An *n*-Dimensional Markov-Functional Interest Rate Model

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Introduction The *n*-dimensional Markov-functional model Pricing tests

Outline

Introduction

The *n*-dimensional Markov-functional model

Pricing tests TARNs and Terminal correlations

Background

Some models for the pricing and hedging of interest rate derivatives:

- Short rate models: Stable and fast computations; not very flexible w.r.t. calibration, smiles.
- LIBOR market models (LMM): Easy to understand, good intuition of model behaviour, flexible/powerful calibration; Computationally very (too) intense; Benchmark model.
- Markov-functional models (MFM).
 - Introduced 1999 by Hunt, Kennedy & Pelsser.
 - Main intuition: Short rate model efficiency (build on a lattice) combined with the LMM flexibility.
 - Quite popular in the city.
 - Only solved for one- or two-dimensional driving state processes

 — potentially limited correlation structure.

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Aim of the paper

- Develop an *n*-dimensional Markov-functional interest rate model (MFM).
- Investigate similarities and differences between the MFM and the LMM \rightarrow can we transfer the intuition from the LMM SDE to the MFM?
- Investigate potential usefulness in practise: Price Targeted Accrual Redemption Notes (TARNs).
 Currently very popular in the market and are typically priced using multifactor LIBOR market models (LMM).

Notation and Setup

- Set of increasing maturities: $today = 0 < T_1 < T_2 < \cdots < T_n < T_{n+1},$
- Zero-coupon bonds: D_{tT},
- LIBOR forward rates: L_t^i
- ► The rolling spot measure, N: The EMM using the discrete savings account as numeraire.

$$N_{t} = D_{tT_{1}}, \quad t \leq T_{1}, \quad (1)$$
$$N_{t} = D_{tT_{i+1}} \cdot \prod_{j=1}^{i} (1 + \alpha_{j} L^{j}_{T_{j}}), \quad T_{i} \leq t \leq T_{i+1}. \quad (2)$$

The LIBOR market model SDE

Let

$$x_t^i = \int_0^t \sigma_s^i dW_s^i, \quad i = 1, \dots, n$$
(3)
$$dW_t^i dW_t^j = \rho^{ij} dt$$
(4)

Then, under \mathbb{N} , each $L^{i}_{T_{i}}$ is given by

$$L_{\mathcal{T}_i}^i = L_0^i \cdot \exp\left(\int_0^{\mathcal{T}_i} \mu(L_t^1, \dots, L_t^i, \sigma, \rho) \mathrm{d}t + x_{\mathcal{T}_i}^i\right)$$
(5)

Note: Stochastic drift term!

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The LIBOR market model: Calibration

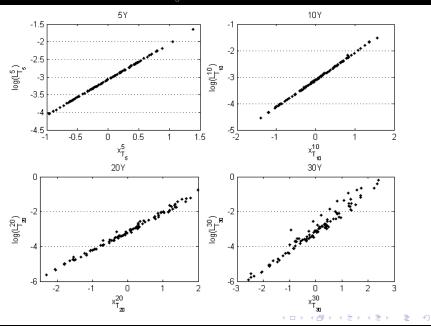
- σ^i : Under the measure transformation $\mathbb{N} \to Q^i$, $\mu(L^1_t, \dots, L^i_t, \sigma, \rho) = 0$. Hence, L^i_t is a lognormal martingale \to Caplet prices by the Black formula $\to \sigma^i$ are given directly from market prices of caplets.
- Instantaneous correlations much harder! Due to efficiency one must use approximation formulas:

$$\operatorname{Corr}(\log(\mathcal{L}_{\mathcal{T}_{i}}^{i}), \log(\mathcal{L}_{\mathcal{T}_{j}}^{j})) \approx \frac{\int_{0}^{\min(\mathcal{T}_{i}, \mathcal{T}_{j})} \sigma_{t}^{i} \sigma_{t}^{j} \rho^{jj} \mathrm{d}t}{\sqrt{\int_{0}^{\mathcal{T}_{i}} (\sigma_{t}^{i})^{2} \mathrm{d}t} \sqrt{\int_{0}^{\mathcal{T}_{j}} (\sigma_{t}^{j})^{2} \mathrm{d}t}}.$$
 (6)

- The trader has a view about Terminal Correlations (typically from historical estimation or implied from the Swaptions market) and changes ρ^{ij}s accordingly.
- Dangerous due to approximation errors?



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Postulate

$$L_{T_i}^i = f^i(x_{T_i}^i), \quad i = 1, \dots, n$$
 (7)

where f^i is some **monotone** function. The functional forms will be found (numerically) by forward induction, forcing the model to be

- arbitrage free, and
- calibrated to Black's formula for Caplets.

To find the functional forms we use digital Caplets in Arrears (DCiA). Value of a DCiA at time 0 under \mathbb{N} :

$$\mathcal{V}_{i}(K) = N_{0} E^{\mathbb{N}} \left[\frac{\mathbf{1} \{ L_{T_{i}}^{i} \geq K \}}{N_{T_{i}}} \right].$$
(8)

 Fact: Pricing DCiA (of all strikes) are equivalent to pricing digital Caplets and Caplets.

Construction: Step 1/3

Suppose we would like to know $f^i(x^*)$.

Define

$$J^{i}(x^{*}) = N_{0}E^{\mathbb{N}}\left[\frac{\mathbf{1}\{x_{T_{i}}^{i} \geq x^{*}\}}{N_{T_{i}}}\right].$$
(9)

Compute the expectation by Monte Carlo integration

$$J^{i}(x^{*}) \approx N_{0} \frac{1}{m} \sum_{k=1}^{m} \frac{\mathbf{1}\{x_{T_{i}}^{i}(\omega_{k}) \geq x^{*}\}}{\prod_{l=1}^{i-1} (1 + \alpha_{l} f^{l}(x_{T_{l}}^{l}(\omega_{k})))}.$$
 (10)

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Construction: Step 2/3

- Market prices of DCiA must be consistent with an arbitrage free model.
- \blacktriangleright Want to mimick the lognormal LMM \rightarrow choose the Black model.

Search for the strike $K(x^*)$ such that

$$V^{i}(K(x^{*})) = J^{i}(x^{*})$$
 (11)

Construction: Step 3/3

Conclude that

$$f^{i}(x^{*}) = K(x^{*})$$
 (12)

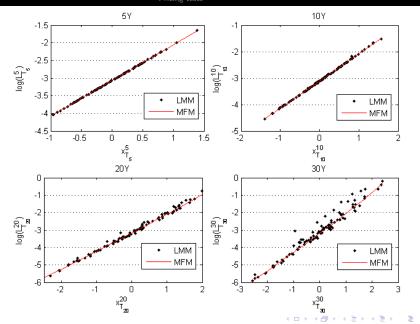
WHY:

$$N_{0}E^{\mathbb{N}}\left[\frac{\mathbf{1}\{L_{T_{i}}^{i} \geq K(x^{*})\}}{N_{T_{i}}}\right] = V^{i}(K(x^{*})) = J^{i}(x^{*}) = N_{0}E^{\mathbb{N}}\left[\frac{\mathbf{1}\{x_{T_{i}}^{i} \geq x^{*}\}}{N_{T_{i}}}\right] = N_{0}E^{\mathbb{N}}\left[\frac{\mathbf{1}\{f^{i}(x_{T_{i}}^{i}) \geq f^{i}(x^{*})\}}{N_{T_{i}}}\right] = N_{0}E^{\mathbb{N}}\left[\frac{\mathbf{1}\{L_{T_{i}}^{i} \geq f^{i}(x^{*})\}}{N_{T_{i}}}\right],$$

▶ Note: The monotonicity assumption is crucial.

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TARNs: definition

- Want to price TARN swaps.
- Receive: Structured coupon; $\max(10\% 2L_{T_i}^i, 0)$.
- ▶ Pay: $2L_{T_i}^i$.
- Continue until final maturity OR when total received coupon is 10 %.
- ▶ Need models with good views on Terminal correlations.

TARNs and Terminal correlations

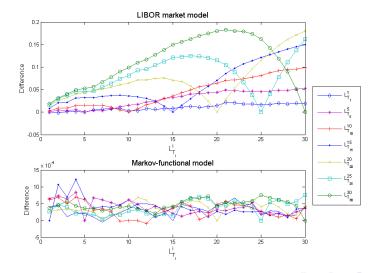
TARN prices

- initial LIBORs $L_0^i = \max(2\% + 0.5\% T_i, 10\%)$
- ► $\sigma_t^i = 20\%, \forall t, i$
- Instantaneous correlations $\rho^{ij} = \exp \{-0.05|T_i T_j|\}$
- Notional 10 000.

	5	10	15	20	25	30
LMM	-187.6	-729.2	-1095.3	-1270.5	-1338.0	-1362.5
MFM	-186.5	-719.2	-1067.4	-1230.9	-1294.0	-1316.7
vega	10.3	21.6	20.6	14.9	10.3	-1362.5 -1316.7 7.5
corr	-1.7	-9.6	-18.2	-22.4	-24.4	-25.2

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Terminal correlations



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Matching the models

Idea: Matching the models Terminal correlations \rightarrow similar properties.

Test: Change the $\rho^{ij}{\rm s}$ for the MFM s.t. it matches the simulated Terminal correlations of the LMM. Results:

	5	10	15	20	25	30
LMM	-187.6	-729.2	-1095.3	-1270.5	-1338.0	-1362.5
			-1067.4			
$\widehat{\mathrm{MFM}}$	-187.0	-726.5	-1090.3	-1266.6	-1337.9	-1365.9
vega	10.3	21.6	20.6	14.9	10.3	7.5
corr	-1.7	-9.6	-18.2	-22.4	-24.4	-25.2

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TARN pricing summary

- \blacktriangleright Calibrate both models using the approximation formula \rightarrow
 - The MFM will give prices consistent with the formula.
 - The LMM will not.
- Need a better approximation formula in order to calibrate the LMM satisfactory.
- For the MFM this is straightforward.

Punchlines

With the n-dimensional Markov-functional model we have a model that is

- ▶ Very similar in spirit to the *n*-factor LIBOR market model.
- Arbitrage free
- Calibrated to the Caplet market

Moreover it resolves/improves two major problems with n-factor LIBOR market models

- Calibration to Terminal correlations.
- Computation times (The MFM is up to 40 times faster in my implementation).

THANK YOU!

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