A Multifrequency Theory of the Interest Rate Term Structure

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Shocks to the interest rate term structure

- Shocks of all frequencies come at the interest rate dynamics/term structure:
  - **Long term:** *Inflation* shocks tend to move the term structure in parallel; *Real GDP growth* shocks tend to move short rates more than long rates.
  - **Intermediate term:** *Monetary policy* shocks are often imposed at the short end and they dissipate through the yield curve via expectations.
  - **Short term:** *Supply/demand* (transactions) shocks enter the yield curve at a particular maturity and dissipate through the yield curve via hedging and yield curve statistical arbitrage trading.

- A successful term structure model must capture the effects of shocks of all frequencies.
The literature

- **Theory:** Dynamic term structure models with $N$ factors are well-developed, with analytical tractability. Examples include the affine class (Duffie, Kan, Pan, and Singleton) and the quadratic class (Leippold and Wu).

- **Practice:** The commonly estimated models are all low-dimensional, mostly with three factors.
  - Three-factor models are successful in capturing major variations in the interest rate level, the term structure slope, and curvature.
  - The remaining movements can be economically significant (in four-leg trades, Bali, Heidari, & Wu).
  - Three-factor models fail miserably in
    - predicting future interest rate movements (Duffee),
    - capturing the cross-correlation between non-overlapping forwards (Dai & Singleton),
    - pricing interest-rate options (Heidari & Wu, Li & Zhao).
Why not estimate a high-dimensional model?

- **Curse of dimensionality:**
  - A generic affine three-factor model has 20-30 parameters (more for quadratic models).
  - The number of parameters increases quadratically with dimensionality.
  - Many of these parameters cannot be effectively identified.
  - These models suffer from the “double whammy” of being:
    - too little — It cannot match all the features of the data.
    - too much — It has too many parameters to be effectively identified.

- We propose a model structure with no curse of dimensionality.
  - ⇒ The model *dimension invariant* — 5 parameters regardless of dimension.
    - Parameter identification is not an issue.
    - Dimension is a choice, but not a concern.
    - We can choose the dimension as high as needed to match the data.
A cascade interest rate dynamics with power law scaling

- The instantaneous interest rate $r_t$ follows a *cascade* dynamics,
  
  $$
  \begin{align*}
  r_t &= x_{n,t}, \\
  dx_{j,t} &= \kappa_j (x_{j-1,t} - x_{j,t}) \, dt + \sigma_j dW_{j,t}, \quad j = n, n-1, \ldots, 1, \\
  x_{0,t} &= \theta_r.
  \end{align*}
  \tag{1}
  $$

- Start the short rate at the highest identifiable frequency $x_{n,t}$.
- Let the short rate mean reverts to a stochastic tendency $x_{n-1,t}$.
  — By design, the tendency $x_{n-1,t}$ moves slower than $x_{n,t}$.
- The tendency mean reverts to another, even slower tendency ... 
- The lowest frequency reverts to a constant mean $\theta_r$.

- IID risks and identical market prices: $\sigma_j = \sigma_r, \quad \gamma_j = \gamma_r$.

- The mean reversion speeds of different frequencies scale via a *power law*:
  
  $$
  \kappa_j = \kappa_r b^{(j-1)}, \quad b > 1. 
  $$
  \tag{2}

$\Rightarrow$ The model becomes *dimension invariant*.

Five parameters ($\theta_r, \sigma_r, \kappa_r, b, \gamma_r$), regardless of the number of factors ($n$).
Comparison to the literature: Cascade v. general affine

A subclass of the general affine Gaussian models (Duffie & Kan, 96): 
\[ r_t = a + b^\top X_t, \ dX_t = K(c - X_t)dt + \Sigma dW. \]

- Factors in the general affine specification can rotate. For example, equivalently, 
  \[ r_t = a' + (b')^\top Z_t, \ dZ_t = -K' Z_t dt + dW, \]
  with 
  \[ a' = a + b^\top c, \ b' = \Sigma b, \ c' = \Sigma^{-1}c, \ K' = \Sigma^{-1}K. \]
  - Economic meaning for each factor is elusive.
  - Many of the parameters are not identifiable.
  — Need careful specification analysis (Dai & Singleton, 2000).

- The *cascade* structure ranks the factors according to frequency.
  — a natural separation/filtration of the different frequency components in the interest rate movements — no more rotation.

- Economic meaning of each factor becomes clearer — helpful for designing models to match data.
  — \(1/\kappa\) has the unit of time.
    - From time series, the highest identifiable frequency is the observation frequency. The lowest frequency is the sample length.
    - From term structure, maturity range determines frequency range.
Comparison to the literature: Power law scaling

- Power-law scaling is a common phenomenon observed in many areas of natural science.

- Approximate power laws are often observed in financial data (Mandelbrot, Calvet & Fisher, Gabaix).

- Together with the iid risk/market price assumption, we use power-law scaling to achieve extreme parsimony and dimension invariant.

  - Using a functional form to approximate a series of discrete coefficients is a common trick used in econometrics to improve identification.

  - Example: Geometric distributed lags model assumes that the effects of an variable $x_t$ diminishes as the lag $j$ becomes larger: $\beta_j = \beta_0 \lambda^j, \lambda < 0$. 
An alternative representation of the short rate dynamics

\[ r_t = \theta_r + \sum_{j=1}^{n} a_j(t)(x_j,0 - \theta_r) + \sigma_r \sum_{j=1}^{n} \int_{0}^{t} a_j(t-s)dW_{j,s}. \]

- \( a_j(\tau) \) — the response function of the short rate to a unit shock from the \( j \)th frequency component at \( \tau \)-time ago.

- It can be solved as \textit{convolutions of exponential density functions}:

\[ a_j(\tau) = (K_j \ast \ldots \ast K_n)(\tau)/\kappa_j, \quad K_j(\tau) = \kappa_j e^{-\kappa_j \tau}, \quad \tau > 0. \]

- The short rate response to \( W_{n,t} \) starts at one and decays exponential, \( a_n(\tau) = e^{-\kappa_n \tau} \). The decay is fast with higher mean reversion.
- The response to \( W_{n-1,t} \) is hump shaped,

\[ a_{n-1}(\tau) = \frac{\kappa_n}{\kappa_n - \kappa_{n-1}} \left( e^{-\kappa_{n-1} \tau} - e^{-\kappa_n \tau} \right). \]

with the maximum response occurring at \( \bar{\tau}_{n-1} = \ln b/(\kappa_{n-1}(b - 1)) \).

- All lower frequency shocks generate hump-shaped responses, with the maxima occurring at progressively longer horizons.
Short rate response functions to shocks from different frequency components, $a_j(\tau)$:

When $\kappa_i \neq \kappa_j$ for all $i \neq j$, the convolution products yield

$$a_j(\tau) = \sum_{i=j}^{n} \alpha_{i,j} \kappa_i e^{-\kappa_i \tau}, \quad \text{with} \quad \alpha_{i,j} = \frac{\kappa_j \cdots \kappa_n}{\kappa_i \kappa_j \prod_{k=j, k \neq i}^{n}(\kappa_k - \kappa_i)}.$$

Numerical example: $\kappa_r = 1/30, \kappa_n = 52, n = 15, b = 1.69.$
The values of zero-coupon bonds are exponential-affine in $X_t = \{x_{j,t}\}_{j=1}^{n}$,

$$P(X_t, \tau) = \mathbb{E}_t^P \left[ \exp \left( - \int_t^T r_s ds \right) \mathcal{E} \left( - \int_t^T \gamma_s \cdot dX_s \right) \right] = e^{-b(\tau) ^\top X_t - c(\tau)},$$

The instantaneous forward rate is affine in the state vector,

$$f(X_t, \tau) = a(\tau) ^\top X_t + e(\tau),$$

The short rate response function $a(\tau)$ across different time lags also determines the contemporaneous response of the forward rate curve.

The intercept has 3 components: long-run mean, risk premium, convexity: $e(\tau) = \begin{cases} \kappa_r \theta_r \sum_{i=1}^{n} \alpha_{i,j} (1 - e^{-\kappa_i \tau}) \\ -\gamma_r \sigma_r^2 \sum_{j=1}^{n} \sum_{i=j}^{n} \alpha_{i,j} (1 - e^{-\kappa_i \tau}) \\ -\frac{\sigma_r^2}{2} \sum_{j=1}^{n} \sum_{i=j}^{n} \sum_{k=j}^{n} \alpha_{i,j} \alpha_{k,j} (1 - e^{-\kappa_k \tau} - e^{-\kappa_i \tau} + e^{-\kappa_i + \kappa_k \tau}) \end{cases}$
Data

- Six LIBOR (at 1, 2, 3, 6, 12 months),
- Nine swap rates (at 2, 3, 4, 5, 7, 10, 15, 20, 30 years).
- Weekly sampled (Wednesday) from January 4, 1995 to December 26, 2007. 678 observations for each series. All together 10,170 observations.
Cast the model into a state space form:

- Regard $X_t$ as the hidden state, regard the LIBOR and swap rates as observations with errors.

Given parameters, use unscented Kalman filter to infer the states $X_t$ from the observations at each date.

Construct the log likelihood by assuming that the forecasting errors on LIBOR and swap rates are normally distributed.

Estimate the 5 parameters by maximizing the likelihood of forecasting errors.
Dimensionality

- Normally, this is the first thing one decides on before one can pin down the parameter space.

- Under our model, the parameter space is invariant to the dimensionality decision. We worry about the dimensionality the last.

- Since we have 15 interest rate series, we estimate 15 models with \( n = 1, 2, 3, \ldots 15 \).

- The estimations of these models are equally easy and fast.

- The extensive estimation exercise serves at least two purposes:
  - Determine how many frequency components the data ask for — This normally depends on the data. More maturities would naturally ask for more frequency components.
  - Analyze how high-dimensional models differ from low-dimensional models in performance.
Parameter estimates and likelihood ratio tests

<table>
<thead>
<tr>
<th>$n$</th>
<th>$\kappa_r$</th>
<th>$\theta_r$</th>
<th>$\sigma_r$</th>
<th>$\theta_r^Q$</th>
<th>$b$</th>
<th>$\sigma_e^2$</th>
<th>$\mathcal{L}$</th>
<th>$\mathcal{V}$</th>
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<td>—</td>
</tr>
</tbody>
</table>

- Vuong test (last column): *More is significantly better.*
- Spacing ($b$) is finer when more is allowed.
- Parameters ($\kappa_r, \sigma_r$) stabilize as $n$ increases.
Power law scaling: Theory and evidence

Circles: $\kappa_i$ as free parameters; Solid line: power-law scaling
## In-sample fitting performance: Pricing error statistics

<table>
<thead>
<tr>
<th>Model</th>
<th>A. Three-factor model</th>
<th>B. 15-factor model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maturity</td>
<td>Mean</td>
<td>Rmse</td>
</tr>
<tr>
<td>1 m</td>
<td>-0.68</td>
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</tr>
<tr>
<td>2 m</td>
<td>0.63</td>
<td>3.82</td>
</tr>
<tr>
<td>3 m</td>
<td>1.61</td>
<td>5.03</td>
</tr>
<tr>
<td>6 m</td>
<td>0.39</td>
<td>6.78</td>
</tr>
<tr>
<td>9 m</td>
<td>-1.74</td>
<td>6.88</td>
</tr>
<tr>
<td>1 y</td>
<td>-3.06</td>
<td>6.74</td>
</tr>
<tr>
<td>2 y</td>
<td>2.11</td>
<td>6.17</td>
</tr>
<tr>
<td>3 y</td>
<td>1.97</td>
<td>6.90</td>
</tr>
<tr>
<td>4 y</td>
<td>0.87</td>
<td>6.32</td>
</tr>
<tr>
<td>5 y</td>
<td>-0.21</td>
<td>5.85</td>
</tr>
<tr>
<td>7 y</td>
<td>-1.89</td>
<td>5.55</td>
</tr>
<tr>
<td>10 y</td>
<td>-2.35</td>
<td>5.17</td>
</tr>
<tr>
<td>15 y</td>
<td>0.88</td>
<td>3.87</td>
</tr>
<tr>
<td>20 y</td>
<td>1.91</td>
<td>5.35</td>
</tr>
<tr>
<td>30 y</td>
<td>-0.76</td>
<td>9.67</td>
</tr>
<tr>
<td>Average</td>
<td>-0.02</td>
<td>6.11</td>
</tr>
</tbody>
</table>
Application: Yield curve stripping

Model-generated forward curves

Similar to Nelson-Siegel (basis function is exponentials), with two advantages:
- Dynamic consistency.
- No longer limit to a three-factor structure — Near-perfect fitting is a must for stripping swap rate curves.
In-sample forecasting performance

**Predictive variation**: \( 1 - \frac{\text{Mean Squared Forecasting Error}}{\text{Mean Squared Interest Rate Change}} \)

<table>
<thead>
<tr>
<th>Model</th>
<th>A. AR(1)</th>
<th>B. Three-factor model</th>
<th>C. 15-factor model</th>
</tr>
</thead>
<tbody>
<tr>
<td>( h )</td>
<td>1 2 3</td>
<td>1 2 3</td>
<td>1 2 3</td>
</tr>
<tr>
<td>LIBOR maturity in months:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>25.85 43.84 57.50</td>
<td>-0.71 32.92 42.84</td>
<td>21.71 40.82 52.16</td>
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<tr>
<td>2</td>
<td>23.83 36.65 47.28</td>
<td>-1.94 15.23 23.31</td>
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<td>3</td>
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<tr>
<td>6</td>
<td>20.85 25.00 31.90</td>
<td>-87.43 -42.16 -24.57</td>
<td>5.77 12.56 16.94</td>
</tr>
</tbody>
</table>

**AR(1) is the best;**

**3-factor model cannot beat random walk.**
Out-of-sample forecasting performance

<table>
<thead>
<tr>
<th>Model</th>
<th>A. AR(1)</th>
<th>B. 15-factor model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predictive variation</td>
<td>Predictive variation</td>
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<tr>
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<td>3</td>
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<td>-4.52</td>
<td>-7.14</td>
</tr>
<tr>
<td>12</td>
<td>-4.90</td>
<td>-7.78</td>
</tr>
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</table>

**LIBOR maturity in months:**

AR(1) is the worst;
15-factor model beats random walk in sample and out of sample!
Where does the forecasting strength come from?

- AR(1) regression neither uses the term structure information nor is it parsimonious.
  - To exploit the term structure information, need a VAR(1) structure.
  - One AR(1) on each series, $15 \times 2 = 30$ parameters already!
  - Forget about a general VAR(1).

- Our model can be regarded as a constrained VAR(1):
  - Exploits information on the term structure.
  - Parsimony generates out-of-sample stability for all our models.

- ... as simple as possible, but not simpler.
  - Low-dimensional models cannot even fit — The forecast is almost surely wrong over short horizons.
    - If the fitting error is 6 bps, the forecasting error over the next second will also be 6bps — no hope of beating random walk.

- Our high-dimensional model is:
  - simple and stable: Similar in and out of sample performance.
  - flexible and fits perfectly: The forecast starts at the right place.
Concluding remarks

Within the dynamic term structure modeling framework, we make several key assumptions:

- **A cascade factor structure**: Eliminate factor rotation. Pin down the meaning of each factor. Provide a natural separation/filtration of different frequency components.
- **IID risk and risk premium**: Two parameters to control the risk and risk premium of all risks.
- **Power law scaling**: Two parameters to control the distribution/allocation of all frequencies.

The result is a class of **dimension-invariant** models: The number of parameters is invariant to the number of factors.

- No more curse of dimensionality: high-dimensional models are just as easy to be estimated as low-dimensional models.
- Evidence: High-dimensional models do provide superior performance in several fronts.