

Stochastic Calculus For Finance - volume 2

Section 5.4 Fundamental Theorems of Assets Pricing

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Terminology

- $W(t) = (W_1(t), W_2(t), \dots, W_d(t))$, is a d -dimensional Brownian motion on the actual probability space $(\Omega, \mathcal{F}, \mathbb{P})$, where \mathbb{P} is the actual probability measure.
- Associating to this Brownian motion, we have the filtration (multidimensional) $F(t)$, also we have a fixed final time T , and we denote $F(T)$ as F .

Theorem 5.4.1 (Girsanov Theorem for Multidimensional)

Theorem 5.4.1 (Girsanov, multiple dimensions). *Let T be a fixed positive time, and let $\Theta(t) = (\Theta_1(t), \dots, \Theta_d(t))$ be a d -dimensional adapted process. Define*

$$Z(t) = \exp \left\{ - \int_0^t \Theta(u) \cdot dW(u) - \frac{1}{2} \int_0^t \|\Theta(u)\|^2 du \right\}, \quad (5.4.1)$$

$$\widetilde{W}(t) = W(t) + \int_0^t \Theta(u) du, \quad (5.4.2)$$

and assume that

$$\mathbb{E} \int_0^T \|\Theta(u)\|^2 Z^2(u) du < \infty. \quad (5.4.3)$$

Set $Z = Z(T)$. Then $\mathbb{E}Z = 1$, and under the probability measure $\widetilde{\mathbb{P}}$ given by

$$\widetilde{\mathbb{P}}(A) = \int_A Z(\omega) d\mathbb{P}(\omega) \text{ for all } A \in \mathcal{F},$$

the process $\widetilde{W}(t)$ is a d -dimensional Brownian motion.

basic concept:

- Multidimensional Ito's integral can be viewed as a matrix form integral:

$$\int_0^T \Theta dW = \int_0^T \begin{pmatrix} \Theta_{11} & \cdots & \Theta_{1d} \\ \vdots & \ddots & \vdots \\ \Theta_{m1} & \cdots & \Theta_{md} \end{pmatrix} d \begin{pmatrix} W_1 \\ \vdots \\ W_d \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^d \int_0^T \Theta_{1j} dW_j \\ \vdots \\ \sum_{j=1}^d \int_0^T \Theta_{mj} dW_j \end{pmatrix}, \text{ and hence } \int_0^t \Theta(u) \cdot dW(u) = \sum_{j=1}^d \int_0^t \Theta_j(u) dW_j(u)$$

- $\|\Theta(u)\|$ denotes the Euclidean norm, which is $\|\Theta(u)\| = ((\sum_{j=1}^d \Theta_j^2(u)))^{\frac{1}{2}}$
- $\widetilde{W} = W(t) + \int_0^t \Theta(u) du$ simply represents $\widetilde{W}_j(t) = W_j(t) + \int_0^t \Theta_j(u) du, j = 1, \dots, d$
- The condition $\mathbb{E}(\int_0^T \|\Theta(u)\|^2 Z^2(u) du) < \infty$ ensures that the defining Ito's integral is well-defined and is a martingale
- Moreover, it ensures the process is in L^2 , and ensures the Hilbert properties

recall: Multidimensional Levy Theorem

- Let $W_1(t), W_2(t), \dots, W_d(t), t \geq 0$, be martingales relative to a filtration $F(t)$.
- All $W_i(0)=0, i=1,2, \dots,d$.
- All $W_i(t)$ has continuous paths.
- All $[W_i, W_i](t)=t$, for all $t \geq 0$.
- All $[W_i, W_j](t)=0$, for all $i \neq j$, and $i,j=1,2, \dots,d$.

Then we have W_1, W_2, \dots, W_d are independent Brownian motions. Or we can also see that let $W(t) = (W_1(t), \dots, W_d(t))$, then W is a standard d -dimensional Brownian motion, and we would like to specifically recall the fact that by definition, $dW_i(t)dW_j(t) = 0, \forall i \neq j$

proof:

We want to show that \widetilde{W} satisfies the Multidimensional Levy's Characterization Theorem and hence we can conclude that \widetilde{W} is a standard d-dimensional Brownian motion.

Before that, we would first prove:

$$Z(t) = \exp\left(-\int_0^t \Theta(u) \cdot dW(u) - \frac{1}{2} \int_0^t \|\Theta(u)\|^2 du\right), \text{ then } \mathbb{E}(Z(t)) = 1, \forall t \geq 0$$

Simply set $f(x) = e^x$, $X(t) = -\int_0^t \Theta(u) \cdot dW(u) - \frac{1}{2} \int_0^t \|\Theta(u)\|^2 du$, then we have

$$\begin{aligned} dZ(t) &= d(f(X(t))) = f'(X(t))dX + \frac{1}{2}f''(X(t))(dX)^2 \\ &= e^{X(t)}\left(-\sum_{j=1}^d \Theta_j(u)dW_j(u) - \frac{1}{2} \|\Theta(u)\|^2 du\right) + \frac{1}{2}e^{X(t)} \|\Theta(u)\|^2 du = -\sum_{j=1}^d \Theta_j(u)Z(t)dW_j(u), \text{ hence martingale.} \end{aligned}$$

Therefore, $\mathbb{E}(Z(t)) = \mathbb{E}(\mathbb{E}(Z(t)|\mathcal{F}(0))) = \mathbb{E}(1) = 1, \forall t \geq 0$

Now we prove the rest:

continue:

Easily observe that all $W_j(u)$ start at 0, having continuous paths, also the quadratic variation can be computed as $\widetilde{dW(t)}^2 = (dW(t) + \Theta(t)dt)^2 = dt$

Also we see that $\widetilde{dW_i(t)}\widetilde{dW_j(t)} = (dW_i(t) + \Theta_i(t)dt)(dW_j(t) + \Theta_j(t)dt) = 0, \forall i \neq j$

To prove that $\widetilde{W(t)}$ is a martingale under $\widetilde{\mathbb{P}}$, consider:

$$\begin{aligned} d(\widetilde{W(t)}Z(t)) &= \widetilde{W(t)}dZ(t) + d\widetilde{W(t)}Z(t) + d\widetilde{W(t)}dZ(t) = \\ \widetilde{W(t)}(-\sum_{j=1}^d \Theta_j(t)Z(t)dW_j(u)) &+ Z(t)(dW(t) + \Theta(t)dt) + (dW(t) + \Theta(t)dt)(-\sum_{j=1}^d \Theta_j(t)Z(t)dW_j(t)) = (-\widetilde{W(t)}\Theta(t) + 1)Z(t)dW(t) \end{aligned}$$

Hence, using Lemma 5.2.2, we obtain $\widetilde{\mathbb{E}}[\widetilde{W(t)}Z(t)|\mathcal{F}(s)] = \frac{1}{Z(s)}\mathbb{E}[\widetilde{W(t)}Z(t)|\mathcal{F}(s)] = \frac{1}{Z(s)}\widetilde{W(s)}Z(s) = \widetilde{W(s)}$,

and the proof is done.

Lemma 5.2.2. *Let s and t satisfying $0 \leq s \leq t \leq T$ be given and let Y be an $\mathcal{F}(t)$ -measurable random variable. Then*

$$\widetilde{\mathbb{E}}[Y|\mathcal{F}(s)] = \frac{1}{Z(s)}\mathbb{E}[YZ(t)|\mathcal{F}(s)]. \quad (5.2.9)$$

Theorem 5.4.2 (Multidimensional Martingale Representation)

Let T be a fixed positive time, and assume that $\mathcal{F}(t)$, $0 \leq t \leq T$, is the filtration generated by the d -dimensional Brownian motion $W(t)$, $0 \leq t \leq T$. Let $M(t)$, $0 \leq t \leq T$, be a martingale with respect to this filtration under \mathbb{P} . Then there is an adapted, d -dimensional process $\Gamma(u) = (\Gamma_1(u), \dots, \Gamma_d(u))$, $0 \leq u \leq T$, such that

$$M(t) = M(0) + \int_0^t \Gamma(u) \cdot dW(u), \quad 0 \leq t \leq T. \quad (5.4.4)$$

If, in addition, we assume the notation and assumptions of Theorem 5.4.1 and if $\widetilde{M}(t)$, $0 \leq t \leq T$, is a $\widetilde{\mathbb{P}}$ -martingale, then there is an adapted, d -dimensional process $\widetilde{\Gamma}(u) = (\widetilde{\Gamma}_1(u), \dots, \widetilde{\Gamma}_d(u))$ such that

$$\widetilde{M}(t) = \widetilde{M}(0) + \int_0^t \widetilde{\Gamma}(u) \cdot d\widetilde{W}(u), \quad 0 \leq t \leq T. \quad (5.4.5)$$

proof(simple):

We first introduce a important theorem,Ito's Representation theorem:

Let $F \in L^2(\mathcal{F}^n(t), \mathbb{P})$, then there uniquely exists a stochastic process $\Theta(t, w)$, which is progressively measurable such that $F(w) = \mathbb{E}(F) + \int_0^T \Theta(t, w) dW(t)$

Now to prove our case. simply take $F=M(t)$ and we are done.

Multidimensional Market model

Assuming there are m stocks, each having SDE $dS_i(t) = \alpha_i(t)S_i(t) dt + S_i(t) \sum_{j=1}^d \sigma_{ij}(t) dW_j(t)$, $i = 1, \dots, m$.

It is clear that these stocks are correlated, to see this we define:

$$\sigma_i(t) = \sqrt{\sum_{j=1}^d \sigma_{ij}^2(t)} \neq 0 \text{ and } B_i(t) = \sum_{j=1}^d \int_0^t \frac{\sigma_{ij}(u)}{\sigma_i(u)} dW_j(u), i = 1, \dots, m$$

We see that each B is a continuous martingale, and $(dB_i(t))^2 = \sum_{j=1}^d \frac{\sigma_{ij}^2(t)}{\sigma_i^2(t)} dt = dt$

By Levy's Theorem, each B is a Brownian motion, then we rewrite:

$$dS_i(t) = \alpha_i(t)S_i(t) dt + \sigma_i(t)S_i(t) dB_i(t).$$

We see that $dB_i(t)dB_k(t) = \sum_{j=1}^d \frac{\sigma_{ij}(t)\sigma_{kj}(t)}{\sigma_i(t)\sigma_k(t)} dt = \rho_{ik}(t)dt, \forall i \neq k$, using product rules:

$$d(B_i(t)B_k(t)) = B_i(t)dB_k(t) + B_k(t)dB_i(t) + dB_i(t)B_k(t)$$

Continue:

We can obtain: $B_i(t)B_k(t) = \int_0^t B_i(u)dB_k(u) + \int_0^t B_k(u)dB_i(u) + \int_0^t \rho_{ik}(u)du$

Taking expectation on both sides: $Cov[B_i(t), B_k(t)] = \mathbb{E}(\int_0^t \rho_{ik}(u)du)$

If $\sigma_{ij}(t), \sigma_{kj}(t)$ is a constant, then $Cov[B_i(t), B_k(t)] = \rho t$, since $B_i(t), B_k(t)$ both have variance t , so the correlation is ρ , which we call it instantaneous correlation.

We note that: $dS_i(t)dS_k(t) = \sigma_i(t)\sigma_k(t)S_i(t)S_k(t)dB_i(t)dB_k(t) = \rho_{ik}(t)\sigma_i(t)\sigma_k(t)S_i(t)S_k(t)dt$

or $\frac{dS_i(t)}{S_i(t)} \cdot \frac{dS_k(t)}{S_k(t)} = \rho_{ik}(t)\sigma_i(t)\sigma_k(t)dt$

Finally we define a *discount process*: $D(t) = e^{-\int_0^t R(u)du}$, assuming that R is an adapted process, then we have:

$$\begin{aligned} d(D(t)S_i(t)) &= D(t)dS_i(t) - R(t)S_i(t)dt = D(t)S_i(t)[(\alpha_i(t) - R(t))dt + \sum_{j=1}^d \sigma_{ij}(t)dW_j(t)] \\ &= D(t)S_i(t)[(\alpha_i(t) - R(t))dt + \sigma_i(t)dB_i(t)], i = 1, \dots, m \end{aligned}$$