

Toward a benchmark GPU platform to simulate XVA

Babacar Diallo

a joint work with Lokman Abbas-Turki

INRIA

6 July 2016

Introduction

Simulation algorithms

Without funding constraints

With funding constraints

Some simulation
results

Common-Shock
Model

Conclusion

Plan

Introduction

Simulation algorithms

Without funding constraints

With funding constraints

Some simulation results

Common-Shock Model

Conclusion

Credit Valuation Adjustment

In a financial transaction between a party C that has to pay another party B some amount V , the CVA value is the price of the insurance contract that covers the default of party C to pay the whole sum V .

$$\text{CVA}_{t,T} = (1 - R)E_t (V_{\tau}^{+} 1_{t < \tau \leq T}) \quad (1)$$

- ▶ R is the recovery to make if the counterparty defaults (Assume $R = 0$),
- ▶ τ is the random default time of the counterparty,
- ▶ T is the protection time horizon.

Numerical simulation

$$\text{CVA}_{0,T} \approx \sum_{k=0}^{N-1} E \left(V_{t_k}^{+} 1_{\tau \in (t_k, t_{k+1}]} \right), \quad (2)$$

$N \leq$ the number of time steps used for SDEs discretization.

Importance

- ▶ Hold sufficient amount of liquid assets to face the counterparty default.
- ▶ Basel III includes the calculation of the CVA (Credit Valuation Adjustment) as an important part of the prudential rules.

TVA definition Total valuation adjustment ($>CVA+DVA+FVA$), it covers:

- ▶ Both defaults: $\tau = \tau^c \wedge \tau^b$, CVA and DVA.
- ▶ Funding our risk and the risk of the counterparty: Nonlinear BSDE part, FVA.

S. Crépey(2012) Ignoring the external funding and denoting $\beta_t = e^{-\int_0^t r_u du}$ where r is the risk-free short rate process, Θ satisfies the following BSDE on $[0, \tau \wedge T]$

$$\beta_t \Theta_t = E \left[\beta_\tau 1_{\tau < T} (V_\tau - R_\tau) + \int_t^{\tau \wedge T} \beta_s g_s (V_s - \Theta_s) ds \middle| \mathcal{G}_t \right] \quad (3)$$

where \mathcal{G} is the extension of \mathcal{F} by the natural filtration generated by τ^c and by τ^b . R is the total close-out cash-flow specified thanks to CSA (Credit Support Annex) and g is the funding coefficient.

TVA BSDE simulation

- ▶ Only for European contracts.
- ▶ Requires a good approximation of the exposure V .
- ▶ Practitioners usually use rough approximations.
- ▶ No trustable procedure in the general case.

Plan

Introduction

Simulation algorithms

Without funding constraints

With funding constraints

Some simulation
results

Common-Shock
Model

Conclusion

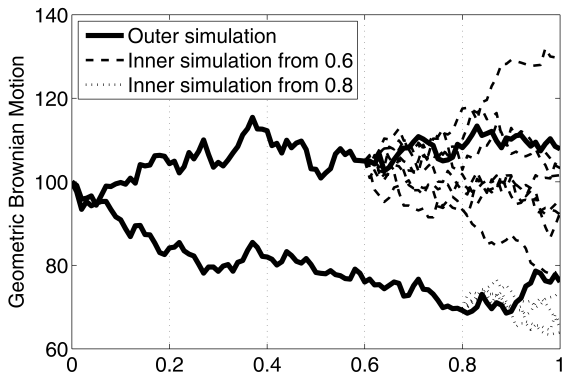
Without funding
constraints

$$\text{CVA}_{0,T} = \sum_{k=0}^{N-1} E \left(P_{k+1}^+ 1_{\tau \in (kh, (k+1)h]} \right), \quad h = \frac{T}{N}.$$

With funding
constraints

$$\Theta_k = \mathbb{E}_k (\Theta_{k+1} + hg(k+1, P_{k+1}, \Theta_{k+1})), \quad \Theta_N = 0.$$

An example of a
two stage
simulation with
 $M_0 = 2$, $M_6 = 8$
and $M_8 = 4$



CVA_{0,T}
approximation

$$\widehat{\text{CVA}}_{0,T} = \sum_{k=0}^{N-1} \frac{1}{M_0} \sum_{i=1}^{M_0} F_{k+1}^2 \left(\widehat{P}_1(S_1^i), \dots, \widehat{P}_{k+1}(S_{k+1}^i) \right) \quad (4)$$

With

$$\begin{cases} F_{k+1}^1(x_1, \dots, x_{k+1}) = E \left(1_{\tau \in (kh, (k+1)h]} | P_1 = x_1, \dots, P_{k+1} = x_{k+1} \right), \\ F_{k+1}^2(x_1, \dots, x_{k+1}) = (x_{k+1})^+ F_{k+1}^1(x_1, \dots, x_{k+1}). \end{cases} \quad (5)$$

Θ_k approximation

$$\begin{cases} \text{For } k = 1, \dots, N-1 \\ \widehat{\Theta}_k(x) = {}^t \psi(x) \Psi_k^{-1} \left[\frac{1}{M_0} \sum_{j=1}^{M_0} \psi(S_k^j) \left(\widehat{\Theta}_{k+1}(S_{k+1}^j) + \frac{1}{N} g(k+1, \widehat{\Theta}_{k+1}(S_{k+1}^j), \widehat{P}_{k+1}(S_{k+1}^j)) \right) \right] \\ \text{and } \widehat{\Theta}_N(x) = 0, \quad \widehat{\Theta}_0(S_0) = \frac{1}{M_0} \sum_{j=1}^{M_0} \left(\widehat{\Theta}_1(S_1^j) + \frac{1}{N} g(1, \widehat{\Theta}_1(S_1^j), \widehat{P}_1(S_1^j)) \right). \end{cases} \quad (6)$$

Where $\Psi_k = \mathfrak{T} \left(\frac{1}{M_0} \sum_{i=0}^{M_0} \psi(\tilde{S}_k^i) {}^t \psi(\tilde{S}_k^i) \right)$ with: $\{S^j\}_{j \in \{1, \dots, M_0\}}$ and $\{\tilde{S}^j\}_{j \in \{1, \dots, M_0\}}$ are two

independent simulations of the underlying asset S , ψ is a basis of monomial functions where K is its cardinal and \mathfrak{T} is an operator that must satisfy some desired properties.

Theorem (Lokman Abbas-Turki - Mohamed Mikou: TVA on American Derivatives)

$$\begin{aligned}
 E \left[\left(\widehat{CVA}_{0,T} - CVA_{0,T} \right)^2 \right] &\leq \frac{N^2}{M_0} \max_{k \in \{0, \dots, N-1\}} \text{Var} \left(F_{k+1}^2 \left(\widehat{P}_1(S_1^i), \dots, \widehat{P}_{k+1}(S_{k+1}^i) \right) \right) \\
 &\quad + \sum_{j=1}^N \frac{1}{4NM_j^2} \left(E \left[V_j(S_j^i) f_j''(P_j(S_j^i)) F_j^3(P_1(S_1^i), \dots, P_j(S_j^i)) \right] \right)^2 \\
 &\quad + \sum_{j=1}^N \frac{1}{4NM_j^2} \left(E \left[V_j(S_j^i) f_j''(P_j(S_j^i)) \sum_{k=j}^{N-1} F_{k+1}^4(P_1(S_1^i), \dots, P_j(S_j^i), S_j^i) \right] \right)^2 \\
 &+ \sum_{j=1}^N \frac{N}{4M_j^2} \left(E \left[V_j(S_j^i) F_j^1(P_1(S_1^i), \dots, P_j(S_j^i)) | P_j(S_j^i) = 0 \right] \varphi_j(0) \right)^2 + N \sum_{j=1}^N (N-j+1)^2 O \left(\frac{1}{M_j} \right)
 \end{aligned}$$

Where φ_j is the density of $P_j(S_j^i)$, $V_j(x) = \text{Var} \left(\sqrt{M_j} \left(\widehat{P}_j(x) - P_j(x) \right) \right)$.

Good choices If $\varphi_j(0)$ is big then take $M_j \sim \sqrt{M_0}$, otherwise $M_j \sim \sqrt{M_0}/N$. In both cases, N must be small when compared to $\sqrt{M_0}$.

For example

$$M_j = \frac{N-j}{N-1} M_1 \text{ with either } M_1 = \frac{\sqrt{M_0}}{N} \text{ or } M_1 = \sqrt{M_0}. \quad (7)$$

Theorem (Lokman Abbas-Turki - Mohamed Mikou: TVA on American Derivatives)
 As long as $\{\Theta_i(x)\}_{0 \leq i \leq N-1}$ are of class C^s on the support of $S \in \mathbb{R}^d$,
 there exists a positive constant C such that for each $0 \leq k \leq N-1$

$$E \left[\left(\widehat{\Theta}_k(S_k^j) - \Theta_k(S_k^j) \right)^2 \right] \leq \frac{CK^{N-1}}{N^2} \sum_{l=k}^{N-1} \left(E \left[\frac{V_{l+1}(S_{l+1}^j) \partial_{Pg}^2 (l+1, \Theta_{l+1}(S_{l+1}^j), P_{l+1}(S_{l+1}^j))}{2M_l} \right]^2 \right) \\ + O \left(\frac{K}{M_0} + \frac{K^2}{N^2 M_0} + \frac{K}{N^4 M_l^2} + \frac{K^{1-2s/d}}{N^2} + K^{-2s/d} \right).$$

Good choice Take $M_l \sim \sqrt{M_0/N}$, N must be sufficiently small $N \sim 10$.

For example

$$M_l = \frac{N-l}{N-1} M_1 \text{ with } M_1 = \sqrt{\frac{M_0}{N}}. \quad (8)$$

Plan

Introduction

Simulation algorithms

Without funding constraints

With funding constraints

**Some simulation
results**

Common-Shock
Model

Conclusion

Within less than 1 minute simulation on GPU:
 $M_0 = 131K$, $N = 10$, $Neds = 50$

European
 Path-dependent
 option

$$\Phi(S_T) = \left(\frac{S_T^1}{2} + \frac{S_T^2}{2} - \bar{S}_T^3 \right)_+$$

M_1	Θ_0	Θ_0 std	$CVA_{0,T}$	$CVA_{0,T}$ std
$\frac{\sqrt{M_0}}{N}$	0.01364	$4 * 10^{-5}$	0.0296	$2 * 10^{-4}$
$\frac{\sqrt{M_0}}{\sqrt{N}}$	0.01307	$4 * 10^{-5}$	0.0294	$2 * 10^{-4}$
$\sqrt{M_0}$	0.01265	$3 * 10^{-5}$	0.0291	$2 * 10^{-4}$

Within less than 1 minute simulation on GPU:
 $M_0 = 131K$, $N = 10$, $Neds = 50$

European
 Path-dependent
 option

$$\Phi(S_T) = \left(\frac{3S_T^1}{10} + \frac{7S_T^2}{10} - \bar{S}_T^3 \right)_+ - \left(\frac{7S_T^1}{10} + \frac{3S_T^2}{10} - \bar{S}_T^3 \right)_+$$

M_1	Θ_0	Θ_0 std	$CVA_{0,T}$	$CVA_{0,T}$ std
$\frac{\sqrt{M_0}}{N}$	$2.72 * 10^{-3}$	10^{-5}	0.0365	$8 * 10^{-4}$
$\frac{\sqrt{M_0}}{\sqrt{N}}$	$2.44 * 10^{-3}$	10^{-5}	0.0453	$8 * 10^{-4}$
$\sqrt{M_0}$	$2.28 * 10^{-3}$	10^{-5}	0.0520	$8 * 10^{-4}$
$\sqrt{N}\sqrt{M_0}$	$2.24 * 10^{-3}$	10^{-5}	0.0528	$8 * 10^{-4}$

Plan

Introduction

Simulation algorithms

Without funding constraints
With funding constraints

Some simulation
results

Common-Shock
Model

Conclusion

Dynamic Marshall-Olkin (DMO)

Default time model $n + 2$ credit names $\{-1, 0, \dots, n\}$.

$$\mathbb{Y} = \{\{-1\}, \{0\}, \dots, \{n\}, I_1, I_2, \dots, I_m\}, \quad (9)$$

I_j contains at least two obligors, $\mathbb{I} = \{I_1, I_2, \dots, I_m\}$.

$\lambda_Y(t, X_t)$ shock intensities, where $X_t = (X_t^Y)_{Y \in \mathbb{Y}}$ Markov factor process

$$\eta_Y = \inf \left\{ t > 0 : \int_0^t \lambda_Y(s, X_s) ds > E_Y \right\}, \quad (10)$$

E_Y random variables i.i.d and exponentially distributed with parameter 1.

If $Y^1 \neq Y^2$, $\mathbb{Q}(\eta_{Y^1} = \eta_{Y^2}) = 0$.

For each obligor i we define

$$\tau_i = \min_{Y \in \mathbb{Y}, i \in Y} \eta_Y, \quad (11)$$

as the default time of obligor i in common-shock model,

$$\tau^b = \tau_{-1}, \tau^c = \tau_0.$$

$$H_t^i = \mathbb{1}_{\tau_i \leq t}. \quad (12)$$



Conditionnal survival probability

(Bielecki; Cousin; Crépey: A Bottom-Up Dynamic Model of Portfolio Credit Risk. Part I: Markov Copula Perspective)

The conditionnal survival probability function of every obligor is given by, for every $t_i \geq t$,

$$\mathbb{Q}(\tau_i > t_i | \mathcal{F}_t(W, H)) = \mathbb{Q}(\tau_i > t_i | H_t, X_t)$$

$$= (1 - H_t^i) \mathbb{E} \left\{ e^{\left(- \int_t^{t_i} \sum_{Y \in \mathbb{Y}, i \in \mathbb{Y}} \lambda_Y(s, X_s^Y) ds \right)} \middle| X_t^i \right\}$$

CDS clean price

$$P_t^i = (1 - H_t^i) \mathbb{E} \left(\int_t^{T_i} e^{-\int_t^s \left(r_u + \sum_{Y \in \mathbb{Y}, i \in \mathbb{Y}} \lambda_Y(u, X_u^Y) \right) du} \times \left[(1 - R_i) \sum_{Y \in \mathbb{Y}, i \in \mathbb{Y}} \lambda_Y(s, X_s^Y) - S_i \right] ds \middle| X_t \right),$$

- ▶ R_i are the recovery rates;
- ▶ S_i are the contractual spreads.

Model example

Individual default intensities

X^i are independent homogenous CIR processes,

$$dX_t^i = a_i(b_i - X_t^i)dt + c_i\sqrt{X_t^i}dW^i.$$

The individual default intensities are function of X_t

$$\lambda_t^i = \kappa_i + X_t^i, \quad (13)$$

where κ_i is a constant.

Systemic shock intensities

$$\lambda_I(t, X_t) = \alpha_I \inf_{i \in I} \lambda_t^i, \quad (14)$$

$(\alpha_I)_{I \in \mathbb{I}}$ are nonnegative constants, $\sum_{I \in \mathbb{I}} \alpha_I \leq 1$.

Idiosyncratic intensities

$$\lambda_i(t, X_t) = \lambda_t^i - \sum_{i \in I} \lambda_I(t, X_t) \geq 0. \quad (15)$$



$$\text{CVA}_{0,T} = \mathbb{E} \left(\mathbb{1}_{\{\tau_0 < T\}} \beta_{\tau_0} (1 - R_0) \left[P_{\tau_0} + \left(\sum_{i \text{ pay}} - \sum_{i \text{ rec}} \right) \mathbb{1}_{\{\tau_i = \tau < T_i\}} (1 - R_i) \right]^+ \right), \quad (16)$$

$$\approx \sum_{k=0}^{N-1} \mathbb{E} \left(\mathbb{1}_{\{\tau_0 \in (t_k, t_{k+1}]\}} \beta_{t_{k+1}} (1 - R_0) \left[P_{t_{k+1}} + \left(\sum_{i \text{ pay}} - \sum_{i \text{ rec}} \right) \mathbb{1}_{\{\tau_i \in (t_k, t_{k+1}]\}} (1 - R_i) \right]^+ \right), \quad (17)$$

where $\tau^c = \tau_0$.

CDS portfolio
clean price

$$P = \left(\sum_{i \text{ pay}} - \sum_{i \text{ rec}} \right) P^i. \quad (18)$$

$$P^i(t_k, H_{t_k}^{i,l}, X_{t_k}^l) \approx (1 - H_{t_k}^{i,l}) \frac{1}{M_k} \sum_{j=1}^{M_k} \left(\sum_{t_q=t_k}^{T_i} e^{-\sum_{t_p=t_k}^{t_q} \left(r_{t_p} + \sum_{Y \in \mathbb{Y}, i \in \mathbb{Y}} \lambda_Y(t_p, X_{t_p}^{Y,l,j}) \right)} (t_p - t_{p-1}) \right. \\ \left. \left[(1 - R_i) \sum_{Y \in \mathbb{Y}, i \in \mathbb{Y}} \lambda_Y(t_q, X_{t_q}^{Y,l,j}) - S_i \right] (t_q - t_{q-1}) \right).$$

Plan

Introduction

Simulation algorithms

Without funding constraints

With funding constraints

Some simulation
results

Common-Shock
Model

Conclusion

Mathematical and computing work suited to GPUs

- ▶ Market factor TVA simulation within a minute.
- ▶ Credit factor CVA simulation with 100 CDS within few minutes.

More to come

- ▶ Better use of GPU cache memory (shared).
- ▶ Compute XVA on any general bank portfolio in less than one hour: simulation of all prices +XVA.

Architecture evolution

- ▶ High bandwidth memory (HBM) on GPU to increase throughput.
- ▶ 3d XPoint non volatile memory to store the huge number of prices.

References

- ▶ L.A. Abbas-Turki and M.A. Mikou. TVA on American Derivatives: <https://hal.archives-ouvertes.fr/hal-01142874>
- ▶ Stéphane Crépey and Tomasz R. Bielecki. Counterparty Risk and Funding A Tale of Two Puzzles. Chapman and HALL
- ▶ Tomasz R. Bielecki; Areski Cousin; Stéphane Crépey. A Bottom-Up Dynamic Model of Portfolio Credit Risk. Part I: Markov Copula Perspective. Recent Advances in Financial Engineering 2012, Takahashi and Y. Muromachi and T. Shibata (Eds.), pp.25-50 and 51-74, 2014.

Thank you

Questions?