

Leeds Building Society

Credit Scoring and Credit Control Conference XVI

Modelling Behavioural Life of Retail Mortgages
Aligning Financial Disciplines with Credit Portfolio Management

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Abstract

Traditionally, creating Behavioural Life Profiles (BLPs) for both assets and liabilities has been the domain of Finance / Treasury / Strategy (hereafter referred to as 'Commercial') functions within a financial institution. Typically, these 'lives' (how long the company will 'own' the loan or savings) have been modelled at a **cohort level**, and have been **backward looking** with little (if any) **sensitivity to forecasted inputs of economic or market conditions**. These 'run off' profiles are important inputs to Product Pricing, Corporate Planning, and a range of Asset and Liability Management (ALM) disciplines.

Whilst this is the prevalent approach for Product Pricing, Corporate Planning and ALM, it results in a disjoint between Commercial disciplines, and portfolio / credit risk modelling based account management techniques. Typically, Credit Risk models provide forward estimates (e.g. 'scores') at account / exposure level which can be used to channel individual exposures into operational decisioning strategy treatments. Thereafter such estimates can be 'aggregated up' for financial purposes – such as calculating minimum capital requirements under IRB, or regulatory returns. In other words, Credit Risk modelling disciplines have historically been more granular than Commercial modelling. In a competitive market with narrowing margins, **increased granularity** of more sophisticated and sensitive modelling techniques could be a key differentiator – informing better strategic decisions.

As part of the **IFRS9 Expected Credit Losses (ECLs) project for residential mortgages**, Leeds Building Society undertook modelling lifetime Probability of Default (PD) using survival analysis at exposure level. Whilst this involves predicting future default event propensity as a function of **borrower and transaction characteristics** over the lifetime of the loan, estimates also need to be **sensitive to housing market and economic conditions** – predicting ECLs in a **range of scenarios**. Furthermore, given very few mortgages amortise and pay down over the full contractual term (as opposed to their 'in product' period), the probability of still being on book at each point in time over the forecast period is an important input to default propensity (and ECL) – and needs to consider **rational decisions** made by customers. These same account level 'on book propensities' used in ECLs, can be used to create BLPs for Commercial disciplines.

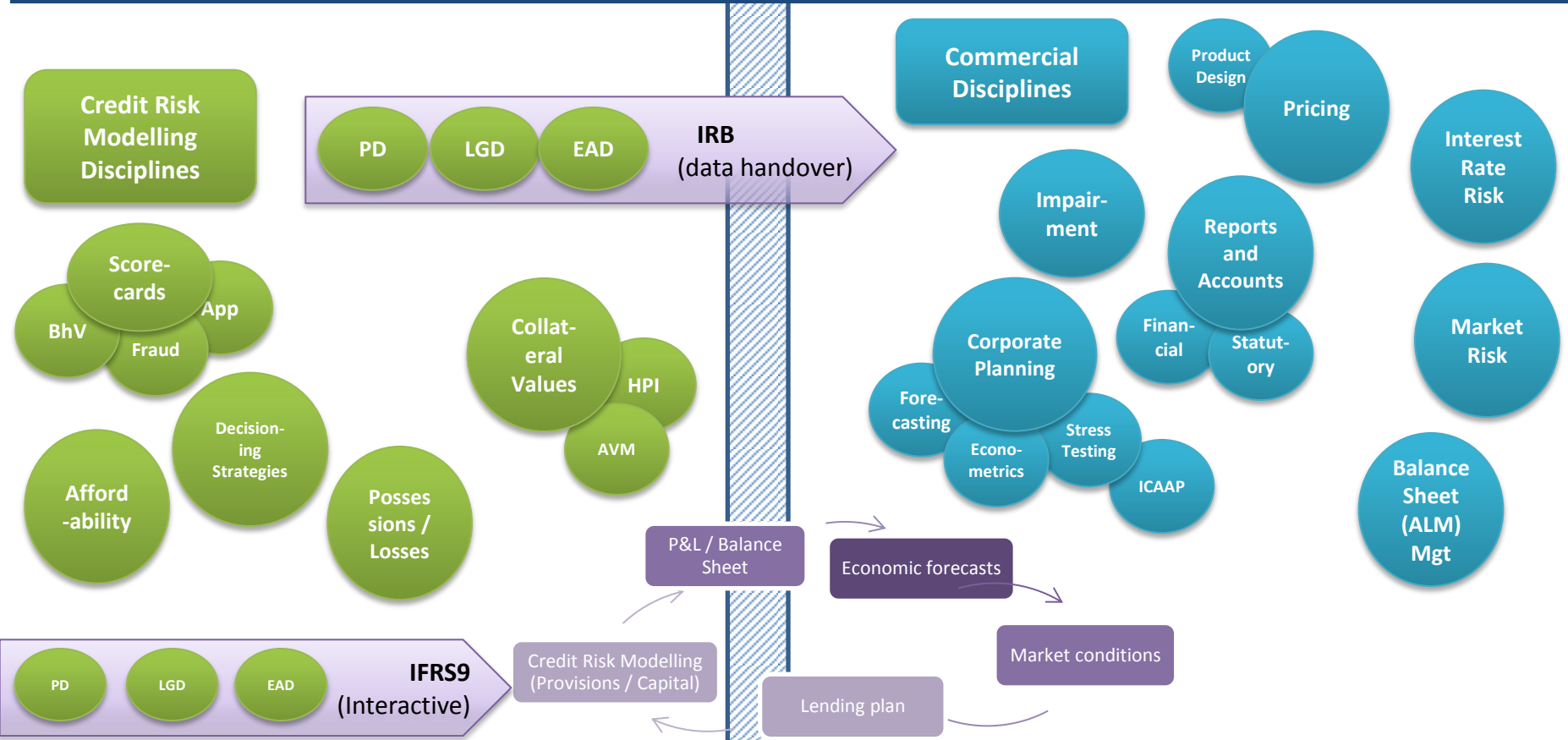
In this presentation, we outline the underlying **methodology and drivers** used in the BLP model development – illustrating how **sensitivity to economic / market drivers** can be achieved, and providing indicative outputs demonstrating these sensitivities.

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Background: Disparate Disciplines in Finance/Credit Risk...and then IFRS9 Came Along

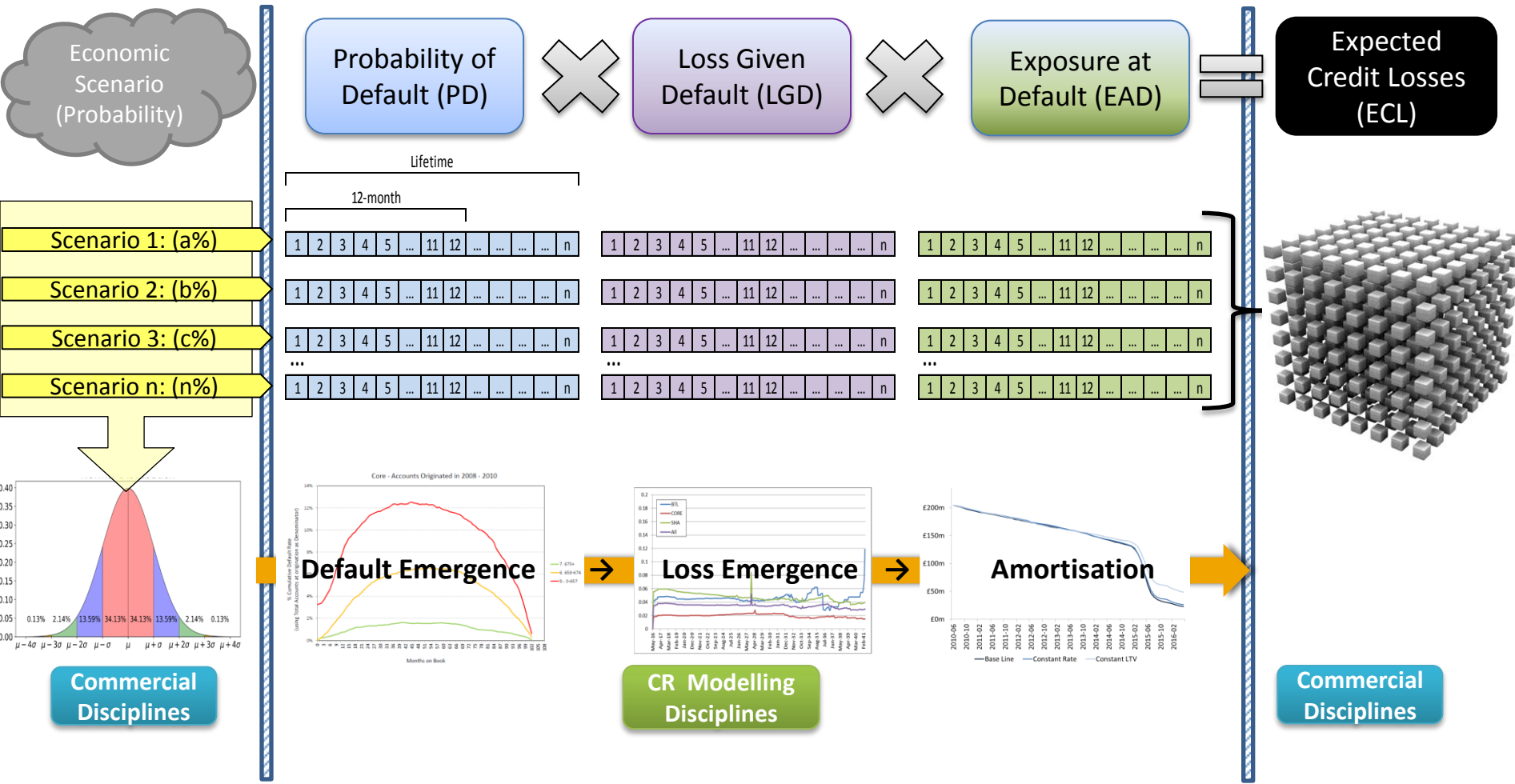
- Historically, Credit Risk & Commercial functions focussed upon own disciplines - modest levels of collaboration
- IRB forged some greater links - in reality, passing model outputs across
- Still relatively little iteration / BAU end-to-end process management...ICAAP aside!



- Introduction of IFRS9 => more prevalent cross-function end-to-end process
- Tasks (corporate planning/refresh activities, pricing, loss forecasting, stress testing) require collaboration & often considerable iteration.

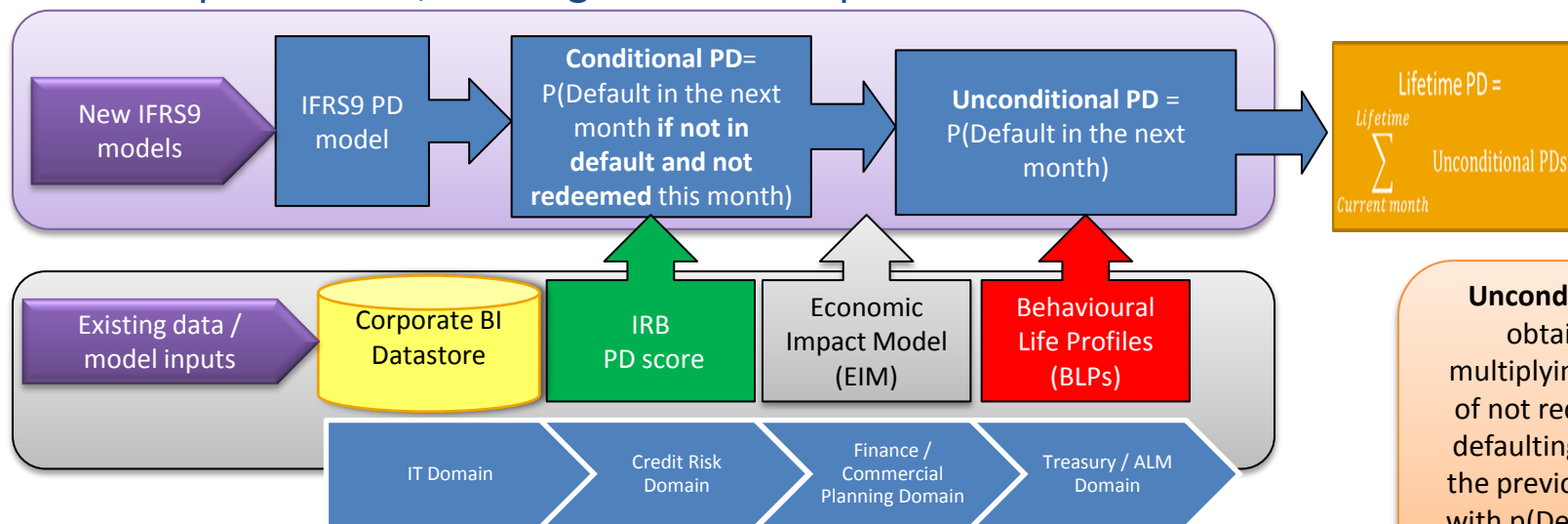
IFRS9 Model Map: Conceptual Overview

- PDs, LGDs and EADs are estimated on a monthly basis over the lifetime of a loan.
- Arrays of estimates are created for each economic scenario. Typically, lenders use a number of scenarios encapsulating Central, Upside & Downside.



IFRS9 PD Model: Combining External and Internal Measures to Predict Default, and Propensity to be On-Book

- PD model is complex due to the nature of what it has to predict over time
- IFRS9 PD Model based on discrete time survival modelling techniques
- IFRS9 PD model takes existing models as inputs to the process.
- Some inputs historically resided in Commercial domain; economic scenarios / modelling, and Behavioural Life Profiles => presents opportunities to harness Credit Risk modelling skills, increase sophistication, and align across disciplines.



Unconditional PD obtained by multiplying the prob. of not redeeming or defaulting in each of the previous months, with $p(\text{Default in that month})$

BLPs
 $P(\text{Redemption in that month})$ i.e. existing account closing good

- PD estimated for every month over the course of an accounts expected lifetime – across multiple scenarios.
- Requires series of conditional probabilities, thereafter combined with redemption probabilities to obtain unconditional probabilities.

Behavioural Life Profile (BLP) Model: Methodology

- As part of IFRS9, the Credit Risk Modelling Team took **different** approach to development of BLPs to the traditional *cohort* based approaches adopted in Treasury / ALM analytics
 - Aim to make more useable in operational strategies...in addition to being available (and aligned) for Finance based tasks such as Product Pricing as Balance Sheet Management.
- The model was developed at **account level**, segmented by the presence (or not) of an Early Redemption Charge (ERC), whereby charges would be incurred should a customer takes the decision to redeem before a particular point in the future.
 - Forms the basis for rational decision drivers in the model; would the customer benefit financially by Remaining 'as-is', or redeeming / transferring.
- Model based upon established techniques used to construct operational scorecards
 - Easier to deploy into operational strategies and systems, e.g. product maturities, contact strategies, etc.
- Model characteristics selected to ensure the model is **sensitive to different economic scenarios** and therefore provide **dynamic BLPs** – based upon the scenarios presented
 - Regulatory expectation under the BSOCs Comprehensive Approach (SS20/15) and emerging Interest Rate Risk in the Banking Book (IRRBB) requirements
 - Enables models give risk based estimates across multiple scenarios – an important range of outcomes for IFRS9, business planning, pricing and ICAAP.

Behavioural Life Profile (BLP) Model: Structure

Inputs

(Account Level and Forecasts)

- Balance
- Prevailing Market Rate
- Loan to Value
- Early Redemption Charge (ERC)
- Current Interest Rate
- Standard Variable Interest Rate
- & Others

BLP Model

- Model for accounts with ERC
- Model for accounts with no ERC

Outputs

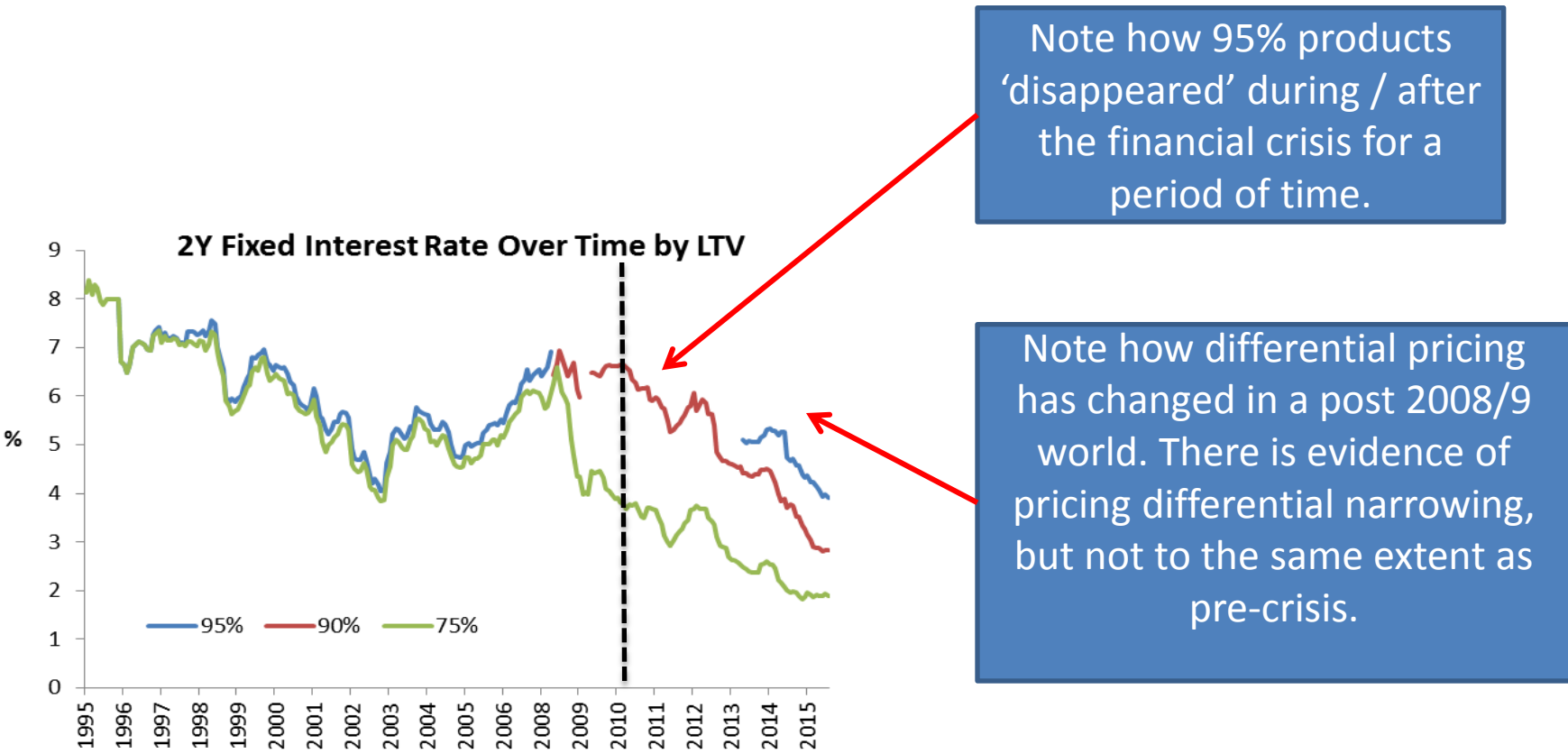
- Probability of Redemption (PR) in the next month
- Probability of Transfer (PT)* in the next month

Combined for non-IFRS9 purposes

We will now focus upon how these inputs have been used to model rational decisions, based upon economic conditions.

Driver: Prevailing Market Rate (External)

- Mortgage Spreads by LTV Band can be freely obtained from the BoE
- LTV key driver of risk, pricing and product availability over economic cycle.



Driver: Prevailing Market Rate (External)

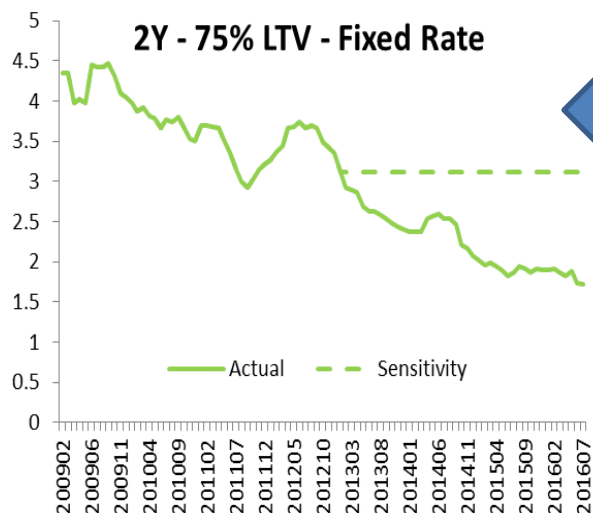
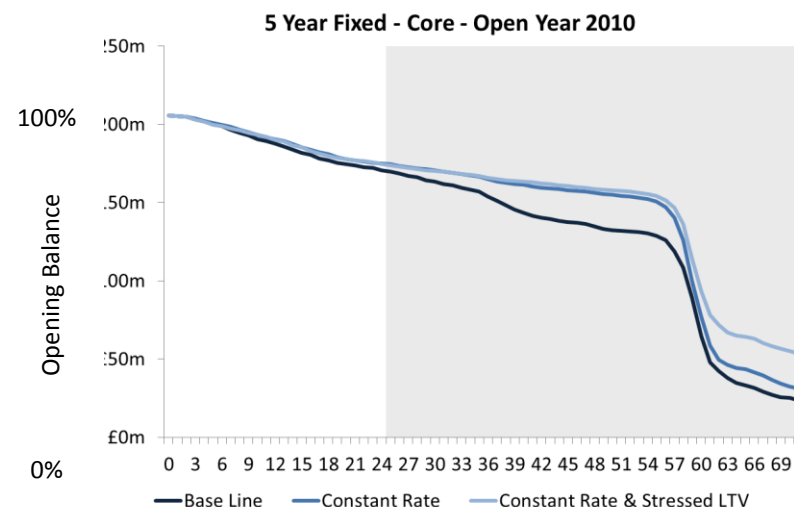
- The 75% LTV Rate for a 2 Year Fixed has been used as a proxy for the ‘**best rate**’, i.e. the one that most customers would seek to secure;
 - the probability of a customer redeeming away will be higher for a customer on a product with a rate higher than “the best rate”, relative to a customer who is already close to “the best rate”.
 - **We refer to this as Rational Decision 1; quantum of cost saving based upon current relative to the best deal available.**
- The difference between a customers’ product rate payment and SVR ‘Payment Shock’ is also a strong driver.
 - A large increase when reverting to SVR is likely to impel a customer to look around for “the best rate” in the period leading up to maturity.
 - The ERC dis-incentivises (but does not eradicate) in-product redemptions – particularly for larger loans.
 - **We refer to this as Rational Decision 2; quantum of Payment Shock at maturity.**

This data enables derivation of a set of premiums / discounts (which can also be forecasted) as inputs to Rational Decision model drivers.

Band	Premium
60% LTV	-0.05%
75% LTV	+0.00%
90% LTV	-1.00%
95% LTV	+2.25%
>95% LTV	+4.50%

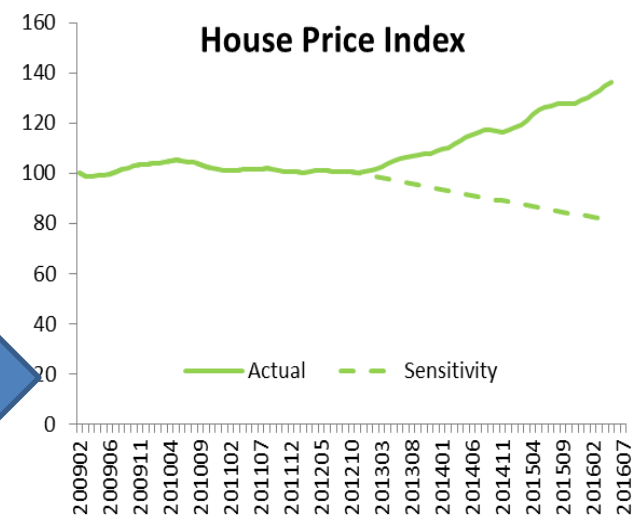
Driver: House Price Movements (External)

- “Best Rate” available partially driven by house price movements (& hence LTV) & forecasts therein too.
- E.g. someone on 80% LTV 5-yr product with ERC may reach a point before the end of the deal where the rational decision is to break the deal when markets have changed, and some amortisation has occurred, and (after incurring ERC changes) take a cheaper 75% deal.
- Example: 5-year fixed originated in 2010
 - **Baseline** pay-down : falling ‘best rates’ and increasing house prices (solid lines below L&R)
 - **Sensitivity 1:** market mortgage rates held constant, dotted line below left.
 - **Sensitivity 2:** house prices were reduced (dotted line bottom right) in combination with constant rates.
 - Both sensitivities reduce pay-down (increasing behavioural life).



Lower ‘best rates’ in the market incentivise attrition activity.

Falling / stagnating house prices reduces LTV migration and therefore best rate options.



Key Model Drivers: (1) Rational Decision and (2) Payment Shock

Rational Decision 1: Best deal available (External):

- **ERC in force:** how much the customer would be expected to save over the remaining ERC term by paying ERC today & taking out new 2 year fixed product at competitor.
- **No ERC in force:** Indicates how much the customer could reduce their monthly interest payment by taken out a 2 year fixed at a competing institution.

Rational Decision 2: Payment Shock (Internal):

- **ERC in force:** Not calculated for accounts with an ERC in force as payment shock is a future internal event, addressed by the No ERC model.
- **No ERC in force:** Indicates how much the monthly interest payment has increased compared to the rate offered on the account's previous product.

Other Model Drivers:

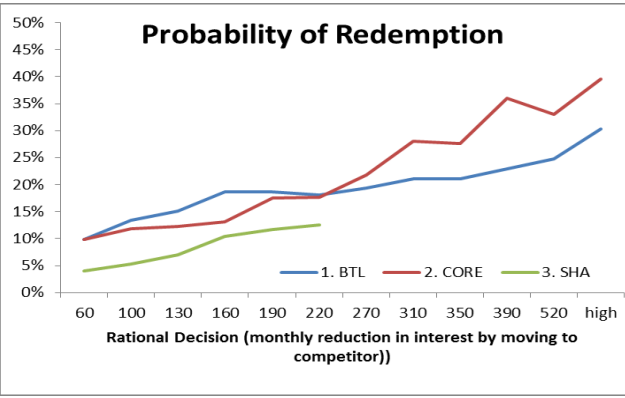
In addition to Payment Shock and Best Deal Available drivers, the models reflect other drivers. Examples include:

Driver	Rationale
Remaining product term	A customer is more likely to redeem away towards or at the end of the product term.
Time on SVR	The first 6 m post-product term are most significant for redemptions and transfers products.
Product	Different segments exhibit varying levels of price sensitivity, e.g. Resi vs BTL,.
Indexed LTV	Is correlated to how many alternative products are available in the market place and best deals.
Loyalty	Is this the first time a customer has gone through the product maturity process?
Application Score	Credit Quality.
Fixed Period	2, 3, 5 or Other years. Reflects the behaviour of the customer.
Fixed/Variable rate	Reflects the behaviour of the customer.

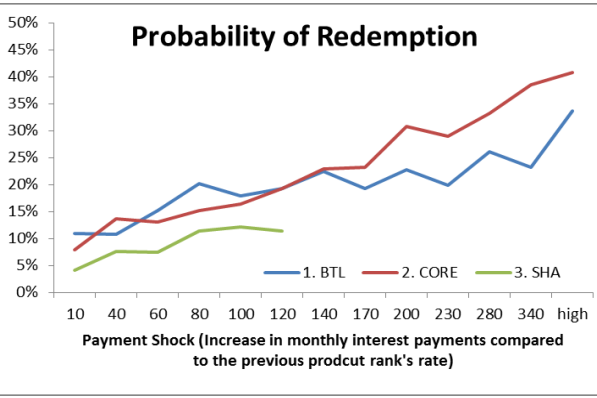
Results: Key Model Drivers: Sensitivity

Graphs show how probability of redemption and transfer increases by both Rational Decisions 1 & 2.

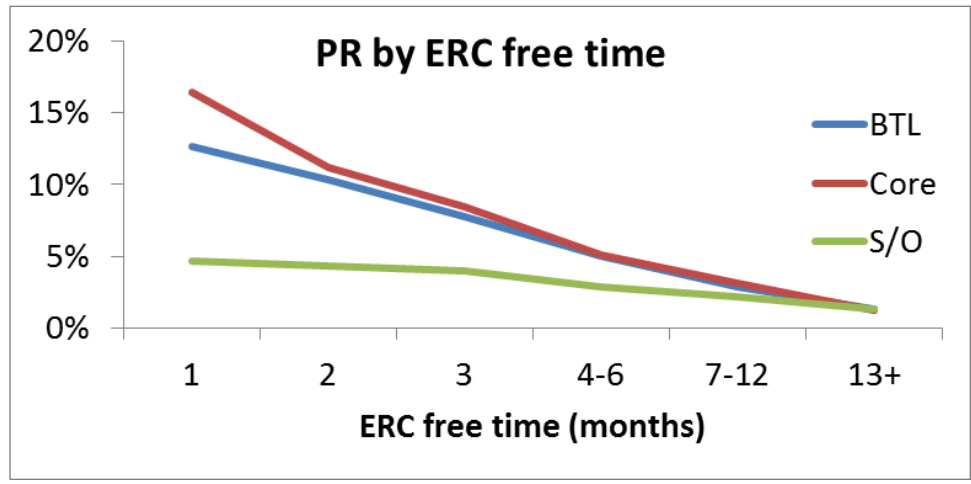
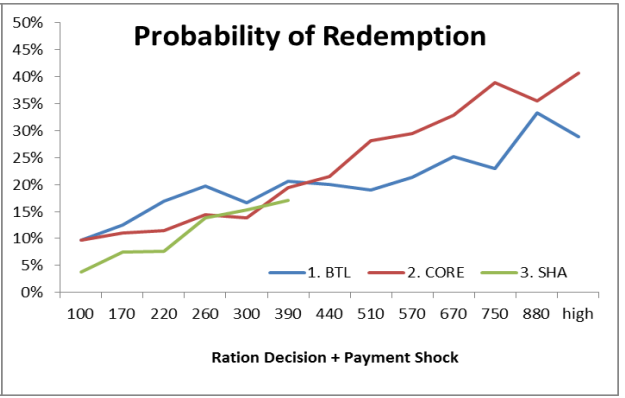
Rational Decision 1



Rational Decision 2



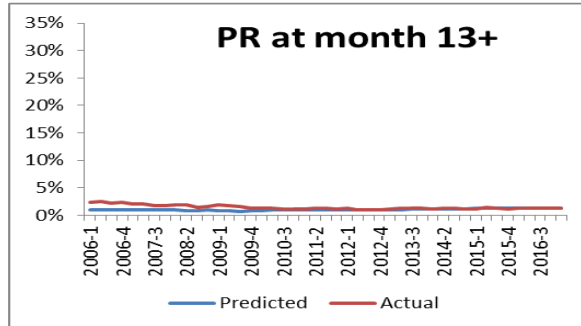
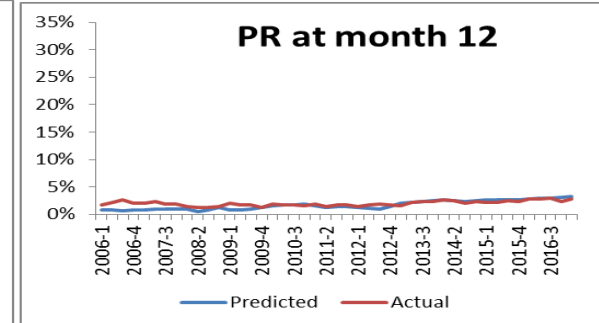
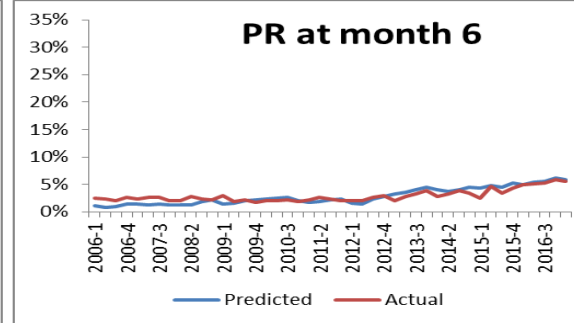
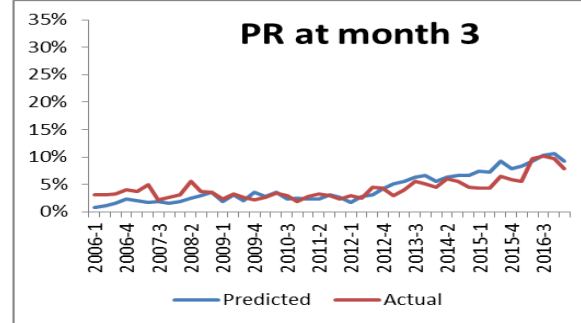
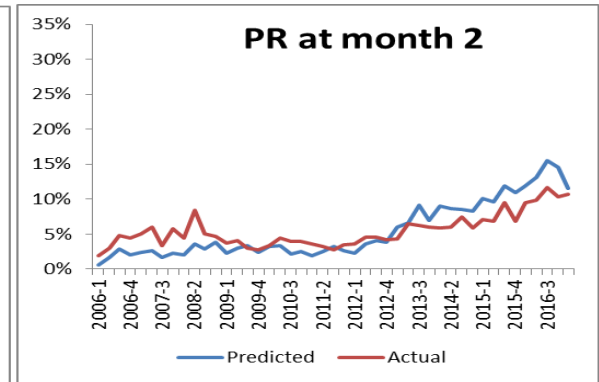
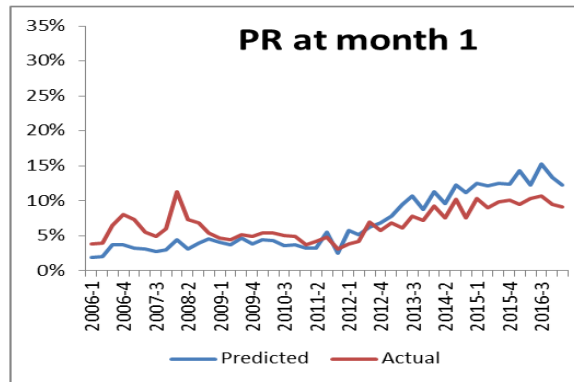
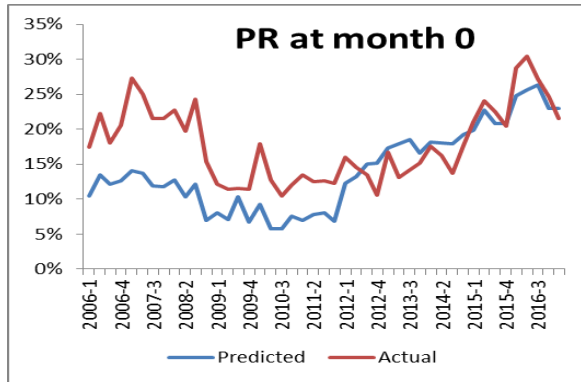
Combined



The probabilities reduce with the number of ERC free months an account has been exposed to.

Model Validation: Probability of Redemption by Non-ERC Groups

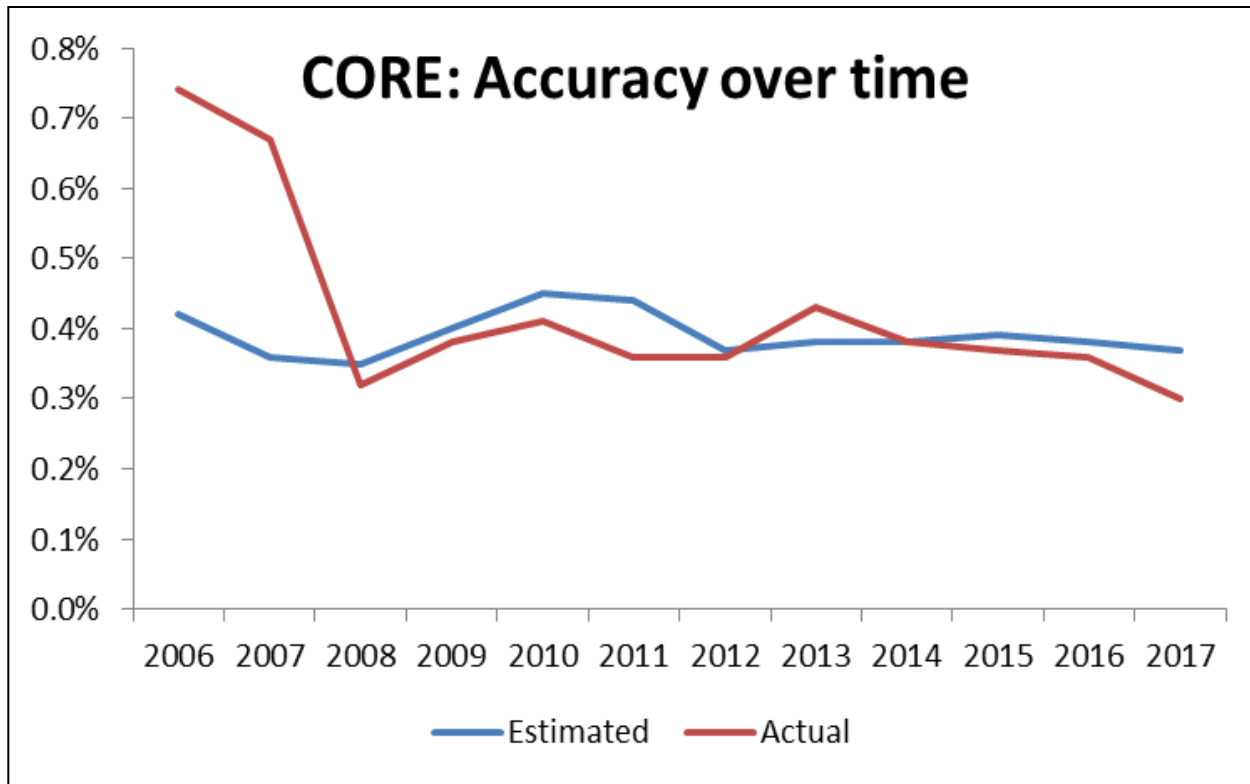
Predicted probability of redemption in next month against actuals by ERC free time.
Month 0 = last month where ERC is attached.



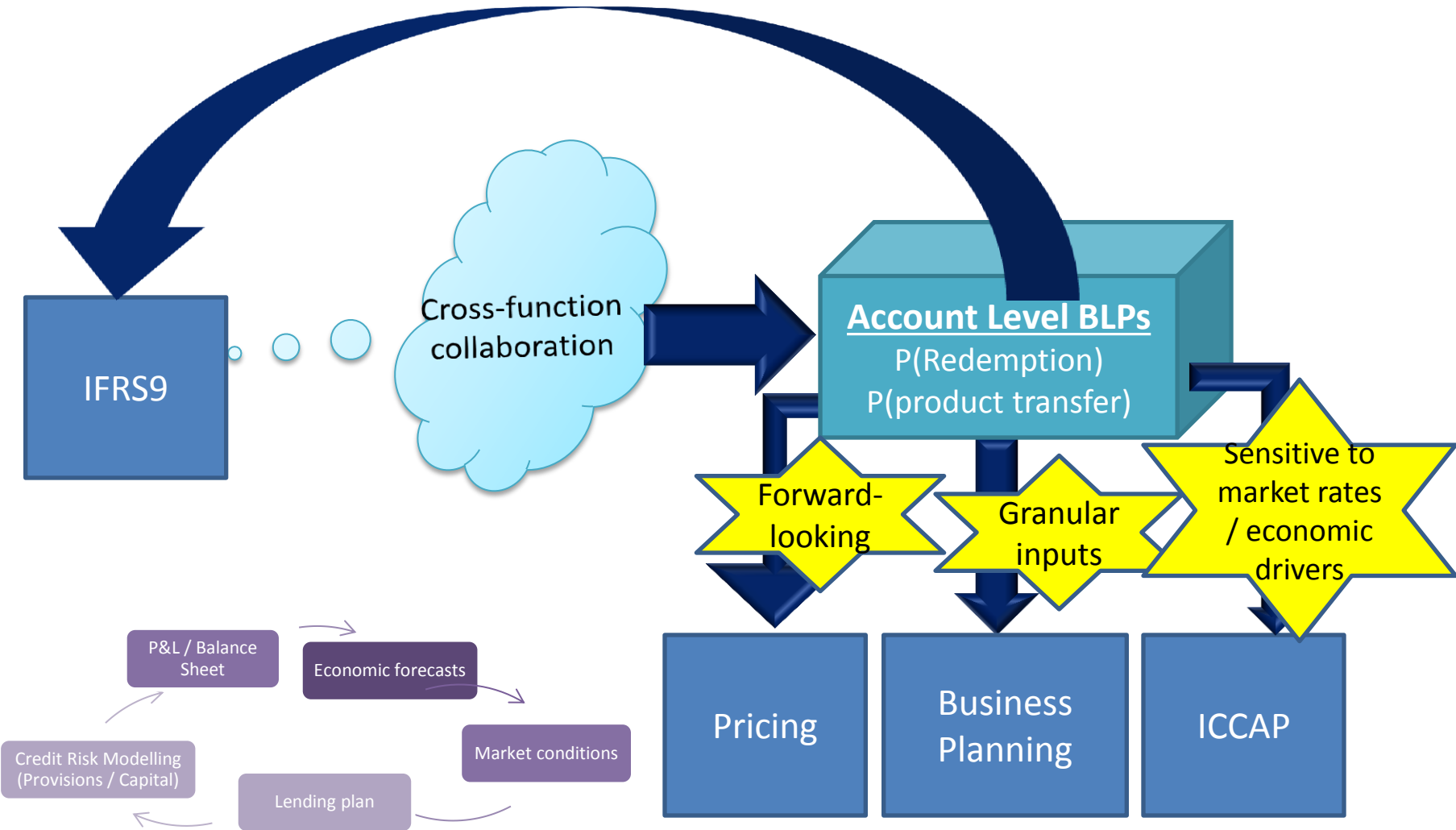
- The probability of redemption (PR) has increased from 2010 => model has picked up this trend
- The model does underestimate redemption rates prior to 2012 => practices have clearly changed over time.
- The model was developed on a 2015/6 sample.

Model Validation: Accounts with an ERC attached.

- The following graph compares predicted against actual redemptions for accounts with an ERC attached
- Note that redemption rates are relatively low, < 1%, and have therefore a relatively low impact compared to accounts that have no ERC attached.
- The position was clearly different in a pre-crisis world.

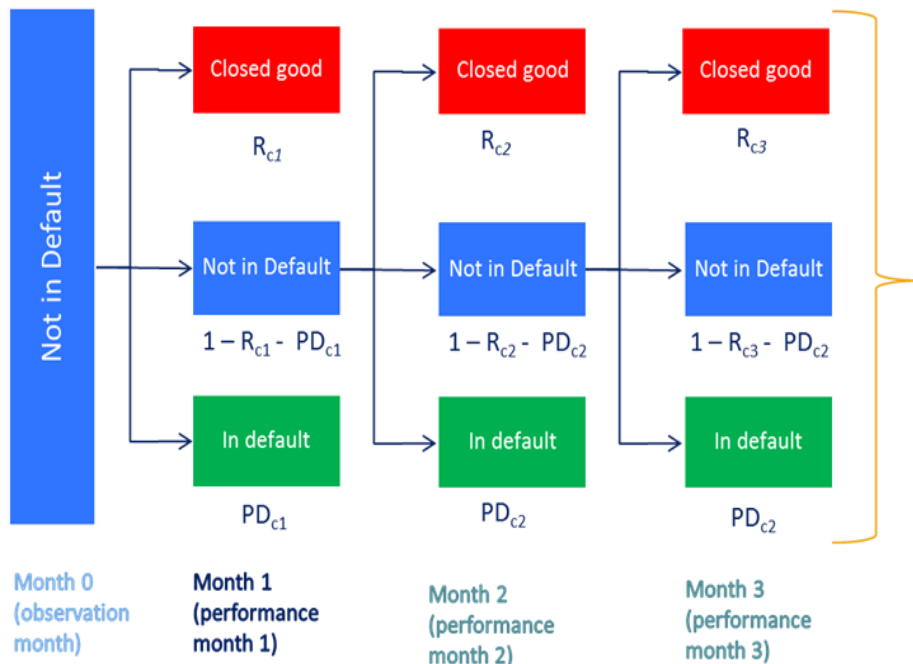


Summary and Conclusions



Appendix: Overview of Conditional / Unconditional Probability

The Lifetime PD model is the most complex model structure in the IFRS9 suite. PDs must be estimated on a monthly basis, for every month-end over the course of an accounts expected lifetime – across each scenario. This requires a series of **conditional probabilities**, which are thereafter combined with redemption probabilities to obtain the **unconditional probabilities**. The following illustrates:



Conditional Probabilities

Unconditional Probability of Default

$$PD_1 = PD_{c1}$$

$$PD_2 = (1 - R_{c1} - PD_{c1}) \times PD_{c2}$$

$$PD_3 = (1 - R_{c1} - PD_{c1}) \times (1 - R_{c2} - PD_{c2}) \times PD_{c3}$$

$$PD_n = (1 - R_{c1} - PD_{c1}) \times (1 - R_{c2} - PD_{c2}) \times \dots \times (1 - R_{cn-1} - PD_{cn-1}) \times PD_{cn}$$

- The conditional PD model provides a likelihood of defaulting at month n+1 having not been in default and still on book at month n .
- A Conditional PD is calculated for each future month from the current date to the contractual lifetime.
- The unconditional probability for a particular month is obtained by multiplying the probabilities of not redeeming or defaulting in each of the previous months with the probability of defaulting in that month.
- We are using our BLP models as an input to PD, to estimate the probability of a redemption i.e. closing good.