}}^2 \times \mathbb{I}_{\mathcal{P}}^2$, define a process by

$$M_t := M_0 + \int_0^t H_s dB_s - K_t. \quad (5.4)$$

An immediate corollary of the above Theorem is the following.

Corollary 5.6 *The process M defined in (5.4) is a G -martingale if and only if the non-increasing process $-K$ is a G -martingale.*

5.3 Increasing G -martingales

In this section we show that the set of non-decreasing G -martingales is a closed set. Indeed, let $MI_{\mathcal{P}}^2$ be the set of all processes $K \in \mathbb{I}_{\mathcal{P}}^2$ such that $-K$ is a G -martingale. Then we have the following closure result which is similar to Theorem 5.4.

Theorem 5.7 *The space $MI_{\mathcal{P}}^2$ is closed under norm $\|\cdot\|_{\mathbb{S}_{\mathcal{P}}^2}$.*

Proof. Consider a sequence $K^n \in MI_{\mathcal{P}}^2$ converging to a process $K \in \mathbb{I}_{\mathcal{P}}^2$ in the norm $\|\cdot\|_{\mathbb{S}_{\mathcal{P}}^2}$. We claim that the limit $-K$ is also a G -martingale and therefore $K \in MI_{\mathcal{P}}^2$. Indeed, for every $0 \leq s \leq t \leq 1$, set $A_t := K_t - K_s$ and $A_t^n := K_t^n - K_s^n$. Then, by the martingale property of the sequence, for every n and $\mathbb{P} \in \mathcal{P}$, we have

$$\operatorname{ess\,inf}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}_s^{\mathbb{P}'} [A_t^n] = 0, \quad \mathbb{P} - \text{a.s.}$$

Moreover, \mathbb{P} -a.s.,

$$\operatorname{ess\,inf}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}_s^{\mathbb{P}'} [A_t] \leq \operatorname{ess\,sup}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}_s^{\mathbb{P}'} |A_t - A_t^n| + \operatorname{ess\,inf}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}_s^{\mathbb{P}'} [A_t^n] = \operatorname{ess\,sup}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}_s^{\mathbb{P}'} |A_t - A_t^n|.$$

The following can be shown directly from the definitions:

$$\sup_{\mathbb{P} \in \mathcal{P}} \mathbb{E}^{\mathbb{P}} \left[\operatorname{ess\,sup}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}_s^{\mathbb{P}'} |A_t - A_t^n| \right] \leq \|A - A^n\|_{\mathbb{S}_{\mathcal{P}}^2}.$$

Hence by the convergence of $\|A - A^n\|_{\mathbb{S}_{\mathcal{P}}^2}$ to zero as n tends to infinity, we conclude that

$$\lim_{n \rightarrow \infty} \operatorname{ess\,sup}_{\mathbb{P}' \in \mathcal{P}(s, \mathbb{P})} \mathbb{E}_s^{\mathbb{P}'} |A_t - A_t^n| = 0, \quad \mathbb{P} - \text{a.s.}$$

Since $0 \leq s \leq t \leq 1$ and $\mathbb{P} \in \mathcal{P}$ are arbitrary, the limit process $-K$ is also a G -martingale. \square

5.4 Estimates

For $(H, K) \in \mathbb{H}_{\mathcal{P}}^2 \times \mathbb{I}_{\mathcal{P}}^2$, let M be defined as in (5.4). In this subsection, we prove certain estimates for H and K in terms of the process M . These estimates are similar to those obtained for reflected backward stochastic differential equations in [5].

Proposition 5.8 *Let H, K, M be as in (5.4). There exists a constant C depending only on the dimension so that*

$$\|H\|_{\mathbb{H}_{\mathcal{P}}^2} + \|K\|_{\mathbb{I}_{\mathcal{P}}^2} \leq C\|M\|_{\mathbb{S}_{\mathcal{P}}^2}.$$

Proof. We directly calculate that

$$d|M_t|^2 = 2M_t H_t dB_t - 2M_t dK_t + d\langle B \rangle_t H_t \cdot H_t.$$

We integrate over $[t, 1]$ to obtain,

$$|M_t|^2 + \int_t^1 d\langle B \rangle_s H_s \cdot H_s = |M_1|^2 + 2 \int_t^1 M_s dK_s - 2 \int_t^1 M_s H_s dB_s.$$

We then take the expected value under an arbitrary $\mathbb{P} \in \mathcal{P}$ to arrive at

$$\mathbb{E}^{\mathbb{P}} \left[|M_t|^2 + \int_0^1 d\langle B \rangle_t H_t \cdot H_t \right] \leq \mathbb{E}^{\mathbb{P}} \left[|M_1|^2 + 2 \int_0^1 |M_t| dK_t \right].$$

Since $dK_t \geq 0$, for any $\varepsilon > 0$, we have the following estimate,

$$\begin{aligned} \mathbb{E}^{\mathbb{P}} \left[|M_t|^2 + \int_0^1 d\langle B \rangle_t H_t \cdot H_t \right] &\leq \mathbb{E}^{\mathbb{P}} \left[|M_1|^2 + 2 \left(\sup_{t \in [0,1]} |M_t| \right) K_1 \right] \\ &\leq (1 + \varepsilon^{-1}) \mathbb{E}^{\mathbb{P}} \left[\sup_{t \in [0,1]} |M_t|^2 \right] + \varepsilon \mathbb{E}^{\mathbb{P}} [K_1^2]. \end{aligned} \quad (5.5)$$

Next we estimate K . Recall that $0 = K_0 \leq K_t$. By the definition of M_t ,

$$\begin{aligned} K_1^2 &= \left(M_1 - M_0 - \int_0^1 H_s dB_s \right)^2 \\ &\leq 3|M_1|^2 + 3|M_0|^2 + 3 \left(\int_0^1 H_s dB_s \right)^2. \end{aligned}$$

We now use (5.5) with $\varepsilon = \frac{1}{6}$. The result is

$$\begin{aligned} \mathbb{E}^{\mathbb{P}} [K_1^2] &\leq \mathbb{E}^{\mathbb{P}} \left[3|M_1|^2 + 3|M_0|^2 + 3 \int_0^1 d\langle B \rangle_t H_t \cdot H_t \right] \\ &\leq 27 \mathbb{E}^{\mathbb{P}} \left[\sup_{t \in [0,1]} |M_t|^2 \right] + \frac{1}{2} \mathbb{E}^{\mathbb{P}} [K_1^2]. \end{aligned}$$

Hence,

$$\mathbb{E}^{\mathbb{P}} [K_1^2] \leq 54 \mathbb{E}^{\mathbb{P}} \left[\sup_{t \in [0,1]} |M_t|^2 \right].$$

This together with (5.5) and the definitions of the norms imply the result. \square

Next we prove an estimate for differences. So for any $(H^i, K^i) \in \mathbb{H}_{\mathcal{P}}^2 \times \mathbb{K}_{\mathcal{P}}^2, i = 1, 2$, let M^i be defined as in (5.4). As before, let $\delta M := M^1 - M^2, \delta H := H^1 - H^2, \delta K := K^1 - K^2$.

Proposition 5.9 *There exists a constant C depending only on the dimension so that*

$$\|\delta H\|_{\mathbb{H}_{\mathcal{P}}^2}^2 + \|\delta K\|_{\mathbb{K}_{\mathcal{P}}^2}^2 \leq C \left[\|\delta M\|_{\mathbb{S}_{\mathcal{P}}^2}^2 + \|\delta M\|_{\mathbb{S}_{\mathcal{P}}^2} \left(\|K^1\|_{\mathbb{S}_{\mathcal{P}}^2} + \|K^2\|_{\mathbb{S}_{\mathcal{P}}^2} \right) \right]. \quad (5.6)$$

The terms $\|K^i\|_{\mathbb{S}_{\mathcal{P}}^2}$ in the above inequality can be estimated using Proposition 5.8.

Proof. The arguments are very similar to the proof of Proposition 5.8. The only difference is the fact that δK is no longer a monotone function. We directly compute that

$$\delta M_t = \delta M_0 + \int_0^t \delta H_s dB_s - \delta K_t.$$

Then we proceed as in the proof of the previous proposition to arrive at

$$\mathbb{E}^{\mathbb{P}} \left[|\delta M_t|^2 + \int_0^1 d\langle B \rangle_t \delta H_t \cdot \delta H_t \right] \leq \mathbb{E}^{\mathbb{P}} [|\delta M_1|^2] + \mathbb{E}^{\mathbb{P}} \left[\int_0^1 |\delta M_s| d|\delta K|_s \right].$$

The last integral term is directly estimated as follows.

$$\begin{aligned} \mathbb{E}^{\mathbb{P}} \left[\int_0^1 |\delta M_s| d|\delta K|_s \right] &\leq \mathbb{E}^{\mathbb{P}} \left[\left(\sup_{t \in [0,1]} |\delta M_t| \right) \left(\sup_{t \in [0,1]} [|K_t^1| + |K_t^2|] \right) \right] \\ &\leq 2 \left[\mathbb{E}^{\mathbb{P}} \sup_{t \in [0,1]} |\delta M_t|^2 \right]^{1/2} \left(\sum_{i=1}^2 \left[\mathbb{E}^{\mathbb{P}} \sup_{t \in [0,1]} |K_t^i|^2 \right]^{1/2} \right) \\ &\leq 2 \|\delta M\|_{\mathbb{S}_{\mathcal{P}}^2} \left(\|K^1\|_{\mathbb{S}_{\mathcal{P}}^2} + \|K^2\|_{\mathbb{S}_{\mathcal{P}}^2} \right). \end{aligned}$$

The estimate of $\|\delta K\|_{\mathbb{S}_{\mathcal{P}}^2}$ is obtained exactly as in the proof of Proposition 5.8 \square

5.5 Proof of Theorem 5.1

We prove uniqueness first. Suppose that there are two pairs (H^i, K^i) satisfying (5.1). Then, we can use Proposition 5.9 with $M_t^i = Y_t = E_t^G[\xi]$. In particular, $\delta M \equiv 0$. By (5.6), we conclude that $\|\delta H\|_{\mathbb{H}_{\mathcal{P}}^2} = \|\delta K\|_{\mathbb{K}_{\mathcal{P}}^2} = 0$.

For the existence, let \mathcal{M} be the subset of $\mathbb{L}_{\mathcal{P}}^2$ so that the martingale representation (5.1) holds for all $\xi \in \mathcal{M}$. We will prove the result by showing that \mathcal{M} is closed in $\mathbb{L}_{\mathcal{P}}^2$ and that $\mathcal{L}_{ip} \subset \mathcal{M}$. The second statement is proved in the Appendix, by an approximation argument.

This is Proposition 6.1. Then for $\xi \in \mathcal{L}_{\mathcal{P}}^2$ these two statements imply the existence of (H, K) as $\mathcal{L}_{\mathcal{P}}^2$ is in the closure of \mathcal{L}_{ip} under the norm $\mathbb{L}_{\mathcal{P}}^2$.

To show that \mathcal{M} is closed, consider a sequence $\xi^n \in \mathcal{M}$ converging to $\xi \in \mathbb{L}_{\mathcal{P}}^2$. Since $\xi^n \in \mathcal{M}$, there are $H^n \in \bar{\mathcal{H}}_G^2$ and $K^n \in \mathbb{I}_{\mathcal{P}}^2$ so that (5.1) holds for each n and $N^n := -K^n$ is a continuous, non-increasing G -martingale. We now use the estimate (5.6) with $M^1 = Y^n$ and $M^2 = Y^m$ for arbitrary n and m . The identity $Y_t^n = E_t^G[\xi^n]$ together with the definition of the conditional expectation \mathbb{E}_t^G imply that for every $t \in [0, 1]$,

$$|Y_t^n - Y_t^m|^2 \leq \mathbb{E}_t^G \left[|\xi^n - \xi^m|^2 \right].$$

Hence the definition of the norm $\|\cdot\|_{\mathbb{L}_{\mathcal{P}}^2}$ yield,

$$\|Y^n - Y^m\|_{\mathbb{S}_{\mathcal{P}}^2} \leq \|\xi^n - \xi^m\|_{\mathbb{L}_{\mathcal{P}}^2}.$$

We now use the results of Propositions 5.8 and 5.9 with $M^1 = Y^n$ and $M^2 = Y^m$. The Proposition 5.8 yields for each n ,

$$\|K^n\|_{\mathbb{S}_{\mathcal{P}}^2} \leq \|\xi^n\|_{\mathbb{L}_{\mathcal{P}}^2} \leq c_0 := \sup_m \|\xi^m\|_{\mathbb{L}_{\mathcal{P}}^2} < \infty.$$

We use this in (5.6). The result is

$$\|H^n - H^m\|_{\mathbb{H}_{\mathcal{P}}^2}^2 + \|K^n - K^m\|_{\mathbb{S}_{\mathcal{P}}^2}^2 \leq C^* \left[\|\xi^n - \xi^m\|_{\mathbb{L}_{\mathcal{P}}^2}^2 + 2c_0 \|\xi^n - \xi^m\|_{\mathbb{L}_{\mathcal{P}}^2} \right].$$

Hence $\{H^n\}_n$ is a Cauchy sequence in $\bar{\mathcal{H}}_G^2$. Therefore by the definition of $\bar{\mathcal{H}}_G^2$, we know that there is a limit $H \in \bar{\mathcal{H}}_G^2$. Moreover, by (5.3) the corresponding stochastic integrals converge in $\mathbb{S}_{\mathcal{P}}^2$. Also $\{K^n\}_n$ is a Cauchy sequence in $\mathbb{S}_{\mathcal{P}}^2$. By Theorem 5.7, we conclude that there is a limit $K \in \mathbb{I}_{\mathcal{P}}^2$ so that $N := -K$ is a G -martingale. Since (Y^n, H^n, K^n) satisfies (5.1) with final data $Y_1^n = \xi^n$, we conclude that the limit processes (Y, H, K) also satisfies (5.1) with final data $Y_1 = \xi$. Hence \mathcal{M} is closed under the norm $\mathbb{L}_{\mathcal{P}}^2$. \square

5.6 Proof of Theorem 5.3

Since $Y_t^i = E_t^G[\xi^i]$, the dual representation of the G -conditional expectation yield that for each $t \in [0, 1]$,

$$|\delta Y_t| = |E_t^G[\xi^1] - E_t^G[\xi^2]| \leq E_t^G \left[|\xi^1 - \xi^2| \right].$$

Hence,

$$\|\delta Y\|_{\mathbb{S}_{\mathcal{P}}^2} \leq \|\delta \xi\|_{\mathbb{L}_{\mathcal{P}}^2}.$$

We now use Proposition 5.9. The result is

$$\|\delta H\|_{\mathbb{H}_{\mathcal{P}}^2} + \|\delta K\|_{\mathbb{S}_{\mathcal{P}}^2} \leq C^* \left[\|\delta Y\|_{\mathbb{S}_{\mathcal{P}}^2} + \|\delta Y\|_{\mathbb{S}_{\mathcal{P}}^2}^{\frac{1}{2}} \left(\|K^1\|_{\mathbb{S}_{\mathcal{P}}^2}^{\frac{1}{2}} + \|K^2\|_{\mathbb{S}_{\mathcal{P}}^2}^{\frac{1}{2}} \right) \right].$$

We now use the estimate (5.2) in the above inequality, together with the fact that $\|\xi^2\|_{\mathbb{S}_{\mathcal{P}}^2} - \|\xi^2\|_{\mathbb{S}_{\mathcal{P}}^2} \leq \|\delta \xi\|_{\mathbb{S}_{\mathcal{P}}^2}$, to complete the proof of the Theorem. \square

6 Appendix

In this Appendix, we construct smooth approximations of the partial differential equations (2.1), (2.2) and study the properties of the integrability class $\mathbb{L}_{\mathcal{P}}^2$.

6.1 Approximation

The main goal of this subsection is to construct a smooth approximation of solutions of (2.2). We require smoothness of these solutions in order to be able to apply the Itô rule. The first obstacle to regularity is the possible degeneracy of the nonlinearity G or equivalently the possible degeneracy of the lower bound \underline{a} . Therefore, we do not expect the equation to regularize the final data. However, even in this case the solution remains twice differentiable provided the final data has this regularity. But the second difficulty in proving smoothness emanates from the fact that the equation (2.2) is solved in several time intervals and in each interval (t_i, t_{i+1}) and the value B_{t_i} enters into the equation as a parameter. Differentiability with respect to these types of parameters is harder to prove. Given these difficulties, we approximate the equation as follows.

For $\epsilon \in (0, 1]$, set $\underline{a}^\epsilon := \underline{a} \vee \epsilon I$ so that

$$\bar{G}^\epsilon(\gamma) := \sup \left\{ \frac{1}{2} a : \gamma \mid \underline{a}^\epsilon \leq a \leq \bar{a} \right\},$$

where we use the short notation $a : \gamma := \text{trace}(a\gamma)$ for two symmetric matrices a, γ . We then mollify \bar{G}^ϵ . Indeed, let $\eta : \mathbb{S}^d \rightarrow [0, 1]$ be a regular bump function, i.e., support of η is B_1 and $\int \eta dx = 1$. We then define

$$G^\epsilon(\gamma) := \int_{B_1} \bar{G}^\epsilon(\gamma + \epsilon\gamma') \eta(\gamma') d\gamma'.$$

It can be shown that

$$\frac{1}{2} \underline{a}^\epsilon : \gamma' \leq G^\epsilon(\gamma + \gamma') - G^\epsilon(\gamma) \leq \frac{1}{2} \bar{a} : \gamma',$$

and that there is a constant C^* satisfying

$$0 \leq G^\epsilon(\gamma) - \bar{G}^\epsilon(\gamma) \leq C^* \epsilon.$$

Moreover G^ϵ is smooth and convex. Thus, we can define the Legendre transform of G^ϵ by

$$L^\epsilon(a) := \sup_{\gamma \in \mathbb{S}^d} \left\{ \frac{1}{2} a : \gamma - G^\epsilon(\gamma) \right\}.$$

Then $L^\epsilon(a)$ is finite only if $\underline{a}^\epsilon \leq a \leq \bar{a}$. Also, $-C^* \epsilon \leq L^\epsilon(a) \leq 0$ for all $\underline{a}^\epsilon \leq a \leq \bar{a}$ and

$$G^\epsilon(\gamma) := \sup_{\underline{a}^\epsilon \leq a \leq \bar{a}} \left\{ \frac{1}{2} a : \gamma - L^\epsilon(a) \right\}.$$

We are now ready to prove the approximation result. Recall that $\mathcal{M} \subset \mathbb{L}_{\mathcal{P}}^2$ is the subset for which the representation (5.1) holds.

Proposition 6.1 $\mathcal{L}_{ip} \subset \mathcal{M}$.

Proof. Let $\xi \in \mathcal{L}_{ip}$. Then $\xi = \varphi(B_{t_1}, \dots, B_{t_n})$ for some bounded Lipschitz function φ and $0 \leq t_1 \leq \dots \leq t_n = 1$. Let $\{v_i\}_{i=1}^n$ be the solutions of (2.2). Then, v_i 's are bounded and Lipschitz continuous. Moreover, by the definition of the G -expectations

$$E_t^G[\xi] = v_i(t, B_{t_1}, \dots, B_{t_{i-1}}, B_t), \quad t \in [t_{i-1}, t_i].$$

We approximate v_i as follows. Let φ^ϵ be smooth, bounded approximation of φ so that $\|\varphi^\epsilon - \varphi\|_\infty$ tends to zero and $\|\nabla \varphi^\epsilon\|_\infty \leq \|\nabla \varphi\|_\infty$. Define $v_i^\epsilon(t, x_1, \dots, x_i, x)$ recursively as in the definition G -expectations in Section 2 with data $\varphi^\epsilon(B_{t_1}, \dots, B_{t_n})$ and the nonlinearity G^ϵ . Indeed, v_i^ϵ is the solution of

$$-\frac{\partial}{\partial t} v_i^\epsilon(t, x_1, \dots, x_{i-1}, x) - G^\epsilon(D_x^2 v_i^\epsilon(t, x_1, \dots, x_{i-1}, x)) = 0, \quad (6.1)$$

on the interval $[t_{i-1}, t_i]$ with final data $v_i^\epsilon(t_i, x_1, \dots, x_{i-1}, x) = v_{i+1}^\epsilon(t_i, x_1, \dots, x_{i-1}, x, x)$. In the interval $[t_{n-1}, 1)$, $v_n^\epsilon(t, x_1, \dots, x_{n-1}, x)$ solves (6.1) with data $v_n^\epsilon(1, x_1, \dots, x_{n-1}, x) = \varphi^\epsilon(x_1, \dots, x_{n-1}, x)$. By the celebrated regularity result of Krylov [10] (Theorem 1, section 6.3, page 292), $v_i^\epsilon(t, x_1, \dots, x_{i-1}, x)$ is a smooth function of $(t, x) \in (t_i, t_{i+1}) \times \mathbb{R}^d$ and it is bounded and Lipschitz in all variables. Moreover the uniform Lipschitz constant of φ is preserved and for each i , we have

$$\lim_{n \rightarrow \infty} \|v_i^\epsilon - v_i\|_\infty = 0, \quad \sup_{0 < \epsilon \leq 1} \|\nabla v_i^\epsilon\|_\infty \leq \|\nabla \varphi\|_\infty.$$

For $t \in (t_i, t_{i+1})$, we set

$$\begin{aligned} M_t^\epsilon &:= v_i^\epsilon(t, B_{t_1}, \dots, B_{t_{i-1}}, B_t), \\ H_t^\epsilon &:= \nabla_x v_i^\epsilon(t, B_{t_1}, \dots, B_{t_{i-1}}, B_t), \\ K_t^\epsilon &:= G^\epsilon(D_x^2 v_i^\epsilon(t, B_{t_1}, \dots, B_{t_{i-1}}, B_t)) - \frac{1}{2} \text{tr} [\hat{a}_t D_x^2 v_i^\epsilon(t, B_{t_1}, \dots, B_{t_{i-1}}, B_t)], \end{aligned}$$

so that

$$dM_t^\epsilon = H^\epsilon \cdot dB_t - dK_t^\epsilon.$$

Let \mathcal{P}_ϵ be defined exactly as \mathcal{P} but with lower bound \underline{a}_ϵ in (3.1). Then, by the definition of G^ϵ and \mathcal{P}_ϵ , we have that K^ϵ is non-decreasing \mathbb{P} almost surely for every $\mathbb{P} \in \mathcal{P}_\epsilon$. But also since $L^\epsilon \geq -C^*\epsilon$, we have

$$-C^*\epsilon \leq \sup_{\mathbb{P} \in \mathcal{P}_\epsilon} \mathbb{E}^\mathbb{P} [-K_1^\epsilon] \leq 0. \quad (6.2)$$

Thus K^ϵ is almost a G -martingale.

It is clear that M_t^ϵ converges to $M_t := E_t^G[\xi]$. Also, $|H_t^\epsilon|$ is uniformly bounded in ϵ due to the Lipschitz estimate on v_i^ϵ . Hence $H^\epsilon \in \mathcal{H}_G^2$. Also the Proposition 5.8 yields,

$$\|K^\epsilon\|_{\mathbb{S}_{\mathcal{P}_\epsilon}^2} \leq C \|M^\epsilon\|_{\mathbb{S}_{\mathcal{P}_\epsilon}^2} \leq C \|\xi\|_\infty.$$

Moreover, by Proposition 5.9 (applied with \mathcal{P}_ϵ instead of \mathcal{P}) we obtain the following estimate

$$\|H^\epsilon - H^{\epsilon'}\|_{\mathbb{H}_{\mathcal{P}_{\epsilon_0}}^2} + \|K^\epsilon - K^{\epsilon'}\|_{\mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2} \leq C(\epsilon_0), \quad 0 < \epsilon, \epsilon' \leq \epsilon_0,$$

where

$$\begin{aligned} C(\epsilon_0) &:= \sup_{0 < \epsilon, \epsilon' \leq \epsilon_0} \left(\|M^\epsilon - M^{\epsilon'}\|_{\mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2} + \|M^\epsilon - M^{\epsilon'}\|_{\mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2}^{1/2} \left(\|K^\epsilon\|_{\mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2} + \|K^{\epsilon'}\|_{\mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2} \right) \right) \\ &\leq \sup_{0 < \epsilon, \epsilon' \leq \epsilon_0} \left(\|M^\epsilon - M^{\epsilon'}\|_{\mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2} + \|M^\epsilon - M^{\epsilon'}\|_{\mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2}^{1/2} (2\|\xi\|_\infty) \right). \end{aligned}$$

Since M^ϵ converges uniformly to M_t , $C(\epsilon_0)$ tends to zero with ϵ_0 . Therefore $\{(H^\epsilon, K^\epsilon)\}_\epsilon$ is a Cauchy sequence in $\mathbb{H}_{\mathcal{P}_{\epsilon_0}}^2 \times \mathbb{S}_{\mathcal{P}_{\epsilon_0}}^2$ for every ϵ_0 .

By the closure results, Theorem 5.4 and Theorem 5.7, we conclude that there are $H \in \mathbb{H}_{\mathcal{P}_\epsilon}^2$ and $K \in \mathbb{I}_{\mathcal{P}_\epsilon}^2$ for every $\epsilon > 0$ and that (M, H, K) satisfies 5.4 and

$$\|H\|_{\mathbb{S}_{\mathcal{P}_\epsilon}^2} + \|K\|_{\mathbb{S}_{\mathcal{P}_\epsilon}^2} \leq C\|\xi\|_\infty. \quad (6.3)$$

Clearly H and K are independent of ϵ . Since by definition and by (3.1)

$$\mathcal{P} = \cup_{\epsilon > 0} \mathcal{P}_\epsilon,$$

we conclude from the uniform estimates (6.3) that $H \in \mathbb{H}_{\mathcal{P}}^2$, $K \in \mathbb{I}_{\mathcal{P}}^2$. Moreover, this yields that $H \in \mathcal{H}_{\mathcal{P}}^2$ and also $-K$ is a G -martingale by (6.2). Since $M_t = E_t^G[\xi]$, we have shown that there is a martingale representation for the arbitrary random variable $\xi \in \mathcal{L}_{ip}$. Hence $\xi \in \mathcal{M}$. \square

6.2 $\mathbb{L}_{\mathcal{P}}^p$ -spaces

In this section we study the properties of the $\mathbb{L}_{\mathcal{P}}^2$ space. The following result together with the example that follows it, imply Lemma 4.1.

Lemma 6.2 *For every $p > 2$, there exists C_p so that for $\xi \in \mathcal{L}_{ip}$,*

$$\|\xi\|_{\mathbb{L}_{\mathcal{P}}^2} \leq C_p \|\xi\|_{\mathcal{L}_G^p}.$$

Proof. Since $\xi \in \mathcal{L}_{ip}$, for each $\mathbb{P} \in \mathcal{P}$, $E_t^G[\xi] = M_t := \text{ess sup}_{\mathbb{P}' \in \mathcal{P}(t, \mathbb{P})} \mathbb{E}_t^{\mathbb{P}'}[\xi]$, \mathbb{P} -a.s.. Set $M_t^* := \sup_{0 \leq s \leq t} M_s$. It suffices to show that

$$\mathbb{E}^{\mathbb{P}}[|M_1^*|^2] \leq C_p \|\xi\|_{\mathbb{L}_{\mathcal{P}}^p}^2 \quad \text{for all } \mathbb{P} \in \mathcal{P}.$$

Now fix $\mathbb{P} \in \mathcal{P}$. Without loss of generality we may assume $\xi \geq 0$.

Since M is a \mathbb{P} -supermartingale, it has a càdlàg version under \mathbb{P} . For any $\lambda > 0$, set $\hat{\tau} := \hat{\tau}_\lambda := \inf\{t : M_t \geq \lambda\}$. Then $\hat{\tau}$ is an \mathbb{F} -stopping time and

$$\mathbb{P}(M_1^* \geq \lambda) = \mathbb{P}(\hat{\tau} \leq 1) \leq \frac{1}{\lambda} \mathbb{E}^\mathbb{P} \left[M_{\hat{\tau}} \mathbf{1}_{\{\hat{\tau} \leq 1\}} \right].$$

By Neveu [11], there exist a sequence $\{\mathbb{P}_j, j \geq 1\} \subset \mathcal{P}(\hat{\tau}, \mathbb{P})$ defined in (3.2) such that

$$M_{\hat{\tau}} = \sup_{j \geq 1} \mathbb{E}_{\hat{\tau}}^{\mathbb{P}_j} [\xi], \quad \mathbb{P} - \text{a.s.}$$

For each $n \geq 1$, denote

$$M_{\hat{\tau}}^n := \sup_{1 \leq j \leq n} \mathbb{E}_{\hat{\tau}}^{\mathbb{P}_j} [\xi].$$

Then $M_{\hat{\tau}}^n \uparrow M_{\hat{\tau}}$, \mathbb{P} -a.s.. Fix n . Set $A_j := \{M_{\hat{\tau}}^n = \mathbb{E}_{\hat{\tau}}^{\mathbb{P}_j} [\xi]\}$, $1 \leq j \leq n$, and $\tilde{A}_1 := A_1$, $\tilde{A}_j := A_j \setminus \cup_{1 \leq i < j} A_i$, $j = 2, \dots, n$. Then $\{\tilde{A}_j, 1 \leq j \leq n\} \subset \mathcal{F}_{\hat{\tau}}^B$ form a partition of Ω . Define $\hat{\mathbb{P}}^n$ by

$$\hat{\mathbb{P}}^n(E) := \sum_{j=1}^n \mathbb{P}_j(E \cap \tilde{A}_j).$$

Clearly $\hat{\mathbb{P}}^n \in \mathcal{P}$. Since $\mathbb{P}_j \in \mathcal{P}(\hat{\tau}, \mathbb{P})$, $j = 1, \dots, n$, it is also clear that $\hat{\mathbb{P}}^n \in \mathcal{P}(\hat{\tau}, \mathbb{P})$. Then we have

$$M_{\hat{\tau}}^n = \mathbb{E}_{\hat{\tau}}^{\hat{\mathbb{P}}^n} [\xi].$$

Since $\hat{\mathbb{P}}^n \in \mathcal{P}(\hat{\tau}, \mathbb{P})$, by definition $\hat{\mathbb{P}}^n = \mathbb{P}$ on $\mathcal{F}_{\hat{\tau}}^B$. Let $q = p/(p-1)$ be the conjugate of p . We directly estimate that

$$\begin{aligned} \mathbb{E}^\mathbb{P} \left[M_{\hat{\tau}}^n \mathbf{1}_{\{\hat{\tau} \leq 1\}} \right] &= \mathbb{E}^{\hat{\mathbb{P}}^n} \left[M_{\hat{\tau}}^n \mathbf{1}_{\{\hat{\tau} \leq 1\}} \right] = \mathbb{E}^{\hat{\mathbb{P}}^n} \left[\mathbb{E}_{\hat{\tau}}^{\hat{\mathbb{P}}^n} [\xi] \mathbf{1}_{\{\hat{\tau} \leq 1\}} \right] = \mathbb{E}^{\hat{\mathbb{P}}^n} \left[\xi \mathbf{1}_{\{\hat{\tau} \leq 1\}} \right] \\ &\leq \left[\mathbb{E}^{\hat{\mathbb{P}}^n} (|\xi|^p) \right]^{\frac{1}{p}} \left[\hat{\mathbb{P}}^n(\hat{\tau} \leq 1) \right]^{\frac{1}{q}} = \left[\mathbb{E}^{\hat{\mathbb{P}}^n} (|\xi|^p) \right]^{\frac{1}{p}} \left[\mathbb{P}(M_1^* \geq \lambda) \right]^{\frac{1}{q}} \\ &\leq \|\xi\|_{\mathbb{L}_G^p} \left[\mathbb{P}(M_1^* \geq \lambda) \right]^{\frac{1}{q}}. \end{aligned}$$

We let $n \rightarrow \infty$ to arrive at

$$\mathbb{P}(M_1^* \geq \lambda) \leq \frac{1}{\lambda} \mathbb{E}^\mathbb{P} \left[M_{\hat{\tau}}^* \mathbf{1}_{\{\hat{\tau} \leq 1\}} \right] \leq \lim_{n \rightarrow \infty} \frac{1}{\lambda} \mathbb{E}^\mathbb{P} \left[M_{\hat{\tau}}^n \mathbf{1}_{\{\hat{\tau} \leq 1\}} \right] \leq \frac{1}{\lambda} \|\xi\|_{\mathbb{L}_G^p} \left[\mathbb{P}(M_1^* \geq \lambda) \right]^{\frac{1}{q}}.$$

Therefore,

$$\mathbb{P}(M_1^* \geq \lambda) \leq \frac{1}{\lambda^p} \|\xi\|_{\mathbb{L}_G^p}^p,$$

so that for any fixed λ_0 ,

$$\begin{aligned}\mathbb{E}^{\mathbb{P}}[|M_1^*|^2] &= 2 \int_0^\infty \lambda \mathbb{P}(M_1^* \geq \lambda) d\lambda \leq 2 \int_0^{\lambda_0} \lambda d\lambda + 2 \int_{\lambda_0}^\infty \lambda \mathbb{P}(M_T^* \geq \lambda) d\lambda \\ &\leq \lambda_0^2 + 2 \|\xi\|_{\mathbb{L}_G^p}^p \int_{\lambda_0}^\infty \frac{d\lambda}{\lambda^{p-1}} = \lambda_0^2 + \frac{2}{p-2} \|\xi\|_{\mathbb{L}_G^p}^p \lambda_0^{2-p}.\end{aligned}$$

We choose $\lambda_0 := \|\xi\|_{\mathbb{L}_G^p}$ to arrive at

$$\mathbb{E}^{\mathbb{P}}[|M_1^*|^2] \leq C_p \|\xi\|_{\mathbb{L}_G^p}^2.$$

□

We next construct a bounded random variable which is not in \mathcal{L}_G^1 .

Example 6.3 Let $d = 1$, $\underline{a} = 1$, $\bar{a} = 2$, $E := \{\overline{\lim}_{t \downarrow 0} B_t / \sqrt{2t \ln \ln \frac{1}{t}} = 1\}$. We claim that $\mathbf{1}_E \notin \mathcal{L}_G^1$. Indeed, assume that $\mathbf{1}_E \in \mathcal{L}_G^1$. Then there exists $\xi_n = \varphi(B_{t_1}, \dots, B_{t_n}) \in \mathcal{L}_{ip}$ such that $\mathbb{E}^G[|\xi_n - \mathbf{1}_E|] < \frac{1}{3}$. For $\theta \in [0, 1]$, denote $a_t^\theta := 1 + \theta \mathbf{1}_{[0, t_1)}(t)$ and $\mathbb{P}^\theta := \mathbb{P}^{a^\theta}$. Define $\psi(x) := \mathbb{E}^{\mathbb{P}^0}[\varphi(x, x + B_{t_2-t_1}, \dots, x + B_{t_n-t_1})]$. Since $E \in \mathcal{F}_{0+} \subset \mathcal{F}_{t_1}$, for any $\theta \in [0, 1]$, we have the following inequality.

$$\begin{aligned}\mathbb{E}^{\mathbb{P}^\theta} \left[\left| \psi(B_{t_1}) - \mathbf{1}_E \right| \right] &= \mathbb{E}^{\mathbb{P}^\theta} \left[\left| \mathbb{E}_{t_1}^{\mathbb{P}^\theta} [\varphi(B_{t_1}, \dots, B_{t_n})] - \mathbf{1}_E \right| \right] \\ &\leq \mathbb{E}^{\mathbb{P}^\theta} \left[\left| \varphi(B_{t_1}, \dots, B_{t_n}) - \mathbf{1}_E \right| \right] < \frac{1}{3}.\end{aligned}$$

Note that $\mathbb{P}^0(E) = 1$ and $\mathbb{P}^\theta(E) = 0$ for all $\theta > 0$. Then

$$\mathbb{E}^{\mathbb{P}^0} \left[\left| \psi(B_{t_1}) - 1 \right| \right] < \frac{1}{3} \quad \text{and} \quad \mathbb{E}^{\mathbb{P}^\theta} \left[\left| \psi(B_{t_1}) \right| \right] < \frac{1}{3} \quad \text{for all } \theta > 0.$$

The latter implies that

$$\mathbb{E}^{\mathbb{P}^0} \left[\left| \psi(B_{t_1}) \right| \right] = \lim_{\theta \downarrow 0} \mathbb{E}^{\mathbb{P}^0} \left[\left| \psi((1 + \theta)^{\frac{1}{2}} B_{t_1}) \right| \right] = \lim_{\theta \downarrow 0} \mathbb{E}^{\mathbb{P}^\theta} \left[\left| \psi(B_{t_1}) \right| \right] \leq \frac{1}{3}.$$

Thus

$$1 \leq \mathbb{E}^{\mathbb{P}^0} \left[\left| \psi(B_{t_1}) - 1 \right| \right] + \mathbb{E}^{\mathbb{P}^0} \left[\left| \psi(B_{t_1}) \right| \right] \leq \frac{1}{3} + \frac{1}{3} = \frac{2}{3},$$

yielding a contradiction. Hence $\mathbf{1}_E \notin \mathcal{L}_G^1$. □

We close the paper with an example that shows that the process K does not have any special structure.

Example 6.4 Let ν be a deterministic Radon measure of $[0, 1]$ and $F : \mathbb{S}_d \rightarrow \mathbb{R}^1$ be a smooth function so that $F(0) = 0$ and $F(a) \geq 0$ for all $a \geq 0$. We define a random variable by

$$\xi := - \int_0^1 F(\hat{a}_s - \underline{a}) \nu(ds).$$

For every integer n , we set

$$\xi^n := - \sum_{i=1}^n F(n[B_{k/n} - B_{(k-1)/n}] \otimes [B_{k/n} - B_{(k-1)/n}] - \underline{a}) \nu \left(\left[\frac{k-1}{n} - \frac{k}{n} \right] \right).$$

Clearly $\xi^n \in \mathcal{L}_{ip}$. If ν does not have any atoms then we can show that ξ^n converges to ξ in $\mathbb{L}_{\mathcal{P}}^p$ for every $p < \infty$. Hence $\xi \in \mathcal{L}_{\mathcal{P}}^p$. Moreover,

$$\mathbb{E}_t^G[\xi] = - \int_0^t F(\hat{a}_s - \underline{a}) \nu(ds).$$

Hence the martingale representation holds with $H \equiv 0$ and $K_t = \mathbb{E}_t^G[\xi]$. □

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