IFRS 9: Does one model fit all?
Lessons from the ashes of the Great Moderation

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August 2017
Introduction
Getting to know you...

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Hugo Chim is an Assistant Manager in the Risk Modelling Team of Deloitte’s Financial Services Risk Advisory Practice. Hugo has been a key modeller and SME in Expected Credit Loss (ECL) models for major European banks with systemic importance.

He has also applied advanced Econometric techniques to both retail and non-retail credit risk problems such as forecasting multiple-scenario PD using Vector Auto-regression and Error Correction, Logistic Models, and EMV techniques. Before joining the FS Practice, he was an Economist in Deloitte Economic Consulting.

Hugo graduated from Warwick University with Distinction in MSc Economics.
Agenda

Topics to cover today

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Current modelling challenges
Why should we care?
Why should we care?

IFRS 9 is expected to have a significant impact on provision stock and pricing.

**Expected significant increase in provisions**

Increase in provision stock under IFRS 9 (vs 2015e level)

**Revenue Source and portfolio composition**

Bank A’s top 100 key clients, Today

Bank A’s top 100 key clients, To target for

**IFRS 9 cyclical and capital impact**

IFRS 9 Pro-cyclical could drive CET1 ratio below 7% in a downturn.

**Cost of product offerings and pricing impact**

Price makers who think IFRS 9 will affect costs in each products:

Price takers who think IFRS 9 will affect costs in each products:

Source: Deloitte Research
The starting point
The common Merton-Vasicek Framework

The Vasicek (2002) model decomposes default risks into systematic ($z_t$) and obligor specific factors ($\varepsilon_i$).

The standard practice is to model default risks as an unobserved latent asset return index ($R_{it}$) that is positively correlated to a given obligor’s asset value on book. Intuitively, a lower expected future return (which leads to a lower asset value) is expected to increase default risks.

When the index falls below a given threshold (default boundary), e.g. when asset values is below liability value, the obligor is expected to default.

Vasicek Model (Yang 2013 Probit-linear formulation)

$$PD(Z_t) = P(R_{it} < \text{threshold}_i | S_{kt}) = \Phi(\alpha + \sum_{k=1}^{m} \beta_k S_{kt} + \tau \varepsilon_i)$$

Where,

- $\sum_{k=1}^{m} \beta_k S_{kt} = \sqrt{\rho} Z_t$, $Z_t \sim N(0,1)$ is the systematic, and
- $\tau \varepsilon_i = \sqrt{1 - \rho} \varepsilon_i$, $\varepsilon_i \sim N(0,1)$ is the idiosyncratic factor.

Merton-Vasicek model (2002)

- The Vasicek (2002) model decomposes default risks into systematic ($z_t$) and obligor specific factors ($\varepsilon_i$).
- The standard practice is to model default risks as an unobserved latent asset return index ($R_{it}$) that is positively correlated to a given obligor’s asset value on book. Intuitively, a lower expected future return (which leads to a lower asset value) is expected to increase default risks.
- When the index falls below a given threshold (default boundary), e.g. when asset values is below liability value, the obligor is expected to default.
Current modelling challenges
Challenges we have come across at our clients when they were modelling the systematic factor under the Vasicek framework.

**Theory**

- Default Risks for Obligor \( i \)
- Obligor \( i \) asset value (returns) index
- Systematic risk factor (\( Z_t \))
- Obligor specific risk factor (\( \varepsilon_i \))

**Empirical Reality**

1. Acyclical (Non-stationary)
2. Optimism bias
3. Paradigm shifts

### Estimated systematic risk from default data

- **Cyclical (Stationary)**
- **Acyclical (Non-stationary)**
- **Long period of decline in risk (Acyclical)**
- **Abrupt change in trend**
- **Overly optimistic trend forecasts**

*Illustration only*
Challenge 1: Absence of cyclical behaviours
Since the last financial crisis, UK mortgage default rates have been decreasing. Cyclical behaviour has not been observed in the last 10 years.

Source: CML 2017
Challenge 1: Absence of cyclical behaviours
Standard models tend to predict the downward trend to continue.

Q1: Is it tenable to argue for cyclical behaviour around a stable TTC PD?

Q2: Can credit risk be trending down indefinitely?

Forecasting results based on observed data post 2008-9 crisis

1. Acyclical (Non-stationary)

2. Mean forecasts

Optimism bias

Source: CML 2017 and Deloitte analysis
In July 2007, Charles Prince (Ex-Citi CEO) told the Financial Times that global liquidity was enormous and only a significant disruptive event could create difficulty in the leveraged buyout market.

"As long as the music is playing, you've got to get up and dance...We're still dancing."

Source: Reuters

Credit: The New York Times
Challenge 2: Good-time optimism bias

During the Great Moderation between the end of 1991 recession and the 2008 financial crisis, the UK experienced 63 consecutive quarters of economic growth. During the UK’s (and the US’) Great Moderation, many argued that the old laws of economics had been abolished.

Source: CML 2017
Challenge 2: Good-time optimism bias
The Great Moderation however did end abruptly and dramatically.

Macroeconomic conditions during the "Great Moderation" in the UK

Mortgage default risk (3+) during the "Great Moderation" in the UK

Source: CML 2017
Challenge 2: Good-time optimism bias

Predictions made based on the data from the Great Moderation period exhibited a continuing downward trend. As such, the forecast errors after the 2008-9 crisis assuming the same trend will be significant and persistent.

Source: CML 2017 and Deloitte Analysis

Forecasted default risk (3+) based on data from the "Great Moderation" period

The model is almost irrelevant for a long period of time during and after the crisis.

Model performance appears to improve after 10 years.
Steve Jobs’ Stanford University Commencement address in 2015.

"If you live each day as if it was your last…"

“someday you’ll most certainly be right.”
"In the long run we are all dead. Economists set themselves too easy, too useless a task if in tempestuous seasons they can only tell us that when the storm is long past the ocean is flat again."
Challenge 3: Paradigm shifts

Based on 48 years of data, we may estimate the long-run 3+ arrears rate to be circa 1.9%; however, over the entire period, it is difficult to argue for any meaningful cyclical behaviour around this long-run value. The 3+ data appears to be so persistent that non-stationarity test often indicates that 3+ data is a random-walk.

Source: CML 2017 and Deloitte Analysis
Paradigm shifts can lead to false non-stationarity test results.

48 years is a long time to have no paradigm shifts.
Challenge 3: Paradigm shift detection

Visual inspection identifies three potential states of the mortgage market: Pre 90s crisis, period around the 90s crisis and periods around the 2008/9 crisis. The dividing line however can be arbitrary.

![Extrapolated 3+ Delinquency Rates](image)

Source: CML 2017 and Deloitte Analysis

**Experimental Results**
Challenge 3: Paradigm shift detection

Historical events may also provide some insights.

Pre 1980s
- Vast majority of mortgage funding came from building societies, which borrowed retail funds from the household sector and lent them to households with secure incomes, a savings history, and a significant deposit.
- It was arguably almost riskless to lenders because interest rates were adjusted to enable flows of funds to be balanced.
- Mortgagors bore all the interest risk.

Late 70s-late 1980s
- (Foreign) Banks and insurance companies started to enter the market.
- Bank of England (1980) lifted the Supplementary Special Deposits regulations ("Corset").
- 1984 changes in regulations meant building societies could then operate like banks.
- 1980s right to buy for council tenants, injecting 1 million households (lower income) into the mortgage market.
- Growth in use of mortgage backed securities by US banks.

1989-1992
- By 1989, institutions were lending at unprecedented income multiples and LTVs.
- Homeownership had spread down the income scale.
- 20% of new loans were at more than 100% LTV.
- 2 million households faced negative equity and repossessions reached a peak in 1991.

1993-2007
- Great Moderation started to take effects.

2008-9
- Global Financial Crisis

2010 - ?
- Gradual recovery with low interest rates, more robust regulations and stronger bank balance sheets.
Challenge 3: Paradigm shifts and bias

For simplicity, if we only consider two possible paradigms: **Baseline** and **Stressed**, what can we say in general about each of these paradigms?

**Possible Paradigms**

- **Baseline Paradigm**
  - Baseline sensitivity to macroeconomic factors
  - Baseline systematic factor volatility
  - Baseline TTC PD

- **Stressed Paradigm**
  - Higher sensitivity to macroeconomic factors
  - Higher systematic factor volatility
  - Higher TTC PD

- Standard Models often predict the average of the two.
  - Over estimate in Baseline paradigm
  - Under estimate in Stressed paradigm
Challenge 3: Conventional approach to paradigm shifts

Dummy variables model the instability of time series in hindsight

• Step 1: Generate period dummies for high volatility periods (stressed), using low volatility period as baseline. Let:
  \[ d_{stress} = \begin{cases} 
  1, & \text{for year from 1980 to 1992, 2008 to 2009} \\
  0, & \text{otherwise} 
  \end{cases} \]

• Step 2: Run regression using both level and multiplicative dummies:
  \[
  \Phi^{-1}(ODF_t) = y_t = \alpha + \sum_{k=1}^{m} \beta_k S_{kt} + \omega d_{stress} + \sum_{k=1}^{m} \delta_k S_{kt} * d_{stress} + v_t
  \]

• Essentially we are estimating two mean models:

<table>
<thead>
<tr>
<th>Baseline Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>( y_t = \alpha + \sum_{k=1}^{m} \beta_k S_{kt} + v_t )</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Stressed Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>( y_t = y_t = \alpha + \omega ) + ( \sum_{k=1}^{m} (\delta_k + \beta_k) S_{kt} + v_t )</td>
</tr>
</tbody>
</table>

Systematic Risk against HPI

Higher sensitivity to HPI changes

Higher average default risk across all possible HPI values.
Challenge 3: Conventional approach to paradigm shifts
Dummy variables model only works in hindsight

In reality, it is hard to say when exactly the Great Moderation actually started.

Methodology issues

• This method is only useful in hindsight.
• This is a crude approach with abrupt arbitrary changing points.
• This method does not assign probabilistic weight to possible future paradigms.
• IFRS 9 requires banks to make scenario forecasts and so information on future paradigms (a form of scenario) is arguably essential.
• Assigning wrong future paradigms to forecasts may lead to bias.
"You only learn who has been swimming naked when the tide goes out,"

"And what we are witnessing at some of our largest financial institutions is an ugly sight."

But perhaps we could assign some probabilities to this event happening?
Proposed approach
Introducing randomness in paradigm shifts
Proposed approach
Mortgage default in a Markov-Switching (MS) framework

MS-Model set up

- The dynamics of the CCI are modelled as a state-dependent process where the state (Stressed or Baseline) is unobserved by the modeller.
- Let \( y_t \) denote the CCI in period \( t \) and suppose that its mean and variance are governed by an unobserved state variable \( s_t = \) (Stressed, Baseline) in our simple two-state example:

\[
y_t = \mu(s_t) + \sigma(s_t)v_t \quad \text{where } v_t \sim i.i.d. N(0,1)
\]

Such that,

\[
\begin{align*}
y_t &= \mu_s + \sigma_s v_t \quad \text{if } s_t = \text{Stressed} \\
y_t &= \mu_b + \sigma_b v_t \quad \text{if } s_t = \text{Baseline}
\end{align*}
\]

Note that the difference between this set up and the dummy-variable regression model is that the state-switching mechanism is a random process. Particularly, the state of the world is governed by an ergodic irreducible hidden Markov Process (mean-reverting without absorbing state):

\[
P = \begin{bmatrix} p_{ss} & p_{sb} \\ p_{bs} & p_{bb} \end{bmatrix}
\]

Where for example \( p_{bs} = P(S_t = \text{Stressed}|S_{t-1} = \text{Base}) \) is the probability that the process is in a Baseline state at time \( t \) given that it was in a Stressed state at time \( t-1 \).
Proposed approach
Mortgage default in a Markov-Switching framework

Forecasting with MS-Model

- Forecasts can be made using the key outputs of the MS-model. For a \( h \)-step ahead forecast based on information at time \( t \),

\[
E(y_{t+h} | I_t) = \hat{\xi}_{t(t|t)} * P^h * \hat{\mu}
\]

Illustration only
Application showcase
The UK mortgage market
AR(1) MS-model estimation outcomes
CML 3+ Arrears data

### Simulation for the Stressed state

![Stressed State Simulation](image1)

### Simulation for the Baseline state

![Baseline State Simulation](image2)

### Stressed state

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity to HPI</td>
<td>1% fall in HPI growth -&gt; <strong>0.8%</strong> fall in implied returns (R) (<strong>4x</strong> more sensitive)</td>
</tr>
<tr>
<td>Asymptotic TTC implied returns (R)</td>
<td><strong>1.4</strong> (<strong>46%</strong> less)</td>
</tr>
<tr>
<td>Asymptotic R volatility ($\sigma_R^2$)</td>
<td><strong>0.037</strong> (<strong>&gt;10x</strong> Baseline)</td>
</tr>
<tr>
<td>Average duration (Forced uniform volatility)</td>
<td><strong>5 years (3 years)</strong></td>
</tr>
</tbody>
</table>

### Baseline state

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity to HPI</td>
<td>1% fall in HPI growth -&gt; <strong>0.2%</strong> fall in implied returns (R)</td>
</tr>
<tr>
<td>Asymptotic TTC implied returns (R)</td>
<td><strong>2.6</strong></td>
</tr>
<tr>
<td>Asymptotic R volatility ($\sigma_R^2$)</td>
<td><strong>0.003</strong></td>
</tr>
<tr>
<td>Average duration (Forced uniform volatility)</td>
<td><strong>4 years (9 years)</strong></td>
</tr>
</tbody>
</table>

**Experimental Results**

\[
P = \begin{bmatrix}
P(S_t = \text{Stressed} | S_{t-1} = \text{Stressed}) & P(S_t = \text{Stressed} | S_{t-1} = \text{Base}) \\
P(S_t = \text{Base} | S_{t-1} = \text{Stressed}) & P(S_t = \text{Base} | S_{t-1} = \text{Base})
\end{bmatrix} = \begin{bmatrix}
0.80 & 0.20 \\
0.27 & 0.73
\end{bmatrix}
\]
In-sample assessment
How well does the model fit the data?
Assessment: actual vs. predicted

AR(1) MS-Model prediction is the average between the **Baseline** and **Stressed** state predictions, weighted by the probabilities of being a given state.

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**Experimental Results**
Assessment: In-sample fit comparison with next-best benchmark model
AR(1) MS-model appears to be able to cope with abrupt turning points (paradigm shifts) better than the benchmark AR(1) model, resulting in a significantly better in-sample fit.

Experimental Results
Assessment: Sensitivity of state detection and sense-checking against real-life events

Our AR(1) MS-model appears to be able to capture a large number of major macroeconomic events that might have led to shifts in macro paradigms.

Historical Smooth State Probability and 3+ Delinquency Rates

- 1974 oil crisis
- 1980 start of deregulation
- 1988 Change in tax rules - Highest level of transactions ever recorded
- 1989 Mortgage Crisis
- Great Moderation and building up risks
- 2004 BOE cut rate
- 2004 BOE raised rate
- 2008 Lehman Brothers Bankruptcy
- QE Era
Forecast performance benchmarking

Does it forecast better than the next-best benchmark model?
Performance benchmarking

For short-run forecasts, forward-chaining 1-step ahead cross-validation indicates that the AR(1)MS-Model outperforms a AR(1) model significantly. For longer-run forecasts, similar conclusion can be reached for a 5 year hold-out sample test.
Areas in further development

What’s next?
### Areas in further development

**Looking ahead**

<table>
<thead>
<tr>
<th>Development areas</th>
<th>Benefits</th>
<th>Drawbacks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extend to VAR MS-model</td>
<td>• Capture interdependency among default risk and macro factors</td>
<td>• Require even more data</td>
</tr>
<tr>
<td></td>
<td><strong>Contagion dynamics</strong></td>
<td>• More complex to implement</td>
</tr>
<tr>
<td></td>
<td>Key topic: <em>does default risk in one market/industry today affects another tomorrow?</em></td>
<td>• May not lead to improve forecast precision</td>
</tr>
<tr>
<td></td>
<td>• Capture shifts in paradigm of macro factors.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Self-sufficient forecasting system.</td>
<td></td>
</tr>
<tr>
<td>Extend to provide interval forecasts</td>
<td>• Align with BOE stress-testing format with multiple scenarios under both baseline and stressed setting.</td>
<td>• No close-form solutions and will require Monte Carlo simulation.</td>
</tr>
<tr>
<td></td>
<td>• Provide a distributional perspective to forecast uncertainties allowing for deviations from normality assumptions.</td>
<td></td>
</tr>
</tbody>
</table>
Questions?
Thank you!