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Attaining sharper Pricing-for-Risk in the U.K. Sub-Prime Mortgage Market

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*(The views and opinions in this article are those of the author
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Contents

Introduction	3
Problem Scope	4
Credit Value Chain Concept	6
The Risk Underwriting Process & the 3Cs	7
1. Credit Character Measures (C1)	10
2. Affordability Capacity Measures (C2)	10
3. Collateral Measures (C3)	10
Basel II Credit Risk Principles	12
Sharper Risk-Based Pricing Approach	19
Risk Adjusted Performance Measures	23
Conclusion	25
Appendices	26
References	28

ABSTRACT

Credit risk analytics facilitates maximal usage of internal and external data measures (including third-party suppliers of predicted U.K. house prices available at a post-code level). Using Basel II Credit Risk principles for measurement of expected loss (PD, LGD, EAD), we demonstrate how mortgage pricing can be decomposed into its key elements including its embedded options (the credit default and prepayment options) plus all remaining mortgage administration costs. PDs can be estimated using distinct models based on each of the traditional three 'C's of credit underwriting. These are: **Character** ('willingness to repay') as measured via traditional modelling such as Application Scoring and/or Bureau Behavioural Scoring and Fraud Models; **Capacity** (the 'ability to repay') as measured by Affordability models and/or Bureau derived Over-Indebtedness Indices; and **Collateral**—measuring future Loan-to-Value (LTV) via the Black-Cox extension of the Merton structural credit risk model. Sub-prime mortgage LGD is largely dependent upon forecast LTV measures for localised property distributions. The pricing-for-risk outcomes can also form part of any Risk Adjusted Performance Measurement (RAPM) framework—given required market and operational risk estimates. Effective use of pricing for credit risk should also assist lenders to abide by the spirit of FSA directives for treating all customers fairly (TCF).

From *The Times*, (Friday the 13th July, 2007)

See link to actual news article story below: ¹

Lenders set to foreclose on 1.8m borrowers in sub-prime crisis

By Tom Bawden in New York

Instead of quoting article above, this (edited) online comment seems more relevant and pertinent to this paper:

“What happened? ...,

- What company/loan officer took the loan application?
- Who got the credit report and verifications of income? (Ratio of debt versus income to repay)
- Who made the appraisal? Was he/she qualified to make it?
- Who approved the loan? (A loan committee or an individual)
- Who packaged these loans for sale to other investors? Who were they? (Domestic or foreign)
- Were these loans sold off the shelf, and did the lender keep the origination fees/points? Or did the lender keep part ownership and the servicing?
- Who handled the collections of past due payments?
- Were the lenders Federal Insured Lenders?
- What was the lenders' underwriting standard?
- Or did anyone really give a damn?

I am an old (76 years old thank God), retired loan officer - who used to approve A LOT of real estate loans, for many years... with VERY, VERY FEW FORECLOSURES.

We use to base a loan on the person; his/her credit history, the collateral of an honest appraisal and the ability to repay (The 3 C's)

...What happened?”

George T. Ziegler, Kearney, Missouri

¹ (http://business.timesonline.co.uk/tol/business/money/property_and_mortgages/article2067174.ece)

Introduction

The famous 1935 Escher lithograph shown in Figure 1 below of the 'Hand With Reflecting Sphere' is an intriguing view that Morgan (1988) uses to illustrate a fundamental epistemological point with modern Accounting's (futile) attempt to portray its discipline as a reality construct (highlighted by the artist Escher viewing his own created image through a crystal ball). **Morgan's argument is that accountants typically construct reality in a very limited, enclosed and one-sided view and he therefore debunks the profession's supposed "objectivity" as some mythical concept and even arguing that accounting should be approached as a form of "dialogue" allowing accountants to construct, "read" and probe situations from a multitude of viewpoints and perspectives. To put this concept in simpler terms: *the map is never the same as the territory!***

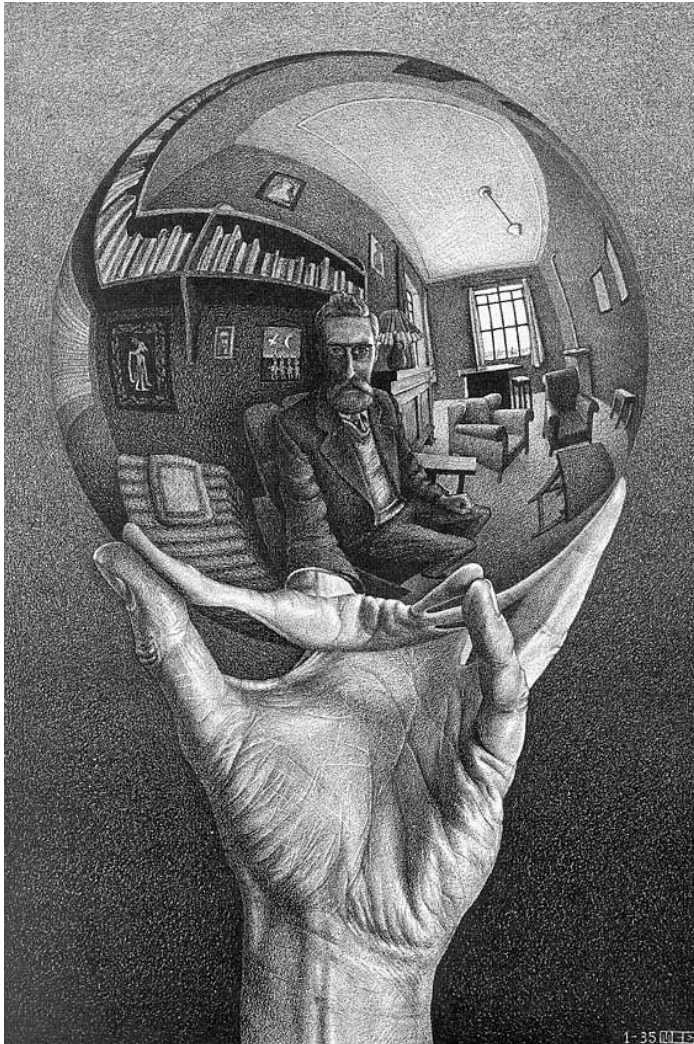


Figure 1
M.C. Escher's "Hand with Reflecting Sphere" © 2007 The M.C. Escher Company-Holland. All rights reserved. www.mcescher.com

I would like to advance the same argument (with perhaps even greater gusto) concerning the 'art-and-science' of risk measurement (covering at the very least credit, market and operational risks). Risk practitioners may like to attain true measures of financial risk (with subsequent control) but after observing the series of major financial calamities that have occurred over the last few decades, you have to conclude that there has been only limited risk management control evident². You can see the cyclical nature of these risk-triggering events in Figure 2 below, indicating a so-called vicious cycle of risk at work (as per Kupper 1999). It can prove to be quite hard to break out of this systemic cycle, once initiated, assuming of course that management even realises that such a process is going on whilst they are busy peering into their own Escher-like 'crystal balls' (the modern equivalent would be electronic dashboard reporting devices).

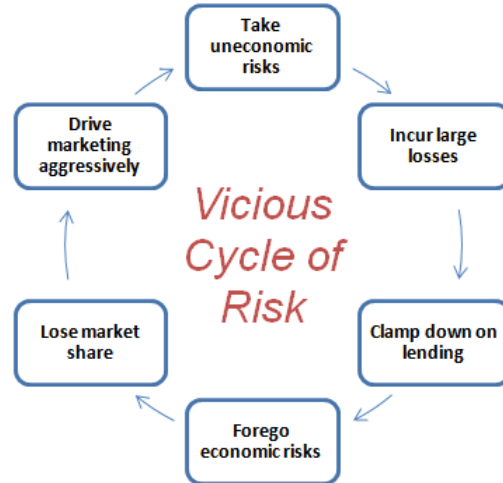


Figure 2

Historically one can observe many "scientific" attempts at forming possible boundary solutions that might help in breaking the cycle above. More recently, under the Basel II framework³, it becomes possible to use a rather crude internal-rating based measure of an obligors' likelihood of experiencing an expected loss over some arbitrarily defined period. Risk practitioners will still need to understand these 'pseudo-scientific' measurement aspects (the Basel II risk framework is a good example—especially concerning the conflict with the accounting "view" in the International Financial Reporting Standards for loss provisioning). However, they should also realise that any such derived measures can only ever form

² Witness for example the 1970s Latin American debt crisis and the 1980s US Savings and Loans debacle. Also, the 1990s Asian financial crisis as well as the Russian crisis involving Hedge Funds (LTCM); and in the 2000s the giant corporate collapses of Enron and WorldCom (as well as the more recent US sub-prime retail mortgage market collapse)—events which serve to remind us of the inherently frail nature that underpins the discipline of risk measurement and management.

³ Basel II: International Convergence of Capital Measurement and Capital Standards: A Revised Framework, Comprehensive Version (BCBS) (June 2006 Revision)

dialogue positions that direct one towards some other nebulous aim (such as maximising profits or minimising potential losses or perhaps the optimal usage of risk capital). Not that encouraging, I must admit from a 'command-and-control' paradigm viewpoint, but at least management will be more aware of their likely limitations rather than have **blind acceptance of some false 'truth'**. Falkenstein (2001) also expresses a similar viewpoint. In his **article titled "The Risk Manager of the Future: Scientist or Poet?"** he makes clever use of the German word *weltanschauung* (in describing the extreme potential impact of the Value-at-Risk concept for *future* portfolios). According to the Merriam-Webster dictionary definition, *weltanschauung* means **"a comprehensive conception or apprehension of the world especially from a specific standpoint"**—somewhat akin to our view of the Escher self-portrait concept in Figure 1. Falkenstein makes the point that the ideal risk manager of the future will be neither scientist nor poet but will need a combined knowledge of the technical tools used in risk analytics and data integration skills, as well as a deeper understanding of how risk measures relate to both strategic and tactical business decisions.

Therefore, by starting with this rather limiting perspective of risk portrayed above, it encourages one to put forward their own **"interpretative" risk measures** without being too concerned over any **supposedly "objective" aspects** that can otherwise stifle such initiatives. Perhaps even, we could actually make good use of the fundamental 3Cs!

Problem Scope

According to the Bank of England (BOE) Act report for 1994/95, it views risk-based pricing as an outcome from systems designed to set a required margin on individual loans in accordance with their risk characteristics. The required analytics for risk-based pricing will need to take into account the following edict:

"... that the loan is priced to cover the various costs incurred by the lender, the direct cost of funding the loan, the credit assessment and other administrative costs associated with providing, servicing and monitoring the loan; the cost of insuring, or self-insuring, against the risk that amounts will be lost because of obligor default ('expected loss' premiums); and, finally, the cost of capital, held to protect the institution against the chance that actual losses will exceed their mean expected magnitude ('unexpected losses')."

Of course, some profit margin also needs to be included to cover the stakeholder perspective but this BOE view is essentially 'cost-plus' in nature. It therefore assumes that Banks and/or the Government can actually control the end

price, which epitomises the form of banking that we are witnessing at present. In the future, other methods may become prevalent that could be more consumer-driven in nature (and hence with less control over pricing): such as community banking, internet lending, micro lending, and lifetime financial management (or the holistic long-term view). Additionally, entities that are not banks or building societies (but can provide broader financial services) will also become more prominent lenders such as giant industrial corporations (GE Capital, GMAC, Tesco or Microsoft), insurance companies (Standard Life) and specialist lenders in mortgage markets (Kensington Mortgages) who can source funding via the capital and banking markets (using securitisation and whole loan sales). Just like auditors seeking to provide a **"true and fair"** view of the year-end financial accounts, risk practitioners **would also like to provide a "true and fair" risk-based pricing framework**, especially so, for credit-challenged consumers, for example in the so-called sub-prime mortgage market. The BOE makes the point that: **"Banks which do not develop formal risk-pricing systems will have to find other ways to price loans according to risk or be in danger of losing their good customers through overcharging while earning an inadequate return from less creditworthy borrowers"**. The BOE also makes the critical (and somewhat prescient) point in 1994 that the **"proper judgement of a system's performance can only be made over a full economic cycle and, a move to risk-based pricing can bring technological, cultural and operational challenges"**.

What constitutes a 'non-conforming', 'sub-prime' or 'adverse credit' mortgage?

The term 'sub-prime' appears to have its genesis within the U.S. mortgage markets during the 1980s specifically with the introduction of the Alternative Mortgage Transaction Parity Act (AMTPA) in 1982. AMTPA effectively overruled state laws that had restricted a number of alternative mortgage aspects (that are now features of the sub-prime market) such as variable interest rates, balloon payments, and negative amortization in **any "loan or credit sale secured by an interest in residential real property made, purchased or enforced by covered lenders"**.⁴ This law change therefore set forward potentially different types of loans that would inevitably grow in number.

As the main funding process for home mortgages in the U.S. was through securitisation or Mortgage Backed Securities (MBS), this process had a mandate for assessment of loan quality for investor bond-rating purposes. Investors readily purchased MBS bonds as they help blend different types of loan risks to yield specific returns for investor classes, using methods such as over-collateralisation, pool insurance and senior-subordinate structures. Essentially, the issuance of mortgage-backed securities channels funds from investors in

⁴ See Temkin *et al.* p.8.

the capital market directly to borrowers, via the mortgage originators. The securitisation process, therefore allows many subprime lenders ready access to liquidity to fund their mortgage originations. Furthermore, since most of the credit risk associated with mortgage lending gets transferred (or sold through the securitization process), from the lender to the security-holders or bond holders, securitisation is not only just a source of diversified collateralised funding, but also a very critical risk management tool.

Further mortgage credit differentiation thus arose from the U.S. government sponsored enterprises (GSEs), Fannie Mae and Freddie Mac with their role of providing a guarantee for the MBS. To provide such a guarantee, the GSEs needed to create a standard setting process—especially for **'prime'** residential mortgage loans known as **'A'** quality loans (or the least likely to default). This quality setting acts to form the bulk of the **'AAA'** bonds within the securitisation vehicle. The rating agencies also helped define this loan grading process through publishing some specific guidelines, such as **Standard & Poor's Loan Quality Guidelines, for example**. Thus, any non-conforming loan that did not meet the **'A'** standard, simply fell into the lower ranking (or adverse) **grades**. Loans that were close to **'A'** standard became known as near prime loans (the **'A-minus'** or **'Alt-A'**) a mildly positive expression. However, the other remaining non-conforming loans (the **'B'**, **'C'** and **'D'** grades), were foisted with the rather glum expression of sub-prime—to help discern them from the two other categories of prime and near prime. The terminology has now become standardised.

According to the U.K. Council of Mortgage Lenders (CML), their definition of sub-prime mortgages are those contracts specifically designed for people who do not qualify for a mainstream mortgage as they have had credit problems in the past or have difficulty proving a regular (or reliable) income. This non-conforming segment arises from those experiencing so-called **'life-changing events'**—such as divorce, unemployment and sickness that can sometimes force these borrowers to miss payments on their mortgage or other financial commitments.

A definition of sub-prime *lenders* would be companies who offer mortgages to borrowers who represent a higher level of risk than borrowers who otherwise meet standard prime underwriting guidelines (a kind of negative definition). A broader categorisation term might be to call these lenders **'Specialists'**—as it covers all of the rating grade categories of Prime, Near Prime and Sub-Prime—not just the adverse part only. Moreover, the specialist lender would be one who can provide the required loan to the appropriate customer—for the **'right' price**. As lenders move closer towards the paradigm of risk-based pricing, in theory, they would not have to outright deny any applicant a loan based

on their credit risk—he or she would receive instead, a higher price—meaning the applicant could then reject the offer, instead of the lender rejecting them for the loan. Thus, the continuum between prime and sub-prime extremes will probably become increasingly irrelevant as specialist lenders step in to offer a superior service to all borrowers using risk-based pricing, and this would help with the overarching goal of treating all customers fairly. Risk-based pricing helps remove cross-subsidisation of prime loans because of the widespread practice of average cost pricing to these customers. Therefore, an interest rate (APR) based on individualised risk profiles seems eminently fairer for all customers, not just sub-prime ones. Nevertheless, from the perspective of pricing the inherent risk, we can make use of the three segment splits in this report for prime, near prime and sub-prime segments, however, most lenders would not openly wish to reveal to any customer what label they have been ascribed. Instead, we would hope that mortgage intermediaries could **"construct"** a mutually acceptable loan arrangement for their clients—with the individually tailored APR outcome forming a significant part of that deal.

Other Mortgage Markets

Although our specific focus in this report is on U.K. sub-prime mortgages,⁵ other geographical markets are also relevant to the proposed methodology. In looking at European mortgages, a report by Mercer Oliver Wyman (MOW) (2005) estimated unmet mortgage demand of at least 15% (or around €500 BN of lending) with 80% of this opportunity within three risk segments that embrace the typical sub-prime market clientele. The segments include **Low Equity** borrowers (with equity of around 10%), **Stretched** borrowers (with a high debt servicing coverage ratio) and **Risky** borrowers (have a previous credit problem, or unconventional credit history such as recent immigrants). The estimate of available potential margins is about double that of the prime segment. MOW believes that significant growth exists in Germany and Italy and to a lesser extent in transition countries like Poland, Hungary and the Czech Republic but not much for mature markets like Denmark and the U.K. whilst Spain is currently experiencing a major housing market recession. **"Winning"** lenders in the European mortgage market according to MOW will have three key characteristics:

- 1) Superior **underwriting** management,
- 2) Superior **risk management** (in risk mitigation and risk transfer via capital markets, mortgage insurance and international balance sheets) and,
- 3) Superior **funding** approaches in compliance with the new Basel II framework (including securitisation, covered bonds and credit derivative usage)

⁵ We focus on the UK market largely for illustrative purposes only.



Currently, the U.S. sub-prime mortgage market is experiencing extreme difficulties, which is perhaps not that surprising given that 50% of sub-prime mortgages comprise 100%+ LTV and about 33% of new lending in 2006 comprised sub-prime and/or Alt-A (Near Prime), whilst 40% of home purchases in 2005 were for either investment or vacation purposes. Some news articles have even reported **'free-spirited' underwriting practices** including property self-appraisals, income self-verification and the use of adjustable rate mortgages (ARMs), and some repayment schemes designed to end up with negative equity positions after 2 years of payments. Between 2000 and 2006, U.S. home prices increased by around 80%—an unprecedented rise over the last 100 years—and within the last 5 years, home ownership increased substantially from 64% to almost 70% for all of the United States. In other words, the U.S. mortgage market was creating its own house price inflation **'bubble' with significant mortgage funding coming from the new 'high leveraged' hedge funds via the capital markets.**

From a risk-based pricing perspective, both White (2004) and McCoy (2006) allude to predatory pricing practices in the U.S. sub-prime markets. McCoy makes the telling point that for the U.S. prime market, lenders will reveal prices freely but for sub-prime borrowers they must first reveal their creditworthiness indicators before lenders can determine any loan prices. This practice imposes the opportunity for significantly higher charges because of the delayed process—not because of the risk-based pricing result (an example of the deal 'form' taking precedence over the 'substance' of the transaction). In the relatively more regulated U.K. market, there is less opportunity for this to take place. However, approximately two-thirds of all new business originates via an intermediary but in the sub-prime market, it is closer to 80%—thereby implying greater scope for the use of delayed pricing and higher lending charges and any undisclosed commissions that could go to the intermediary.

Credit Value Chain Concept

A credit provider will display a certain 'appetite for risk', which in turn is somewhat dependent on what phase of the credit cycle of risk they are in, as per Figure 2 – Vicious Cycle of Risk. It is important to distinguish between risk management and risk avoidance—two distinctly different concepts. The aim of risk-based pricing is to manage risk (not to avoid it), but at the same time, to accurately measure the likely outcome and thus attempt to compensate for this measured risk by adjusting the price (or APR). The difficulty lies in obtaining a balanced deal that will hold across the entire credit value "chain". Aguais and Forest (2000) portray an end-to-end credit view (similar in scope to Figure 3 below) illustrating the four broad phases of the credit value process, which in turn are

interlinked sequentially and economically. Significant economic value exists within the first chain link of business planning (product design, marketing and loan initiation) but, in this credit-value chain view, we believe that link number two has the highest potential profit contribution across the full process. The third and fourth links of the credit value chain in the figure are also vital but are largely outside of the scope of this paper. It is worth bearing in mind though, that any feedback loops in operation from this chain (or system) will serve to enlighten any future adjustments to the overall process. For example, unusually high repossession rates in chain link number three above could be indicative of either poor loan design or improper underwriting execution (chain link numbers one and two), or perhaps symptomatic of an inaccurate measurement and monitoring process within this link. The ultimate aim of course is to ensure that there are no obvious 'weak links' throughout your credit value chain design.

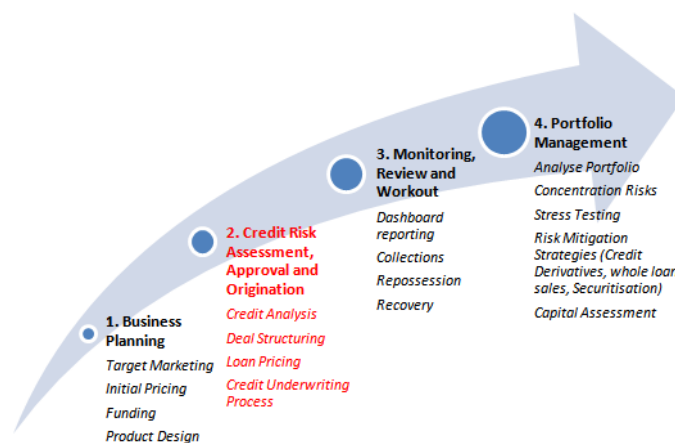


Figure 3 - Credit Value Chain Concept

Automated Underwriting Systems

Many prime lenders prefer to use automated underwriting systems for their high volume processing (low cost advantage) instead of relying on manual underwriting where there is also greater scope for human preferences and biases. However, a well-trained and experienced manual underwriter should be able to identify any specific extenuating circumstances that an automated process may struggle with under its set rules. For example, a non-recurring illness may have been the reason for a reduction in past income and hence the recording of an adverse credit position. Presumably, under the manual approach, this reason would be easier to factor into the overall credit risk than for an automated system. It is unlikely that 100% auto-decision systems will be possible in the near future but lenders should exercise caution about downgrading the **manual underwriting skills especially around the 'grey' or unclear zone of underwriting cases.** Experienced lenders like George Ziegler are getting older and rarer!

The Risk Underwriting Process & the 3Cs

According to Barnes *et al.* (2007) in explaining how S&P issues ratings for Residential Mortgage Backed Securities (RMBS), each of the characteristics of every loan in a securitised pool has a probability of default and therefore an ultimate loss. S&P's analysis addresses this via a layered risk—or multiple characteristics of risk approach—as in:

- 1) **Loan structure review** (checking for adjustable rate mortgages or income verification details),
- 2) Borrower **credit character assessment** (through the use of FICO credit scores),
- 3) Assessing borrower's **ability to repay** the loan (or capacity) and,
- 4) Determining amount of **equity** (or collateral) a borrower may have in their home.

These characteristics are combined into a sophisticated stress simulation test and analysis before any given asset tranche can be subjectively rated 'AAA' or 'A', for example. To this list of requirements, S&P impose a crucial aspect, namely fraud risk control, especially concerning data integrity measures.

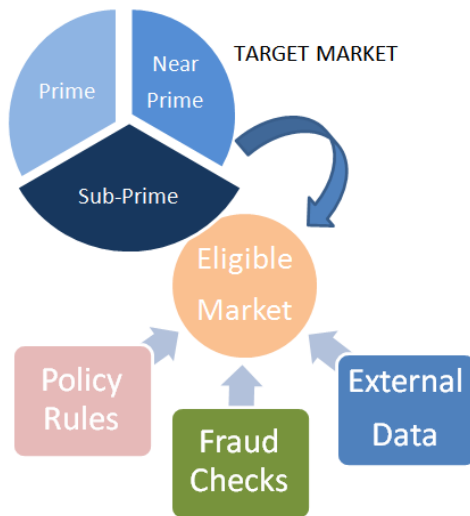


Figure 4 - Reduced Target Market after Filtering Rules

We can illustrate a broad process for making underwriting decisions as in Figure 4 above. The approach above also relates to a version of the process that Van Dijk and Garga (2006) illustrate in their CML Mortgage Underwriting Report covering the various parts of the underwriting system. In essence, this crucial underwriting system depicts an appropriate methodology for blending external and internal data. The data inputs will not necessarily be of equal importance across different applicants for final decision-making purposes, but it is still crucial to ensure availability of additional data, if required. The blue coloured box in

Figure 4 reflects external information that helps augment the internal measures (obtained from the application form and other sources). To some extent, the policy rules will thus need to encapsulate this external information in order to allow for cancellation of the current application if it breaches some pre-defined parameter (or otherwise to demand a reconfiguration of terms and conditions in order to obtain final underwriting approval). Therefore, the process parts of 1) policy rules and 2) fraud checks, together with 3) external data sources, will **effectively act as 'filters' over the target market**—reducing the number of applicants to only those able to pass through these general policy barriers.

We can illustrate a more detailed underwriting design below:

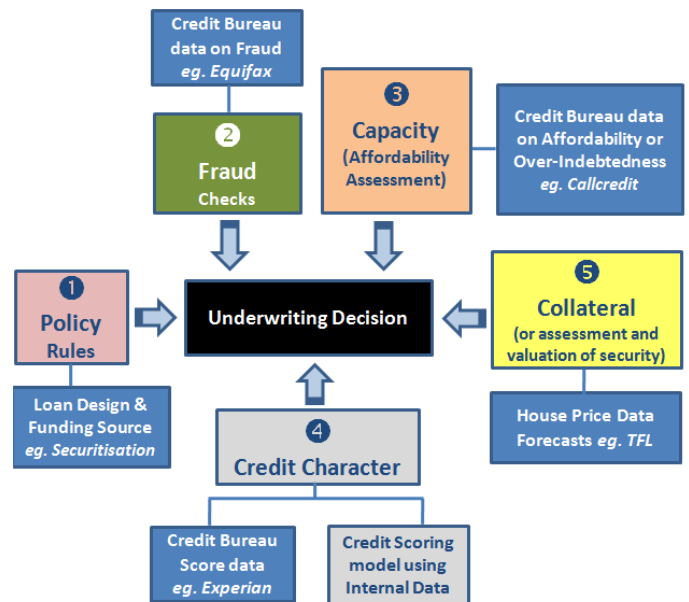


Figure 5 - Overview of the Underwriting Process

Of note, is that the PD of an applicant can actually change during this underwriting process, especially as the deal is being put together (somewhat akin to how the odds of winning can rapidly change during live betting for sports events). For example, applicants who want a bigger more expensive home than their previous one will be creating greater potential for default, especially for the maximum possible loan and as it transpires, the affordability measure proves to be inaccurate even though they have good credit character and are very willing to repay the loan. In addition to internal scoring approaches, one should also investigate any external measures of credit character as provided by credit bureaux. These additional sources of information can help refine the internal models, or otherwise confirm a decision for applicants that are not definitively in the good or poor character segments. We can elaborate further on the main constituent parts of this Underwriting process in the following sections.

Policy Rules and Loan Design

Policy Rules

Policy rules help shape loan applications and eliminate others. In the sub-prime market, according to Van Dijk and Garga (2006), lenders with manual processes serve a significantly larger proportion of applicants. Thus, more applications will receive manual reviews by sub-prime lenders using partly automated processes than in the prime market. They view this as an expected outcome, given that sub-prime applicants are more likely to have characteristics that may not be acceptable under automated policy rules, and so are more likely to require manual assessment. Therefore, greater reliance on policy rules under partial manual processing is necessary—until further automation of the process occurs, (assuming that the efficiency and effectiveness benefits from automation will exceed any increased losses that may result from having less experienced judgement applied).

Policy rules will tend to focus upon the applicant and the loan details—that is, the policy rules will form the minimum criteria that the applicant must satisfy in order to qualify for the loan. The applicant criteria may cover, for example:

- Minimum and maximum age of applicant,
- Criteria for unacceptable credit history,
- Legal entity of borrower and jurisdiction,
- Minimum and maximum loan amounts requested,
- Maximum loan-to-value ratios permitted (LTVs),
- Maximum income multiples, and
- Thresholds (or cut-off points) for any credit score

The lender creates most of these policy rules (from empirical evidence and regular adjustment) but the regulator (FSA) could proscribe some of them, or even the securitisation participants could stipulate policy (or otherwise the institution to which an originator intends to sell, any complete or whole-loans could stipulate policy).

There will also be policy rules surrounding the property—these policy rules will form the minimum criteria that the property must satisfy in order to grant the loan. Property criteria may include, for example:

- Type of property (detached or semi-detached, flat, bungalow, terraced etc.),
- Construction method (or materials used) and certain building company exclusions,
- Date of construction period,
- What constitutes a defective property, and
- Locale restrictions or certain postcode exclusions

In general, the lender specifies these criteria, but it may also reflect the requirements of insurers and securitisation vehicles especially for concentration risk issues.

Loan Design

One of the more curious aspects of the U.K. mortgage market, in general, is the proliferation of mortgage 'products', which in effect amount to nothing more than a simple variation of the general mortgage contract (for example, applying for a mortgage with a lower LTV band could therefore mean a different product is now applicable). This aspect results in thousands of such 'products' becoming available, even though the essence of each variation still requires a repayment schedule at some interest rate for a loan amount borrowed over a period of time. Marketing departments tend to use the product variation primarily for *dual* purposes: 1) to segment the market for increased penetration of volume and 2) as a means of applying a rather crude industry-wide standard of generic creditworthiness. Under this generic credit classification scheme (could refer to it as the 'ABCD' approach), it relies on variations of certain parameters about the applicant credit history in terms of:

- a) **A**rrears record (maximum of X missed payments in last Y months);
- b) **B**ankruptcy/Involuntary Arrangement (IVA) evidence indicating satisfied/discharged within set period;
- c) **C**ounty Court Judgements (CCJs – up to £X in last Y years, or otherwise unlimited);
- d) **D**efaults (X number of defaults permitted for previous rent payments or unsecured loans)

On the basis of how any individual fits within the arbitrary criteria set suggested above, the applicant will thus become eligible for a 'product' that might be described as 'Very Minor', 'Minor', 'Medium', 'Heavy' or 'Unlimited' for example. Each of these 'products' will have an arbitrary margin for risk added to the base funding mechanism (e.g., LIBOR) and for any other variations selected (e.g., Self-certification or Buy-to-let purpose). Interestingly, whenever you create an internal credit-scoring model using all available data, it is usually the case that none of the above criteria is automatically selected as being predictive by the modelling tool but they may instead be incorporated as part of the generic product group. Nevertheless, the industry appears to place great faith on these criteria and they therefore form an integral part of the automated product selection system in use by brokers and packagers.

It should also be borne in mind that the current design of sub-prime mortgages provides for early exit fees (via early redemption penalties) such that the securitisation funding mechanism expects these additional cash flows as part of the income for retention by the issuer. Not surprisingly, if the borrow behaviour is not as anticipated, then a funding crisis can result, whereas if instead, a charge was made upfront to cover the prepayment option, then this loan design would assist the customer by creating more flexibility (but it may also prove to be less lucrative overall from the lender viewpoint).



Fraud Checks

Various forms of fraud currently exist within the mortgage industry and undoubtedly, newer types will spring up as existing controls start to contain current fraud. Much of the problem relates to *data veracity* as the core issue.

According to the CML, **application fraud** occurs whenever an individual knowingly submits incorrect or misleading information on their mortgage application. Some examples of application fraud include:

- Exaggerating borrower income to qualify for a larger advance;
- Applying for an owner-occupier mortgage for a property (or properties) intended solely for letting.

One method for mitigating application fraud is to subscribe to a consistency checking service such as that provided by the National Hunter system (developed in 1993 by the credit reference agencies with input from the CML), that has virtually all U.K. lenders participating. It searches for other applications made to relevant organisations by the same person at the same address, and looks for inconsistencies or patterns. Such a system could supplement in-house data mining tools that seek unusual patterns or evidence of fraudulent problems.

Identity theft is now a growing worldwide issue. However, many U.K. lenders can now conduct identity fraud checks on mortgage applications using the CIFAS system, which searches for signs of this type of fraud.

Another growing concern relates to property **valuation fraud**. According to the CML, the industry has put in place a number of remedial steps to ensure lenders have accurate and relevant information on property valuations. This is particularly relevant to the so-called 'new build' properties where valuations on 'off-plan' properties are not directly comparable. It is possible to use specific analytical analysis involving measurement of historical price appreciation for individual properties to thwart this practice also known as 'flipping'. This is where a seemingly legitimate sale of a house is made during rapidly rising markets at a grossly over-inflated value and then the deal is re-mortgaged (or 'flipped') to a new lender and usually the new borrower tends to default early (thus crystallising a fraudulent benefit to the previous vendor). Individual property price history data can help set a believable compound annual growth rate boundary that would help mitigate this practice.

A crucial underlying assumption behind any underwriting methodology is that the data truly represents the actual risk potential—otherwise, if fraudulent or misrepresentative data exists, then this will undermine the final analysis. Robust systems for fraud detection are therefore fundamentally

necessary before any meaningful credit risk analysis can take place. According to S&P's recent ratings review report⁶:

*"Data quality is fundamental to our rating analysis. The loan performance associated with the data to date has been anomalous in a way that calls into question the accuracy of some of the initial data provided to us regarding the loan and borrower characteristics. A discriminate analysis was performed to identify the characteristics associated with the group of transactions performing within initial expectations and those performing below initial expectations. The following characteristics associated with each group were analyzed: LTV, CLTV, FICO, debt-to-income (DTI), weighted-average coupon (WAC), margin, payment cap, rate adjustment frequency, periodic rate cap on first adjustment, periodic rate cap subsequent to first adjustment, lifetime max rate, term, and issuer. Our results show **no** statistically significant differentiation between the two groups of transactions on any of the above characteristics. Reports of alleged underwriting fraud tend to grow over time, as suspected fraud incidents are detected upon investigation following a loan default."*

The FSA has also launched an intermediary fraud initiative⁷ in April 2006 that targets broker fraud by having lenders report on the following aspects:

Proven fraud

- Actual fraudulent documentation, (i.e., bank statements, utility bills, wage slips, accountant references, P60s, passports, driving licenses, etc);
- False employment or income details; and
- Inconsistent information relating to the same applicant, (i.e., various applications made with different incomes or details either to the same lender or lenders within a group, different details on mortgage applications to other finances, e.g., bank accounts, etc.)

Suspected fraud

- Where there is doubt over income or employment details.
- Suspicious behaviour or trends occurring on completed accounts. For example, a broker whose completed cases have an unusual rate of suspicious arrears or repossessions, benefit claims or fraud complaints.
- Any links with other applicants where one suspects fraud, such as shared addresses, accountants, purchases on same development, identical loan amounts, etc.
- Any links between different mortgage applicants, (i.e., shared bank accounts, addresses, etc.)
- Sudden cancellation of an application whenever one requires further information or verification.
- Any suspected fraudulent documentation.

⁶ Standard & Poor's Rating Direct: 612 U.S. Subprime RMBS Classes Put On Watch Negative; Methodology Revisions Announced, July 10, 2007

⁷ <http://www.cml.org.uk/cml/policy/issues/1164>

1. Credit Character Measures (C1)

Credit character measures tends to be performed by a combination of credit scoring (credit scoring models and credit bureau data) plus tailored credit policy rules as part of the underwriting decision and of course fraud tests for direct rejection. Regardless of which party bears **responsibility for diligent underwriting—either broker, packager, lender, rating agency, investors or even a fully automated 'underwriting system'—measurement of the credit character of a borrower is generally considered paramount, especially for prime borrowers.** Before the use of securitisation funding, the credit provider was usually the lender who retained the loan risk on their own balance sheet but with the advent of securitisation, the underwriting decision now has a degree of coercion from other entities that profit from loan volumes, and therefore have minimal involvement with the future performance of those loans. Such a design structure will inevitably increase the incentive for third-party intermediary credit brokers to write new loans but also reduces their incentive to consider how these loans will perform over time. In any efficient performing market, such problematic practices should self-correct over time, as originators will become more liable for **creating quality books (e.g., 'claw-back' profit arrangements on bad deals).**

The ultimate aim of the credit character measuring process is to stratify applicants into meaningful segments or risk grades that will assist in risk-based pricing. During the application stage for credit, it will be possible to use combinations of credit bureau scores coupled with any available application credit scoring and required policy rule restrictions and fraud testing elimination. If pricing-for-risk after acceptance (say at set future intervals), then a behavioural score in conjunction with a bureau score would be measures that are more preferable (as behaviour of the account will be readily available giving a stronger prediction of risk than from the application score).

2. Affordability Capacity Measures (C2)

Some research exists on tests for affordability measure for predicting credit problems in the credit risk literature. Wilkinson and Tingay (2002) report that affordability does marginally add to the lending decision using a comparison of the performance of credit score models (with and without affordability measures for *personal loans*). Although this research is useful, an affordability test for personal credit usage is definitely not of the same scale as one for home mortgages—a sizable difference in both scope and end outcome. In addition, research by Russell (2005) shows clever use of a bureau Affordability Index (AI) that supplements their Delphi bureau score to deliver richer

selection criteria and strategy. This is an example of a top-down measurement of affordability. Another available external measure is the over-indebtedness (OI) index provided by the Callcredit bureau that helps identify any serial credit card users or applicants who have very large or insurmountable debt accumulation. This useful measure of personal debt is truly global in nature and hence provides additional evidence of **'true' affordability for the mortgage application in hand.**

Since mortgage regulation in October 2004, there has been a greater onus on lenders to demonstrate responsible lending to ensure that they are indeed treating customers fairly. Therefore, it has become a mandatory requirement that each lender now shows evidence of an individual applicant's ability to repay. According to Van Dijk and Garga (2006), lenders active in the sub-prime market are more likely to use an affordability model than lenders in the prime market. They see this trend as not that surprising, given that applications within the sub-prime market are more likely to be of higher risk, thus warranting a more detailed assessment of whether the applicant can truly afford the mortgage.

With Capacity PD measures, it is possible to use either an internal or an external measurement. One form of an internal measure would be from the application of a suitable mortgage affordability calculator. The main purpose for the construction of an affordability calculator would be to help any lender better comply with mortgage regulation requirements including that of being a responsible lender. Responsible lending mandates that applicants are genuinely able to service their loan obligations.

Perhaps what is required from the regulators though, in the future, is for an industry-wide standard on what constitutes true affordability for a loan. For example, a cursory website examination of several prominent lenders advertising affordability calculators indicates that considerable variation exists amongst the maximum possible loan, given similar input variables.

3. Collateral Measures (C3)

The relatively complex mortgage contract contains two key embedded options, namely:

- 1) A **put option**⁸ for default exercise whereby the borrower **has the right to transfer ownership of (or to 'put') the house back to the lender either by forced foreclosure (or**

⁸ In a similar vein to the use of options on equity valuation, we use a put option for mortgage contracts instead of a call option, since by engaging in default the borrower is thus disposing of an asset instead of acquiring one. You can treat this as a European-style put option because any such defaulter will rationally exercise it on a set foreclosure date. A variant of the Merton model: the Black-Cox extension allows for early defaults.



Basel II Credit Risk Principles

Expected Loss Components

Under Basel II, Expected Loss (EL) equates to the Probability of Default (PD) times Loss Given Default (LGD) times Exposure at Default (EAD), or in symbolic form:

$$EL = PD \times LGD \times EAD$$

In turn, we can expand each of these components further. An FSA definition stipulates mortgage default (D) to be 180 days of arrears¹¹ as the guideline within retail exposures. Using the 3Cs approach for default measures, we can set conditional probability of default in Bayesian notation as:

$$P(D|Mortgage\ Type) = P(D|C_1, C_2, C_3) \\ = \alpha P(D|C_1) + \beta P(D|C_2) + \gamma P(D|C_3)$$

Mortgage Type can refer to the three main market segments of Prime, Near Prime and Sub-Prime but depends on the Character result to determine which type is finally applicable. The weighting parameters alpha(α), beta(β), and gamma(γ) above, (always sum to one) will determine the overall influence of the PD measurements for Character (C_1) and Capacity (C_2) and Collateral (C_3).

For prime mortgages, one would expect Character to be paramount. You would also expect to treat Collateral as merely security underpinning the loan whilst Capacity would have an influence somewhere in between these two measures. However, under sub-prime mortgages Collateral is paramount, and then Capacity in relative influence and finally Character (as most applicants have had a chequered credit history by simply qualifying for these types of loans). We could therefore assume the following initial values for the relative influence of these PD sub-parts:

Table 1 – PD Relative Influence Weights - 3Cs & Mortgage Types

Mortgage Types & the 3Cs PD Weightings	Prime	Near Prime	Sub-Prime
Character-C1 (α) =	50%	35%	20%
Capacity-C2 (β) =	30%	30%	30%
Collateral-C3 (γ) =	20%	35%	50%
Total	100%	100%	100%

¹¹ BIPRU 4.6.19-For retail exposures to counterparts situated within the United Kingdom the number of days past due is 180 days with the exception of retail SME exposures (90 days).

As evidence of this view especially for the Collateral Sub-prime component, we can examine the CML Repossession Risk Review report. Authors Cunningham and Panell (2007) cite that "...the adverse credit loans in non-conforming RMBS have substantially higher arrears rates than prime home-buyer mortgages and the adverse credit sector accounts for a much larger share of repossessions than its 5-6% share of new lending business. In a number of locations in London, the cumulative repossession rates since issue on non-conforming RMBS portfolios are around 5%, compared with the overall industry average for 2006 of 0.15%." Therefore, for sub-prime or non-conforming mortgages, given evidence of the readiness of the sector to repossess properties, one therefore needs to over-emphasise the Collateral component more so than the Character aspect and Capacity could be set relatively equal regardless of the mortgage type. Near-prime mortgages would also need to have PD relative influences set within the risk extremes of prime and sub-prime. You could also adjust the component part values of alpha, beta and gamma to reflect the overall risk appetite control and perhaps as part of the conditional PD measure adjustments for more accurate reflection of the current stage of the housing cycle. By way of practical application, a typical specialist lender might have the following segments within their mortgage portfolio: Sub-prime 60%, Near Prime 20% and Prime 20%.

PD Character Measurement [P(D|C₁)]

For P(D|C₁) it is possible to derive a PD measure of credit character from a credit bureau score or by using an internal application score (or even a combination of both). For an initial risk-based pricing approach, the bureau or application score is required. However, for any on-going risk adjustment offers (for example, through a customer retention initiative), it would be better to use a behavioural score and/or a bureau score to derive the required PD. The use of mortgage bureau scores have gained in popularity since 2000 with U.S. ones being similar to U.K. bureaux except that less information is recorded. According to Thomas *et al.* (2002), such scores will rely upon the following general types of data:

1. Personal information (name; address; former address; date of birth; name of current and former employers; and identifiers: such as Social Security number in the U.S.)
2. Public record information (county court judgements; bankruptcy; Involuntary agreements; and electoral roll data)
3. Credit accounts history (type of account; credit limit; payments up-to-date; arrears data and balances outstanding)
4. Inquiries (type of credit grantors and date of inquiry)
5. Aggregated information (percent of houses at a postcode with CCJs for example)



Credit Scoring & Credit Control X

For specifically mapping a bureau score to the Probability of Default, we can make use of the well known Odds Ratio (or good-to-bad odds) as per Dev (2004):

$$\text{Odds Ratio} = \frac{(1 - PD)}{PD}$$

Or re-expressed in terms of PD as

$$PD = \frac{1}{(1 + \text{Odds Ratio})}$$

The bureau score (assuming it was also Basel II orientated for a 1-year PD horizon) could return a score that has an implicit Odds Ratio attached (or Good/Bad ratio) that we can use to derive the required $P(D|C_1)$ measure as in the following table of FICO¹² bureau scores:

Table 2 – Example Mapping of Score to PDs for $P(D|C_1)$

Mapping Bureau Scores to PDs

FICO Score	Odds Ratio (OR)	$P(D C_1) = 1/(1+OR)$	Target Markets
>800	999.0:1	0.10%	Assume: Prime >720
780-799	665.7:1	0.15%	
760-779	499.0:1	0.20%	
740-759	284.7:1	0.35%	
720-739	132.3:1	0.75%	Near Prime 640-720
700-719	81.6:1	1.21%	
680-699	55.5:1	1.77%	
660-679	40.2:1	2.43%	
640-659	27.1:1	3.56%	Sub-Prime <640
620-639	21.2:1	4.50%	
600-619	18.9:1	5.03%	
580-599	16.8:1	5.61%	
560-579	13.2:1	7.05%	
540-559	10.5:1	8.68%	
520-539	9.5:1	9.50%	
500-519	7.9:1	11.29%	
<500	4.8:1	17.36%	

Alternative Character PD measurement approaches

The above approach is fine but if you wanted more sophistication in deriving a suitable Character PD measure, you could use a generic rating scale (and perhaps even replace their PDs with your own PD master scale). A conceptual example of such a rating scale might be the S&P risk grades that are in use for mortgage ratings in Residential Mortgage Backed Securitisations (RMBS), shown in the table below. One possible PD mapping process is to use both the bureau score and the LTV measure (as a partial indicator of credit character) that maps onto this 1-to-10 scale.

¹² FICO refers to the Fair, Isaac and Company, Inc.

Table 3

Risk Grades	Approx. percent of loans	Average probability of default (based on MTI)	Definitions
1	Best 12%	0.74%	Superior Quality (Prime) Loans exhibiting lowest default potential
2	Next 3%	1.27%	Significantly Above Average Quality (Prime) Expected to outperform market overall
3	Next 19%	1.56%	Above Average Quality (Near Prime) Above average quality loans
4	Next 28%	2.74%	Slightly Above Average Quality (Near Prime or Sub-Prime) Slightly above the quality exhibited by Agency Underwriting
5	Next 25%	5.24%	Average Quality Loans (Sub-Prime) Exhibits default rates generally expected of loans underwritten to guidelines
6	Next 5%	6.55%	Slightly Below Average Quality (Sub-Prime) Slightly below the quality exhibited by Agency Underwriting
7	Next 5%	7.52%	Below Average Quality (Sub-Prime) Below average quality loans
8	Next 1%	10.44%	Significantly Below Average Quality (Sub-Prime) Loans with default rates at significant multiples of the average loans
9	Next 1%	16.57%	Near Default Loans exhibiting the highest risk of default
10	Worst 1%	22.81%	Default Grade Loans in default (as per FSA definition of 180-days in arrears)

MTI — Mnemonic Technology Inc.

The two drivers of this PD mapping approach are the LTV and the bureau score as shown in the table below.

Table 4

		'CCC' Base Frequency of Foreclosure% - 30 Year Fixed-Rate Mortgages														
		FICO Score														
		580	600	620	640	660	680	700	720	740	760	780	800	820	SCORES	
LTV	60	1.6	1.2	0.9	0.7	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2	0.2		
	65	2.3	1.6	1.2	0.9	0.7	0.5	0.4	0.4	0.3	0.3	0.3	0.2	0.2		
	70	3.3	2.3	1.7	1.2	0.9	0.7	0.5	0.4	0.4	0.3	0.3	0.3	0.2		
	75	4.8	3.4	2.4	1.7	1.2	0.9	0.7	0.6	0.5	0.4	0.3	0.3	0.3		
	80	6.9	4.9	3.4	2.4	1.7	1.2	0.9	0.7	0.6	0.5	0.4	0.3	0.3		
	85	9.7	7.0	5.0	3.5	2.5	1.8	1.3	0.9	0.7	0.6	0.5	0.4	0.3		
	90	13.2	9.9	7.2	5.1	3.6	2.5	1.8	1.3	1.0	0.7	0.6	0.5	0.4		
	95	17.4	13.4	10.0	7.3	5.2	3.7	2.6	1.8	1.3	1.0	0.7	0.6	0.5		
	100	22.1	17.7	13.6	10.2	7.4	5.3	3.7	2.6	1.9	1.3	1.0	0.7	0.6		
	Assumes full documentation, purchase, primary occupancy, single family detached, LTV, FICO															
		S&P Stylized Risk Grades applied to Fitch IBCA Residential Foreclosure Frequency Model														
		FICO Score														
		580	600	620	640	660	680	700	720	740	760	780	800	820		
LTV	60	3	2	2	2	1	1	1	1	1	1	1	1	1		
	65	4	3	2	2	1	1	1	1	1	1	1	1	1		
	70	5	4	3	2	2	1	1	1	1	1	1	1	1		
	75	5	4	3	2	2	1	1	1	1	1	1	1	1		
	80	6	5	4	3	2	2	1	1	1	1	1	1	1		
	85	8	6	5	4	3	2	2	1	1	1	1	1	1		
	90	9	8	6	5	4	3	2	2	1	1	1	1	1		
	95	10	9	8	6	5	4	3	2	2	1	1	1	1		
	100	10	10	9	8	7	5	5	4	4	3	2	2	1	1	

The intersection of the LTV measure and the FICO score in the example table above, facilitates a straightforward mapping process to either of the three broad risk bands groups, which could be Prime (lower risk), Near Prime (medium risk) or Sub-prime (higher risk)—that is, from a diagonal split rather than a cross-sectional one as per Table 2. Therefore, a higher bureau score with a low LTV would suggest a lower risk (or prime candidate). You could then simply apply the S&P PD definition that matches this 1-to-10 outcome in order to generate the required $P(D|C_1)$ measure¹³. The above approach relies on some external PD measures, yet if the current mortgage portfolio also has suitable seasoned data, then an internal process can be utilised instead with internally derived PDs.

¹³ If the Rating Agency could provide it, then you could use something similar to the pre-allocated foreclosure 'CCC' base frequency percentages as finer PD measures, as per the Fitch IBCA Residential Mortgage Research example table above.

PD Capacity Measurement [P(D|C₂)]

For deriving Capacity PD measures, we can make use of an affordability calculator that can calculate the maximum possible loan given all relevant inputs. To illustrate its possible usage we can apply it across a seasoned portfolio of loans and form a distribution of the ratio of the maximum possible loans to the actual loans. We could then examine the default rates for each interval along the distribution range and simply map these outcomes to a suitable PD estimate. However, a possible problem from this approach is the likelihood of finding very low numbers of defaults for any given interval. The Financial Services Authority (FSA) researchers Benjamin, Cathcart and Ryan (2006) suggest an appropriate estimation process for deriving low portfolio PDs (given relatively few defaults) and we will make use of this approach for deriving P(D|C₂) - see further explanation in the Appendix section.

Affordability Calculator Example

AFFORDABILITY CALCULATOR

Annual Income	Main Applicant	Other Applicants
Basic Wage or Salary	£ 65,000	£ 10,000
Overtime		£ 5,000
Bonus / Commission	£ 10,000	
Self Certification		
Self Employed Net Profits		
Secondary Income		
Unsocial hours payment		
Regional weighting		
Shift allowance		
Company car cash allowance		
Private or occupational Pension income		
Child Tax Credit and working Tax Credit		
Mortgage subsidy		
Maintenance payments		
Incapacity benefit		
Disability Living Allowance		
Foster Parent Income		
Other Income (but not in list below)		
Grand Total - Gross Income	£90,000	
State Benefits		
Travel Allowances/Expenses		
Rental Income		
Investment Income		
	Not Acceptable	

Annual Outgoings	All Applicants
Unsecured Loans (Annual Repayment)	£ -
Credit Cards (Closing Balance Amount)	£ -
All Other Commitments (Repayment p.a.)	£ -
Number of Adults in Household	Two
Number of Child Dependents	Two
Geographic Region (within UK only)	London

Loan Details	All Applicants
Loan Amount Requested	£ 380,000 ✓
Estimated Property Valuation	£ 425,000
Loan Term (Years)	25
Initial (Discount) Rate	6.00%
Discount Rate Period (Years)	Two
Variable Rate (or reversionary rate)	6.95%
Total (Upfront) Loan Fees	£ 1,830
Percentage Loan Remaining (at term end)	60.00%

Calculation Outputs	All Applicants
Loan-To-Value (LTV)	89.41% ✓
Annual Percentage Rate (APR)	6.9%
Estimated Total Tax & Nil Amount	£28,313
Mortgage Annual Debt to Gross Income%	31.6%
Loan Amount to Gross Income Multiple	4.22 X
Maximum Loan (based on Affordability)	£386,959 1.02X

Important Information: This is for intermediary use only and must not be given to the general public. The affordability estimate shown is for information only and is not binding. The information provided does not contain all the details a customer needs to choose a mortgage. Please make sure the customer receives and is advised to read a Key Facts Illustration before they make a decision. Think carefully before securing other debts against your home. Your home may be repossessed if you do not keep up repayments on your mortgage.

Figure 7 – Affordability Calculator - Illustration Only

The example affordability calculator template shown above could help a mortgage intermediary, on behalf of its clients, determine whether they can adequately service a loan, given the client's gross income, their taxation obligations (including income tax, national insurance and council taxes) and annual outgoings and the loan details. Within the annual outgoings, an estimate is made of the household lifestyle expense (given number of adults and children) based on the U.K. National household expenditure survey for 2005-06 for a range of income deciles and for regional variations. The calculator uses the current loan application details to derive the comparison rate (or APR) as part of the estimation of the maximum loan possible. The maximum loan amount, in turn, is dependent upon the amount of income remaining after all known deductions. Other information on loan multiples and debt servicing ratios can help inform the underwriting decision.

As a practical demonstration of this affordability measure (the ratio of maximum loan to actual loan amount), we can apply it across a hypothetical loan portfolio as per Figure 7 below (with some assumptions for required inputs).

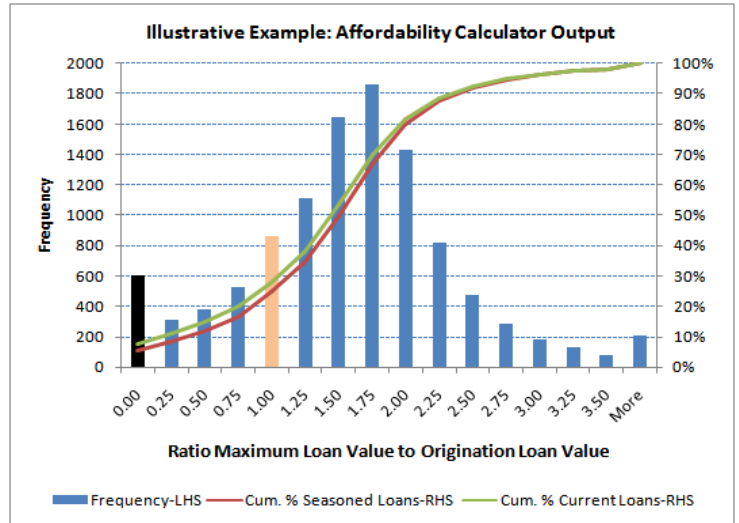


Figure 8 - Illustration Only - Relative affordability measures

In this illustrative example above, it would appear that the majority of the sample portfolio could adequately afford to borrow the original loan amount relative to the maximum loan amount. However, until we examine the default rate outcomes from the seasoned loans it will not be possible to easily differentiate the riskier groups from the less risky groups. In particular, for this sample dataset, the more current loan group (green curve) indicate lower affordability than the seasoned group (the cumulative curve is higher at lower ratio levels). The table below shows mapping results of the Maximum Loan ratios (using FSA low probability of default) to the default rates from the seasoned loan sample. Note the differences in PD rank for the various interval outcomes.

Table 5 - Mapping Maximum Affordable Loan Ratios to PD Scale

	Max Loan Ratio	PD Rank	P(D C ₂)
1	0.00	3	6.32%
2	0.25	15	8.95%
3	0.50	10	7.83%
4	0.75	8	7.56%
5	1.00	6	6.92%
6	1.25	5	6.69%
7	1.50	16	9.17%
8	1.75	9	7.63%
9	2.00	13	8.54%
10	2.25	7	7.37%
11	2.50	11	8.14%
12	2.75	2	5.84%
13	3.00	1	5.73%
14	3.25	4	6.48%
15	3.50	14	8.86%
16	>3.50	12	8.23%
	Total		7.35%

PD Collateral Measurement [P(D|C₃)]

The collateral measure involves deriving a value for the default option component embedded within the mortgage contract, as per the Black-Cox variant of the Merton Structural default model¹⁴. The main advantages of using the Black & Cox PD structural model (or refinement of the Merton model) are that it allows for early exercise and it includes an adjustable default level (a kind of PD precision measurement advantage). In the diagram below, the probability of default (PD) measure is the shaded area of the distribution of future house prices (assume to be normal) for any given property value (V_T).

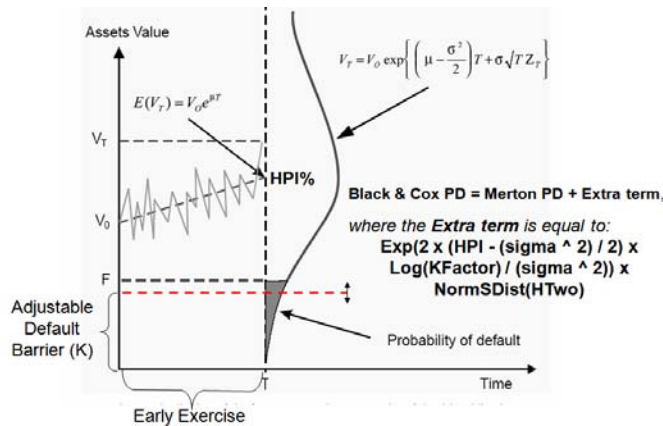


Figure 9 - Option like PD measurement for Collateral

The future possible house value in turn depends upon the volatility of prices (σ) around the average growth rate for house price inflation (μ) over a given term (T). Of course, for early exercise of this contract we need to account for the starting point or loan to value level (F) and the adjustable barrier level (K) which will influence the likelihood of any such option exercise. Thus, there are five inputs (showing numerical examples below) required:

- 1) Loan to value ratio (LTV): e.g. 85.581%,
- 2) Expected House Price Inflation rate (HPI) over the expected term as an annualised rate: e.g. 7.388%,
- 3) Estimated HPI volatility measure, as per derivative model calculations over time: e.g. 10.302%,
- 4) Typical term (will be the term of the securitisation pool of say 4 years duration rather than the original mortgage term) and,
- 5) Barrier factor (can itself be dependent upon the LTV value above): e.g. 120% if LTV>85%,

The required equations and the input parameters are summarised in the Microsoft Visual Basic for Applications code box below (comments in green font). We can also apply this routine in the form of a Collateral PD calculator using MS Excel, which shows an example result as per the assumed input values.

¹⁴ See Chacko, George, Abders Sjomann, Hideto Motohashi and Vincent Dessain (2006), Credit Derivatives – A primer on Credit Risk, Modeling, and Instruments, Wharton School Publishing pp.104-114.

Public Function PDBlackCox(h, LTV, HPI, sigma, k)

'Calculates the Black & Cox variation of the Merton Model of Probability of Default'
 'inputs required
 'h is the time Horizon
 'LTV is Loan to Value
 'HPI is mu or house price inflation
 'Sigma is the HPI volatility
 'k is the barrier factor

'All inputs should be input as a whole number i.e., 75 for 75%, but can accept percentages
 If LTV > 2 Then LTV = LTV / 100 'convert to decimal
 If HPI > 2 Then HPI = HPI / 100
 If sigma > 2 Then sigma = sigma / 100
 If k > 2 Then k = k / 100

A = 100
 D = LTV * A
 KDB = k * D 'barrier function

'Black-Cox Variation to Merton Model

HOne = ((Log(KDB / (Exp(h * HPI) * A)) + (sigma ^ 2) / 2 * h)) / (sigma * Sqr(h))
 HTwo = HOne - (sigma * Sqr(h))

MultiYearPD = Application.WorksheetFunction.Min(1,
 Application.WorksheetFunction.NormSDist(HOne) +
 Exp(2 * (HPI - (sigma ^ 2) / 2) * Log(KDB / A) * 1 / (sigma ^ 2)) *
 Application.WorksheetFunction.NormSDist(HTwo))

'convert to an annual PD rate = 1 - (1 - MultiYearPD)^(1/h)
 'PDBlackCox = 1 - (1 - MultiYearPD)^(1/h)
 PDBlackCox = MultiYearPD 'leave as PD for given term

End Function

Calculating Mortgage Default Probabilities (using Black & Cox Option Pricing Model)

Inputs

	Symbol	Input Values	
Typical Term	H	4.0	years
Expected House Price Inflation	HPI	7.388	% pa
HPI Volatility	Sigma	10.302	% pa
Loan To Value Ratio	LTV	89.410	% (at Origination)

Outputs

	Symbol	Output Values	
Default Barrier Level	K	120.00	(BarrierFactors, LTV)
Black & Cox PD		44.90%	

Figure 10 - VBA Code and Calculator Example for Collateral PD

Note that the PD output in the calculator example above is for a multi-period PD over a 4-year term. To convert to an annual PD we can use the following formula:

$$PD = 1 - (1 - MultiYrPD)^{\frac{1}{N}}$$

$$PD = 1 - (1 - 44.9\%)^{\frac{1}{4}}$$

$$PD = 1 - 0.86156 = 13.84\%$$

Thus, in this example $P(D|C_3) = 13.84\%$

Of course, any model will be only as useful as the accuracy of its underlying inputs. Further refinement of this model in terms of its input measures is possible by using a third party service such as Technical Forecasts Ltd (TFL¹⁵) who use Land Registry data to create smoothed historic house price series to postcode sector level (comprises about 2,000 dwellings) for each of four property types: detached, semi-detached and terraced houses, and flats & maisonettes. TFL could therefore provide model inputs for forecast U.K. house prices (and for estimates of HPI volatility) at a postcode level of accuracy up to five years forward. Otherwise, it would still be possible to use cruder historical estimates based on regional data for particular property types as supplied by the Nationwide or HBOS regional house price time series, for example.

However, the design of the Black-Cox model is for forward value estimates, so presumably skilled aggregation and analysis of local house price data should enable a more accurate estimate of both the current mortgage portfolio value and its future value. The TFL methodology ensures that Land Registry data is both valid and properly aggregated into relevant neighbourhood time series and **then smoothed (or "filtered")**. They then use a matching process to ensure that around 150 relevant econometric time series (interest rates, unemployment rates etc) will help predict each neighbourhood house price as a monthly time series (TFL checks which series add most information using a complexity-optimised, non-linear forecasting model). Six hundred such models can generate each of the thirty thousand neighbourhood house prices (or time series), and their individual forecasts are then averaged to further reduce errors. An example using a prediction set of one time series illustrates the five-year forecast for a Manchester terraced property below.

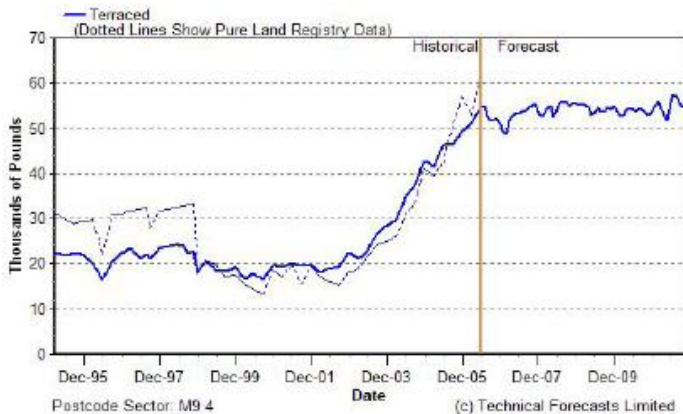


Figure 11 - Third-party Data for U.K. House Price Predictions

Presumably, a more simplistic linear forecast would have anticipated a continuation of the steep price rise before the forecast event, but in this case, there was some modelling of an earlier non-linear experience in the time series. This then results in an outcome that is more of a contrarian forecast thus indicating a forthcoming period of price consolidation, rather than a naive increase. Such clever use of analytics ensures that the PD option models will not readily under-price the risk of default, as would be the case, if the higher HPI estimate were the input instead.

¹⁵ <http://www.propertyforecasts.co.uk/>

PD Measurement Summary

Using the 3Cs approach for default measures above, we set the conditional probability of default in Bayesian notation as:

$$P(D|Mortgage\ Type) = P(D|C_1, C_2, C_3) \\ = \alpha P(D|C_1) + \beta P(D|C_2) + \gamma P(D|C_3)$$

For a numerical example, assume we have an applicant with a bureau score of 650, suggesting his initial Mortgage Type is Near Prime, then the following weights are applicable: ($\alpha = 35\%$, $\beta = 30\%$, $\gamma = 35\%$). In addition, assume he also has an LTV equal to 89.41% as per the prior illustrative examples.

- For Character PD measurement, if we used the simpler, $P(D|C_1)$ approach, a score of 650 would imply a Near Prime risk of 3.56% as applicable (or odds ratio of 27:1). However, with the more sophisticated approach, that uses the LTV as well, he now moves **down** a quality rating (from 4 to 5) because of the high LTV causing him to fall into the average quality loan group (or **sub-prime** as we have arbitrarily labelled it) and this now relates to a PD of 5.24%. (*Incidentally, this aspect neatly highlights the earlier comment regarding how an applicant can change PD during the deal structuring stage based on the parameter measures.*) Thus, for illustrative purpose we can set $P(D|C_1) = 5.24\%$ but his rating now becomes sub-prime, so the following weights are required: ($\alpha = 20\%$, $\beta = 30\%$, $\gamma = 50\%$).
- For Capacity measurement, with the example inputs the Affordability calculator gave a maximum loan ratio of 1.02 implying a $P(D|C_2) = 6.69\%$.
- For Collateral measurement, using the Black-Cox calculator for the hypothetical example we had an annualised PD estimate of 13.84%, so we can set $P(D|C_3) = 13.84\%$.
- In summary then:

$$P(D|C_1, C_2, C_3) = \alpha P(D|C_1) + \beta P(D|C_2) + \gamma P(D|C_3) \\ P(D|C_1, C_2, C_3) = (20\% \times 5.24\%) + (30\% \times 6.69\%) + (50\% \times 13.84\%) \\ P(D|C_1, C_2, C_3) = 1.048\% + 2.007\% + 6.92\% \\ P(D|C_1, C_2, C_3) = 9.975\%$$

This example highlights the dominance of the LTV factor but note, that if the candidate had instead remained near prime, from the Character driver assessment, then the resultant PD measure would have been only 8.685%. In the next section, we estimate the other Basel II component parts in order to derive the expected loss number, as part of the sharper pricing-for-risk approach. However, one tricky aspect for risk-based pricing (given a number of interdependencies) is that the price adjustment process can in turn cause a change in the risk measures. An iterative solution is nevertheless possible as the boundary change points can be set wide enough to generate workable outcomes.

Loss Given Default (LGD) and EAD Measures

Norgate (2004)¹⁶ argues that it is perhaps more sensible to measure Loss Given Default (especially for mortgages at point of loan application), by breaking this Basel II component into two further parts, namely:

$$LGD = P(R|D) \times LGR$$

where,

$P(R|D)$ = Probability of Repossession Given Default

(see model below)

LGR = Loss Given Repossession

$$LGR\% = \frac{\text{Max}(0, EAD - RV)}{EAD}$$

LGR will be either a positive or zero number (any surplus recovery is always a refund to the customer) that can in turn be broken further into these parts:

EAD = Exposure at default (generally 105% of loan value else 115% if $P(R|D)$ ranges from 50 to 80% to cover greater uncertainty on ultimate repossession status or 110% if $P(R|D)$ exceeds 80% as faster wind-up more probable)

RV = Recoverable Value (Need to discount to Present Value @ (LIBOR + Risk Premium) from ultimate property sale date)

$RV = (1 - \text{Trash Factor } \% - \text{Recovery Costs } \%) \times \text{Market Value}$

Trash Factor % = 15% x Market Value (assumes that the property gets 'trashed' at repossession with an average estimate)

Recovery Costs % = 6% x Market Value (legal fees, sales and marketing costs etc.)

Market Value = Future Value of property (at least 18 months beyond default date or 24 months at loan inception) that should be estimated using the same forward valuation approach as for the Probability of Default given Collateral estimate above.

- 1) Measuring the first part of probability of repossession (given a 180-day default definition) will require a special model that has a non-random set of data as the basis for the modelling. This is to both facilitate the accuracy of the classification output and to ensure full use of all data available to measure the chance of going from a 180-day default to ultimate repossession status (that depends on a number of factors).
- 2) The second component part of Loss Given Repossession is to derive a salvaging figure for the actual gross loss upon forced sale of the property into the market at some future date. The key driver behind this value estimate is the expected property price that you can estimate at least 24 months beyond the loan origination date.

¹⁶ Owing to the nebulous aspect of loan status moving up and down from 'cures' and collection actions, see Chapter 11 "IRB-Compliant Models in Retail Banking" Richard Norgate, KPMG, in The Basel Handbook ed. M.K. Ong

Measuring Probability of Repossession Given Default

Using the Microsoft Bayesian Classification methodology on a specially selected sample dataset, a statistically strong level of discrimination (at nearly 89% accuracy using model sample) is available for predicting which customers are likely to go into repossession. We can list the predictive features (none of which are anachronistic in nature) in clockwise order of importance below. At the 12 o'clock position, the most predictive is the Method of Payment (Cash or direct debit). Unsurprisingly, a customer likely to have difficulty meeting payments will opt for a cash payment method instead of a direct debit method. As we proceed around the clock-face of the Bayesian network diagram below, we can see that the types of data selected by this data-mining tool are also indicative of the 3Cs. For example, in terms of measures of Capacity, we have the Balance remaining from Gross Income and Current Income ratio, for Character, we have the marketing customer segment description and product selection choices whilst for Collateral there is maximum LTV and the more precise LTV band by 1% intervals. A measure is available for any given applicant's probability of going into repossession. This process is much like the alternative method of using a look-up table instead.



Figure 12 – Predictors derived using a Bayesian Dependency

Classification Matrix Outcomes

Table 6 – Prob(Repossession | Default) Classification Accuracy Results

Counts of correct/incorrect classification for model 'Classify AccountStatus' on column 'AccountStatus'

Rows correspond to predicted values	
Total correct:	88.80 %
Total misclassified:	11.20 %
Total	100.00 %

Results as Percentages

	Non-Repossess (Actual)	Repossess (Actual)
NonRepossess	82.82 %	7.24 %
Repossess	17.18 %	92.76 %

Correct	82.82 %	92.76 %
Misclassified	17.18 %	7.24 %

Measuring the Competing Risks of a Mortgage

Specifically we can derive the put-option default component within the mortgage contract using the Black-Cox structural approach as in the collateral PD risk measure, which in turn forms part of the overall probability of default (or the total option-like measure of the mortgage contract). Together with the loss (if any) from default, the expected loss amount equates to the total default option premium that covers this risk component. We also need to value the other competing risk option for early prepayment risk.

We can estimate a call-option value for prepayment risk using a technique advocated by Sherris (1994) that sets out in algorithmic form, a one-factor term structure model of interest rates for the valuation of loans with prepayment provisions. Deriving this premium affords a lender the choice of replacing the existing early redemption penalty with an upfront charge instead. The algorithm allows for stochastic interest rates but only requires just the one-factor for the term structure of interest model. It is "arbitrage-free" in the sense that the parameters of the one-factor term structure are chosen to ensure that prices of traded zero-coupon bonds derived by the algorithm are equal to the market prices of such bonds on the valuation date. These zero-coupon prices are readily available as input factors via the Bank of England website, for example. This methodology prices these contracts is a general algorithm-based approach that is not dependent on the structure of the loan cash flows. A calculator example shown below for the Sherris methodology highlights the model outputs given the term structure of interest rates available as at the date of calculation, the interest rate volatility for the given term and the amount of the loan.



Figure 13 - Prepayment Option Pricing Calculator

The prepayment risk calculator tool above derives an estimated premium of £993.15 for a £100,000 5-year loan amount from using special interest rate option pricing algorithms that make use of the current interest rate yield curves (from BOE) and the use of a "tree-pricing"

methodology to find a rational option price (as an upfront loan fee). The upfront fee could form part of the overall fees in calculating the APR and thus, from a comparison rate sense, we could reflect the option price by inclusion of the additional fee into the loan affordability calculator to derive a higher APR. The difference in APRs (with and without the option premium) would therefore be the rate impact from provision of the prepayment option as an upfront fee.

Having derived a rational option premium for the risk of prepayment given the loan details, we then need to apportion this average price fairly across the spectrum of borrowers most likely to make greater use of the valuable option. Perry, Robinson and Rowland (2001) conducted a study on mortgage prepayment risk on behalf of the Actuarial Profession for a number of large U.K. lenders. They discovered four interacting factors (that we can make use of in modelling propensity to prepay) to *explain* the causes of prepayment, namely:

- 1) **Age** of the fixed rate loan (seasoning, inertia and timing);
- 2) **House Price Inflation** (if high then more house moves and hence more prepayments);
- 3) **Interest Differential** (higher interest differentials encourages prepayment);
- 4) **Prepayment Charges** (act to constrain prepayment likelihood but limited to a certain level only).

A model making use of at least the first three factors above and the output from the probability of default measures will help classify customers into one of the four quadrant segments shown below. Then with this model's predictions you simply apply an appropriate allocation rule to the average prepayment premium thus ensuring application of the 'user pays' principle.

Table 7 - Embedded Options: Competing Risk Matrix

		Propensity to Default	
		HIGH	LOW
Propensity to Prepay	HIGH	GAMBLERS Customers in this cell will exhibit both high risk of default and high prepayment propensity: implying that they are using the loan to "gamble" on rising House Price Inflation	PRIME (or NEAR-PRIME) Customers in this cell will exhibit both low default risk and high prepayment risk: implying that they are either Prime or Near-Prime borrowers
	LOW	SUB-PRIME Customers in this cell will exhibit both high risk of default and low prepayment risk: these will be the classic sub-prime segment	GOLD NUGGETS Customers in this cell will exhibit both low risk of default and low prepayment: these customers will be 'gold nuggets' (from a sub-prime lender's view) as they will be both safe and stable

Sharper Risk-Based Pricing Approach

Raiter and Parisi (2004) indicate that the success of risk-based pricing is dependent upon the ability of lenders to scrutinise application information for risk ranking purposes. Early adopters in the U.S. came to realise the significance of the relationship between FICO scores and borrowers LTV ratios in underwriting acceptance and then for pricing of mortgage loans (although we cover these aspects in assessing the Credit character component only of the overall PD estimate). Nevertheless, this risk reward recognition assists in breaking out of the price averaging process of the 'prime arena', and into the new risk-based 'non-prime arena'. We can see a clear example of the pioneer lender's use of risk-based pricing matrix in the sample Matrix Pricing Sheet below, for the twin drivers of FICO scores and LTV ranges.

Sample Matrix Pricing Sheet

Credit Scores	LTV Ranges				
	90-85	85-80	80-75	75-65	<65
>660	9.750	9.250	9.125	9.000	8.875
651-660	9.875	9.375	9.250	9.125	9.000
641-650	10.000	9.500	9.375	9.250	9.125
631-640	10.250	9.875	9.750	9.625	9.500
621-630	10.375	10.000	9.875	9.750	9.625
611-620	10.500	10.125	10.000	9.875	9.750
601-610	-	10.375	10.250	10.125	10.000
591-600	-	10.500	10.375	10.250	10.125
581-590	-	10.625	10.500	10.375	10.250
571-580	-	-	-	11.000	10.875
561-570	-	-	-	11.250	11.000
551-560	-	-	-	11.250	11.125
541-550	-	-	-	-	12.000
<=540	-	-	-	-	12.125

Figure 14 - 1990s U.S. Sample Matrix Pricing Sheet Example

From the table above we can note that the best rate quote is 8.875% for those borrowers with FICO scores of 660 or more and an LTV of less than 65%. The highest price is 12.125% for applicants with FICO scores less than 540 even though they too have the lowest LTV range of 65% or less. Whilst a useful attempt, this pricing sheet approach seems to have only gone part way towards full risk-based pricing. For example, the absence of any price quotes at all in the high LTV ranges and lower score ranges, indicates that the lenders realised that they were dealing with a non-linear APR requirement for these gaps. However, they were probably unsure of exactly how to measure such a price or even whether they could impose such a price, especially if it were set too high from a regulatory perspective. The graph below shows the waterfall problem or absence of a full playing field for risk-based pricing.

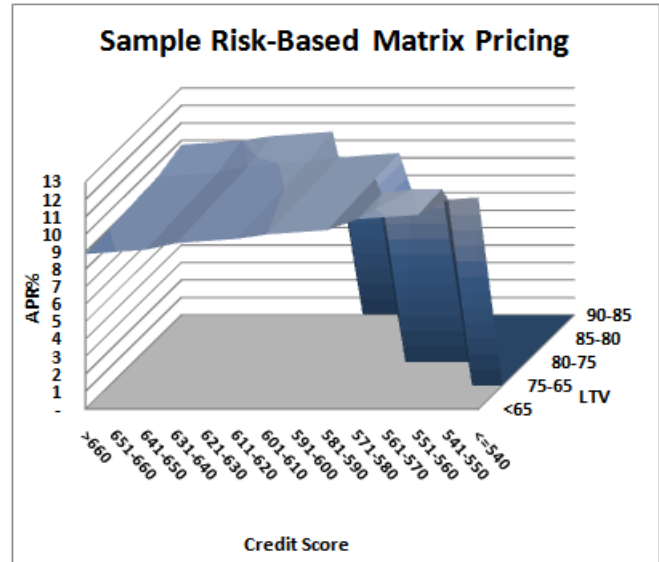


Figure 15 - Waterfall Chart of Matrix pricing excluding extreme risks

Research by Standard & Poor's confirms that the risk-based pricing became much sharper in the U.S. during the 1990s but their tests were only over the range of FICO scores in excess of 580. Temkin *et al.* (2002) cite research in the U.S. sub-prime market where average rates charged to sub-prime borrowers by four major lenders during the 1990s ranged from around 11 percent to 14 percent. In general, A-grade mortgages had a rate that is 200 basis points higher than for a typical GSE agency rate; B-grade loans had a 300-point premium; C-grade 400 points and D-grade 600 basis points over the agency conforming rate. In its study of subprime loans, the Office of Thrift Supervision found that A- loans, in 1999, had an average coupon interest rate of 9.9 percent; the rate for B, C and D loans was 10.6, 11.5 and 12.6 respectively compared to average prime coupon rates of 7.5 percent. Thus, during the 1990s and with 2 different research reports of pricing within the U.S. sub-prime market we can see range premium spreads of 600 basis points for 4 large banks and 510 basis points as per the Thrift Supervisor. Presumably, if the sample matrix pricing sheets shown above had top prime borrower coupon rates of 7.5 percent, then the highest spread would also be over 460 basis points over its truncated range.

Given around at least a 500 basis point spread for full risk margins we therefore have a potentially wide range that encompasses a large number of borrowers across the risk spectrum. However, with the inclusion of the missing components of the borrower Capacity and issues around the Collateral it could therefore make the potential audience even larger still. Hence, we endeavour to show how such measures of additional information (over and above just risk grades alone) could help set at least a theoretical price across a wider range and what that potential outcome may look like. Sub-prime lending has wider margins and higher risks so the risk premium charge needs to reflect this reality position.

We can achieve a similar initial classification of market segment for any mortgage applicant from a credit Character PD measure within the U.K. market by replacing the FICO score with a similar U.K. score, for example, the Experian Delphi scores. The application of the Delphi score and LTV split to our illustrative portfolio yields these outcomes:

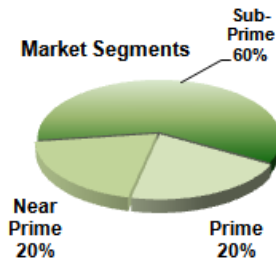


Table 8 - Illustrative Only - Credit Segmenting By LTV & Scores

Segmenting by Credit Measures: Avg Worst Arrears

		Delphi Scores			By LTV Bands
		<600	600-699	700+	
LTV Band	<80	2.42	1.49	0.86	1.78
	80-89	3.13	2.16	1.26	2.20
	>89	3.81	3.02	2.46	3.04
By Score Bands		2.72	1.91	1.32	2.08

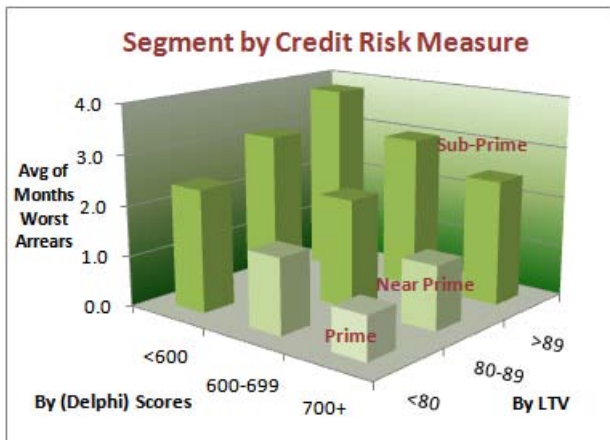


Figure 16 - Illustrative Only - Sample Outcomes by LTV & Scores

Using somewhat arbitrary splits of the underlying measure of average worst-ever arrears within a two-year observation period; we can simply split the scores into ranges of 700 and above, between 600 and 700 and below 600. For LTV, a universal split of 80% and below, between 80 to 89%, and then greater than 89% (just three broad classes for illustrative purposes). For the next step, we can set some credit measures based on arrears performance which facilitates splits of below 1 for prime, between 1 and 2 for near prime and above 2 for sub-prime. From using this simple basis, the overall segments in the pie chart above, have Prime and Near Prime segments each comprising 20%

shares and sub-prime having the largest component at 60%. Clearly, from the three-dimensional chart above, there is a meaningful risk differentiation evident. To convert these cells into PDs we can make use of the Low Portfolio Default PD measurement approach as one possible mapping process (See Appendix for further details on the FSA researchers suggested low probability of default methodology). Potentially, this approach could usurp the so-called "ABCD" mortgage market approach for broad risk classification, as it also takes into account the vital LTV aspect, which forms part of the C3 component.

From a pricing perspective, we can check the extent of current risk-based pricing through a cross-tabulation of the same sample within the grid for Delphi scores and LTV bands.

Table 9 - Illustrative Only - Possible Margin Outcomes by LTV & Scores

Current Risk-Based Pricing for Mature Margins

		Delphi Scores		
		<600	600-699	700+
LTV Bands	<80	3.37	3.03	2.69
	80-89	3.61	3.34	3.05
	>89	3.49	3.30	3.23

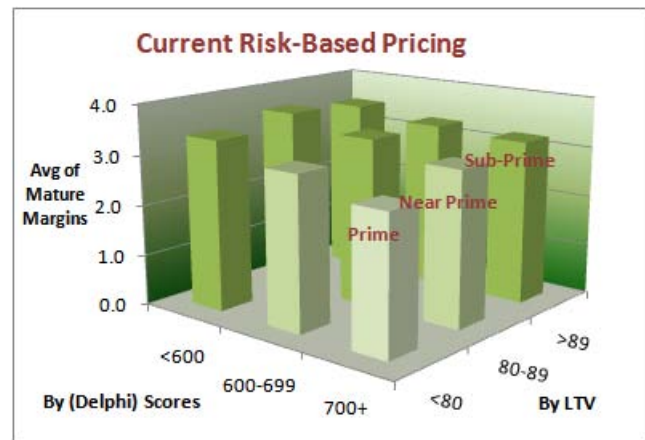


Figure 17 - Illustrative Only - Current Risk-Based Pricing Example

Although the above example uses illustrative data only, nevertheless the picture does tell the story! An outcome like this would be clear evidence of the need for attaining sharper pricing-for-risk outcomes within the specialist mortgage market. From the use of just two criteria for risk segmenting applied to the average mature margins at loan inception, we can see that there is some evidence of risk-based pricing in the figures above, yet it is also apparent that this outcome could have far more differentiation across these margin risk profiles. It can hardly please the prime customer to have a margin spread that is relatively similar to the sub-prime customer, nor does it make much business sense to *not* charge



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the sub-prime customer more, especially if that risk level is evident from their credit history. In applying the proposed risk-based methodology we can make use of the broad risk groups above from an illustrative perspective (could use finer gradation if required) and align the PD for Credit Character to these cells (using the arrears performance and mapping this to a PD using the Low Portfolio default methodology). The table shows what this outcome looks like and reflects the sharper delineation needed for attaining risk-based pricing.

Table 10
P(D|C1) using Low Portfolio PD mapping process

		Delphi Scores			Total
		<600	600-699	700+	
LTV Bands	<80	10.42%	5.81%	4.38%	7.78%
	80-89	14.08%	10.36%	5.68%	9.96%
	>89	17.49%	14.70%	11.44%	14.04%
	Total	11.67%	8.15%	6.21%	9.39%

Most of the key pricing inputs for sharpening the risk-based pricing approach are set out in the figure below (illustrative only).

Table 11

Illustrative Only - Pricing for Risk Measures			
Rate Basis Contribution			
-1	Gross APR (+ ERC)	9.58 %	120.5%
0	Annual Percent Rate (APR)	7.95 %	100.0%
1	Cost of Funds	-3.77 %	47.4%
2	Gross Margin	4.18 %	52.6%
3	Early Redemption Charges (ERC)	+1.63 %	20.5%
4	Gross Margin + ERC	5.81 %	73.1%
5	Option Premium Elements		
6	Estimated Prepayment Risk	-0.50 %	6.3%
7	Derived Default Risk	-0.49 %	6.2%
8	Assumed Fraud Risk	-0.10 %	1.3%
9	Risk Adjusted Margin	4.72 %	59.4%
10	Administration Costs	-2.50 %	31.4%
11	Taxation	-0.67 %	8.4%
12	Attributable to Stakeholders	1.55 %	19.5%

From this pricing summary table, we can check the basic requirements as per the BOE guidelines outlined previously, as:

- 1) *Direct cost of funding the loan: **3.77%** (LIBOR + Funding margin)*

- 2) *Credit assessment and other administrative costs associated with providing, servicing and monitoring the loan: **2.50%***
- 3) *Cost of insuring, or self-insuring, against the risk that amounts will be lost because of obligor default ('expected loss' premiums): **0.49%** for default risk (and **0.50%** for prepayment risk plus **0.10%** for fraud risk)*
- 4) *We can also include taxation (**0.67%**) and Early Redemption Charges of **+1.63%** (as a revenue item post-APR calculation). The Gross APR is therefore **9.58%** instead of the stated APR of **7.95%** (which includes introductory discount rate, fees and charges¹⁷ and reversionary rate combined into a comparison number that forms part of the mandatory Key Facts Illustration that is presented to every client)*

Note that in this illustration, the original customer APR of 7.95% will inevitably increase across the mortgage pool as a number of customers will prepay their mortgages and incur an early redemption penalty charge (ERC). Therefore, by factoring in an estimate of what this could have been if known at the outset, the average APR has to increase but the customer can never know for sure if this penalty will apply to them, so it cannot be included in the normal APR quote. This component can however, make a significant difference to the overall pricing dynamics and makes it more difficult to apply a risk margin to any account (we show it as being in excess of the 100% level for the customer APR).

For setting the target risk-based price, we need to specify base margins for each of the target sectors (now risk identified). Hence, prime risk could require a 2% target margin for example, near prime 3% (the broad average overall) and the sub-prime at (say) 4%. To this target spread, you can add in a premium for each of the different risk exposures (Credit, Market and Operational risks). Assume that for purposes of illustration we keep the prepayment and fraud risk premiums constant at 50 and 10 basis points respectively. The derived default risks will of course be the expected loss estimate (EL) expressed on the same basis as the annualised APR. In this risk-based pricing example, the main change agent will be reflective of the EL components, but the prepayment risk dynamics, should also have a significant impact because of its prepayment modelling influence. The pricing approach is for the individual level, but we can show what the portfolio impact might be assuming acceptance by the customers of any higher risk charge. For effective risk-based pricing, the intermediaries would need to ensure that the customer receives the appropriate APR to reflect their risk status—and not the just the lowest price that helps them earn a higher commission from higher volumes!

¹⁷ Examples of fees include: Telegraphic Transfer, Application, Valuation, Completion, Deeds Release, Redemption Admin, LA Search, Insurance Cover, Legal and Arrangement. In total, they could range from £1,500 to £2,000.

Risk-based Pricing Application & Comparison

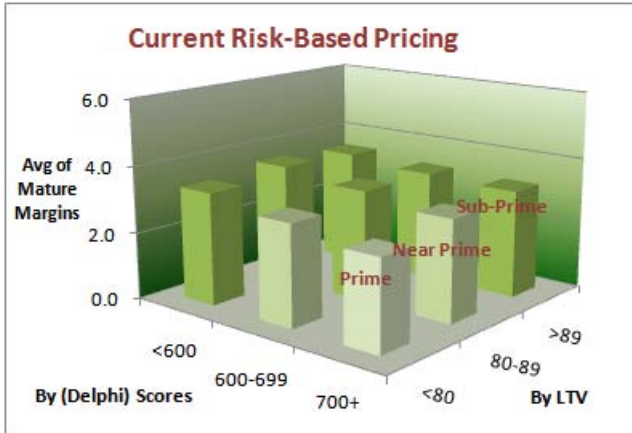


Figure 18 - Illustrative Only - Current Risk-Based Pricing Example

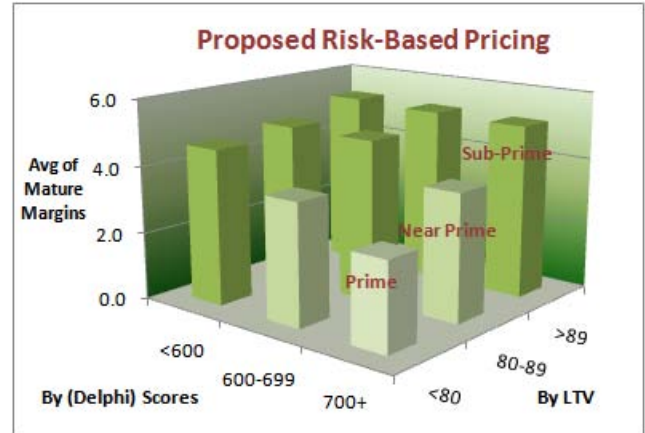


Figure 19 - Illustrative Only - Proposed Risk-Based Pricing Example

In the proposed risk-based pricing framework results, the back-end 'blocks' symbolise that sub-prime borrowers have risen in 'height' quite considerably whilst the prime and near prime 'blocks' are relatively similar. This example, serves to highlight the obvious point that the price to charge needs to properly reflect the measured risks (individually and collectively for the risk class) and is thus a clear example of attaining a sharper pricing for risk outcome. Note that with the figures above, we have set them with the same vertical scale to facilitate comparison for current risk-based pricing outcomes. To generate the numbers underlying the chart on the right required considerable analytical efforts. However, once a sound credit risk framework and methodology has been set up, you can derive these numbers routinely and store them in a corporate data warehouse. *Of course, whether or not you can readily persuade your customers to accept a higher APR will depend upon the confluence of factors such as the framework of operation, the incentives for intermediaries and a required cultural shift in the market place.*

To use an analogy, risk-based pricing is a little like optimal use of gears on a bicycle. You use the front three gear sprockets for a choice of terrains (main customer segments). The largest size sprocket is for going down hills (prime), the next is for going along flat surfaces (near prime) and the smallest one for going up hills (sub-prime). Having chosen the main gear you can then use the back six sprockets to fine-tune these selections (the PD & LGD variations).



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Risk Adjusted Performance Measures

RAROC Illustrative Example Only

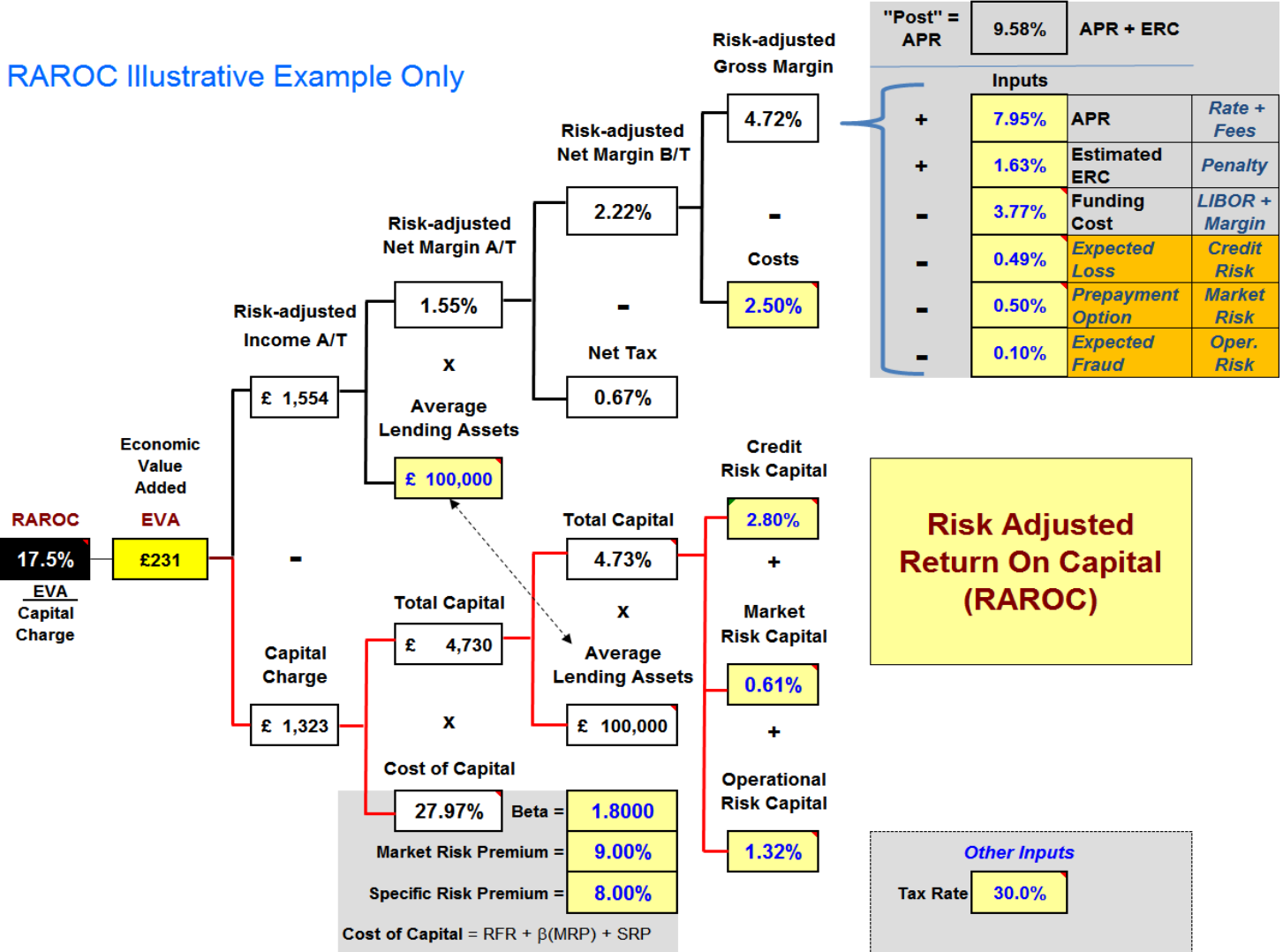


Figure 20 - RAROC Concept Application Example

Using a RAROC framework as outlined above helps address the other BOE requirement for "the cost of capital, held to protect the institution against the chance that actual losses will exceed their mean expected magnitude ('unexpected losses')". RAROC forms part of the capital aspect of loan evaluation criteria. The top half of the tree involves the income streams and associated costs whilst the bottom branch addresses capital measures. Each of the three Basel II capital estimates for Credit, Market and Operational risk are part of the total economic capital available. Moving along the tree from right to left we can see that loan size is irrelevant so this analysis could be applied at an individual loan level, securitisation pool level or for all of a homogenous asset portfolio such residential mortgages.

If the RAROC result exceeds zero then this implies that the return meets the minimum performance requirements from a capital market perspective. Usually, management or the board sets a target objective and the framework thus helps clarify whether the proposed pricing structure is within appropriate boundaries from a top-down perspective. Note that each of the capital risks (for unexpected losses) has its corresponding insurance style premium component as part of the top branch for expected loss deductibles from gross revenue. Usually a RAROC range from 10 to 30% would be sustainable. Keeping the APR consistent with competitive risk levels should help achieve an optimal RAROC over time. It is not a panacea for capital control but is another tool that can guide management for risk-based pricing decisions.

Table 12 - Basel II Minimum Credit Risk Capital Calculations

Residential Mortgages Securitisation Basel II Capital Requirements

Assessment of the Basel II Framework on typical U.K. Portfolios (as per S&P - Ratings Direct)

Input Values

Symbol	Prime	Sub-prime	Description
PD =	0.83%	3.32%	Probability of Default (Pool exposure weighted average)
LGD =	15.57%	18.53%	Loss Given Default (Pool exposure weighted average)
EAD =	100%	100%	Exposure At Default
EL =	0.13%	0.62%	Expected Loss = PD x LGD x EAD

Unsecuritised Portfolios

Output Values

(SA) Min. Standardised =	2.80%	2.80%	Set at 35% of normal 8% charge for LTV<80% otherwise 6% for LTV>80%
Typical Standardised =	4.40%	4.40%	Assume portfolio has 50% LTV<80% and 50% LTV>80%
(RBA) Kirb = (Also includes an EL provision added to UL or the overall effective capital charge)	1.51%	4.52%	where, $r = 0.15$ 'constant and supplied by Basel 2 Group $K_{IRB} = KIRBHL (LGD, PD, EAD) + EL$ $K_{IRB} = (LGD * myN(((1 - r) ^ -0.5) * InverseCDF(PD) + ((r / (1 - r)) ^ 0.5) * InverseCDF(0.999)) - PD * LGD) + EL$

Securitised Portfolios Summary

(SA) Standardised =	3.55%	4.83%	Externally Rated (tranche-rated risk weights set by supervisor)
(RBA) Kirb =	2.38%	2.46%	Externally Rated (risk weights depend upon seniority of tranche)
(SF) Supervisory Formula =	2.28%	5.43%	Unrated Portfolio

Applying the Basel II capital requirements for credit risk for minimum levels only, across securitised and unsecuritised pools for the same class of assets, shows that different capital requirements will result from the use of different methods that you can adopt. This is a peculiar outcome given that the underlying asset pools are all the same in this example. For sub-prime mortgages, under the advanced approach, the rated securitisation method results in the lowest requirement of capital whilst for prime mortgages the ratings based approach yields the lowest capital requirement. The chart opposite highlights these stark variations possible by methods and by type of pool composition. A rated securitised sub-prime mortgage can actually require less minimum capital than for a prime mortgage pool using the standardised approach. The outputs from this capital measure exercise can be the inputs for the RAROC methodology above for each of the risk capital numbers in the lower part of the tree.

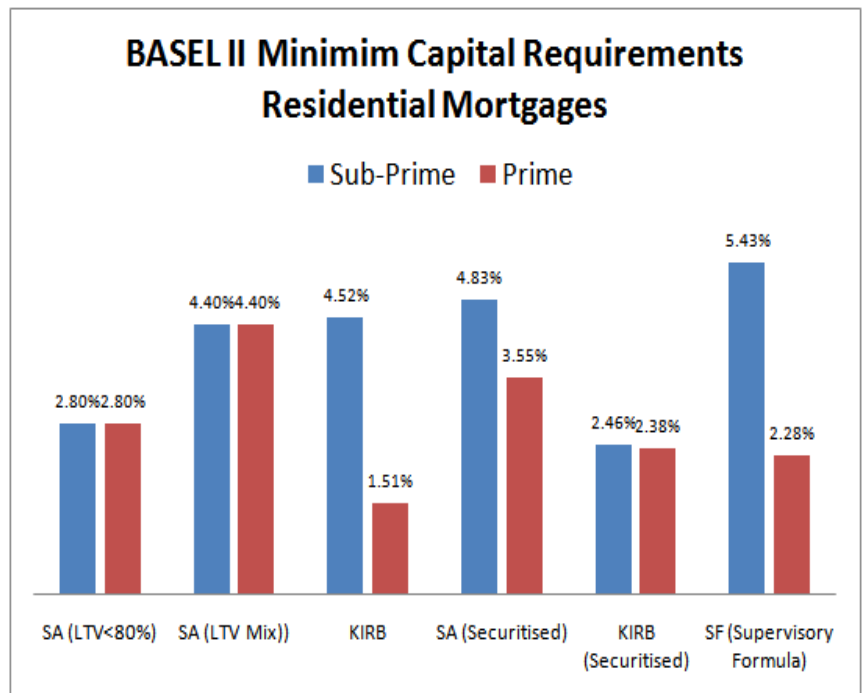


Figure 21 - Basel II Minimum Credit Capital Requirements



Conclusion

A recent CML report¹⁸ purports that since the sub-prime segment has provided significantly higher returns in recent years (compared with prime mortgages) that many new entrants have been tempted to enter the market. It suggests that some of these new lenders may have deliberately under-priced risk in order to gain market share—a situation that is clearly unsustainable longer term. The Basel II capital requirements under the advanced IRB approach can now readily reflect this higher credit risk aspect—**much** more so than under the standardised approach. However, those lenders who adopt the advanced internal ratings models will be able to effectively price more accurately along the risk spectrum—assuming they apply the Basel II capital factors **via the 'Basel Use Test' in their pricing mechanism. However,** the key point made by the CML report is that those lenders without such ratings models and tools—will attract and retain much more of the higher risk business—and unknowingly, under price for this risk, thereby exposing their stakeholders to higher losses as the cycle turns. Clearly, not being able to measure risk and price accordingly, potentially threatens the entire viability of an organisation.

Currently, a separation exists in the marketplace between the sub-prime and prime mortgage markets, but this line will commence to fade as risk-based pricing practices start to prevail. Average cost pricing of interest rates coupon rates for prime mortgages is a widespread practice (as is the case for each class within the sub-prime market). Yet, if prime lenders were more willing to adopt risk-based pricing, they could lend far more of their funds to the riskier sub-prime segment, since an increase in rates will offset the higher risk. As a result, the fuzzy line that divides the market into prime and sub-prime may simply vanish as prime lenders start focussing on sub-prime customers as a normal component of their mortgage business.

Risk-based pricing, if well executed by industry participants **may prove to be a 'two-edged sword'**. In theory, a market that can readily sanction mortgages at a price commensurate with risk, instead of setting a risk floor and then approving no one beneath this level, will inevitably expand. Thus, prime lenders could thus start to increase volume and profits using risk-based pricing perhaps far in excess of their current share. However, companies that still specialise in sub-prime lending may become less profitable, because increased competition will drive their profit margins down. If the current sub-prime lenders continue to offer credit-impaired borrowers a rate they cannot afford (i.e., no rejection by the customer from a very high offer rate), then they will force that borrower to ultimately exit the mortgage market.

¹⁸ Page 29, CML Report on "Basel 2 and the UK mortgage market - Challenges and Opportunities", June 2007 by Brian Jaggard (Ernst & Young LLP)

However, with risk-based pricing from prime lenders they might be able to offer these troubled borrowers a more competitive price because of their lower cost of capital structure, and thus grow their already large customer base further. Some participants will simply be better able to use the tool of risk-based pricing than others will.

Whether or not this methodology and approach ultimately succeeds depends on the interaction of lender, intermediary and end-customer within their current economic climate. However, to set prices only by market forces is to risk longer-term survival in this market. Market prices may be out of **alignment with the requirements of the organisations' major stakeholders** and thus the real challenge is to be able to **ensure that service providers are not just 'order-takers' but instead are trained 'sales-makers' who in turn will be appropriately rewarded by longer-term viable transactions and not from churning existing customers.** Is the customer really better off by repeating a mortgage deal a mere 2 years after completing the previous one? Surely, mortgage contracts need to be over a longer period spanning at least 5 years duration. Thus, the APR quoted to the customer, needs to reflect at least a 5-year period with a fixed rate, thus **assisting the customer to avoid any payment 'shock', at the end of a 'teaser' period with an initial discounted rate.** Perhaps this is something that only the regulator can fix.

Mortgage industry participants may also have to develop new ways of advertising and educating their intermediaries and hence potential customers. Currently, the process of obtaining a mortgage is confusing for borrowers because of the proliferation of products and options. With the adoption of risk-based pricing, this process may become even more confusing, as consumers may not be able to shop around for rates using standard advertisements. Instead of a single rate that would be offered for all borrowers, lenders will have to devise new methods of how to inform borrowers about the cost of a mortgage or perhaps use a scenario to show how **their product meets that borrower's specific profile.**

This paper outlines a proposal for the practical achievement of a risk-based pricing framework. It draws on a number of best-practice approaches within the context of new capital adequacy directives. It has a core set of principles that draw on a tried-and-true methodology that prime lenders have been using for a long time—the so-called **"Three Cs" of credit** namely, Character, Capacity and Collateral. The effective and efficient application of these principles—in **today's** mortgage market place—**perhaps** lessens the chance for someone from the previous generation of lenders, like Mr. George T. Ziegler to ask: **"What happened?"...**

Appendices

Appendix A - FSA Low Default Portfolio PD Methodology

Algorithms and Formulae

(Adaptation of Low Default Portfolio – Default Probability Estimation Approach) as per Benjamin et al. (FSA, 2006)

1. Use the Binomial Probability function to find a solution for p assuming defaults occur **independently** to satisfy equation below,

$$1 - \gamma = \sum_{k=0}^{\tau} \binom{n}{k} p^k (1 - p)^{n-k}$$

Where,

γ = Confidence level required eg. 80%

τ = Number of defaults eg. 10

n = Total number of obligors eg. 500

k = Integer increments from 0 to τ by steps of 1

p = Initial probability solution

Example:

$$(1 - 0.8) = 0.2 = \sum_{k=0}^{10} \binom{500}{k} p^k (1 - p)^{500-k}$$

Solving for $p = 2.72\%$ for 1-year PD outcome

Using MS Excel's Binomial Distribution Function

BINOMDIST(number_s, trials, probability_s, cumulative) = RHS	
Solve (using Goal Seek) for p =	2.720%
RHS: BINOMDIST(10, 500, p, TRUE) =	20.0%
LHS: 1 - γ =	20.0%
Set to Zero the Difference = 0.00%	

2. Now use the Binomial Probability function to find a solution for p assuming defaults are **dependent** within the Vasicek model to satisfy equation below over a one-year time period only.

Note that p now becomes "enveloped" inside of Vasicek model before solving within Binomial Function:

$$p \Rightarrow \Phi \left(\frac{\Phi^{-1}(p) + y\sqrt{\rho}}{\sqrt{1-\rho}} \right) \quad \text{Vasicek model}$$

Where,

y = Random standard normal variable (\cong range from -3 to $+3$)

ρ = Pairwise correlation between assets e. g., 15%

$\Phi, (\Phi^{-1})$ = Cumulative Normal Distribution function and its (Inverse)

Hence substituting for p and taking the expectation across all possible values of the risk factor Y the PD solution can be solved (same as for the independent case above).

$$1 - \gamma = E \left[\sum_{k=0}^{\tau} \binom{n}{k} \left(\Phi \left(\frac{\Phi^{-1}(p) + y\sqrt{\rho}}{\sqrt{1-\rho}} \right) \right)^k \left(1 - \Phi \left(\frac{\Phi^{-1}(p) + y\sqrt{\rho}}{\sqrt{1-\rho}} \right) \right)^{n-k} \right]$$

By simulating for N independent standard normal variables of Y_i (e.g., Box-Muller) and solving for p ,

$$1 - \gamma = \frac{1}{N} \sum_{i=1}^N \left[\sum_{k=0}^{\tau} \binom{n}{k} \left(\Phi \left(\frac{\Phi^{-1}(p) + y_i\sqrt{\rho}}{\sqrt{1-\rho}} \right) \right)^k \left(1 - \Phi \left(\frac{\Phi^{-1}(p) + y_i\sqrt{\rho}}{\sqrt{1-\rho}} \right) \right)^{n-k} \right]$$

For example, solving for $p=2.79\%$ above, depending upon random variable y_i generated

3. Extending above **dependent** PD solution to cover **multi-year** observations, involves use of the 'single risk factor' model where for an observation period of T years with n initial obligors, the change in $V_{i,t}$ in asset value of obligor i in Year t is modelled as:

$$V_{i,t} = \sqrt{\rho} S_t + \sqrt{1-\rho} X_{i,t} \quad \text{Single Risk Factor Model}$$

Where S_t is the systematic factor common to all obligors, $X_{i,t}$ the idiosyncratic factor (assumed to be an independent standard normal variable as for the single year case above), and ρ the pair-wise correlation between assets of different obligors in any given year. S_t can vary across years and is modelled as a multivariate standard normal variable with correlation matrix as below (with a numerical example for 5 years with $\theta = 30\%$), such that the correlation between years i and j is $\theta^{|T-1|}$.

Year-to-Year Default Correlation matrix ($T = 5$ years)

$$\begin{bmatrix} 1 & \theta & \dots & \theta^{T-1} \\ \theta & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \theta \\ \theta^{T-1} & \dots & \theta & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 100\% & 30\% & 9\% & 2.7\% & 0.81\% \\ 30\% & 100\% & 30\% & 9\% & 2.7\% \\ 9\% & 30\% & 100\% & 30\% & 9\% \\ 2.7\% & 9\% & 30\% & 100\% & 30\% \\ 0.81\% & 2.7\% & 9\% & 30\% & 100\% \end{bmatrix}$$

To ensure that the simulations are properly correlated across time we can make use of the Cholesky decomposition factor for the independent random numbers z_1 and z_2 below, such that:

$$\begin{bmatrix} 1 & 0 \\ \rho & \sqrt{1-\rho^2} \end{bmatrix} \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} X \\ Y \end{bmatrix} \quad \text{Cholesky decomposition}$$

Thus, given the set ($S_1 \dots S_T$) of the systematic factor, then the probability that an obligor defaults in any given year within the observation period is:

$$\pi(S_1 \dots S_T) = 1 - \prod_{t=1}^T \left(1 - \Phi \left(\frac{\Phi^{-1}(p) - S_T \sqrt{\rho}}{\sqrt{1-\rho}} \right) \right)$$

$$1 - \gamma = E \left[\sum_{k=0}^{\tau} \binom{n}{k} (\pi(S_1 \dots S_T))^k (1 - \pi(S_1 \dots S_T))^{n-k} \right]$$

Hence substituting for p , and taking the expectation across all possible values of the risk factor Y the PD solution can be solved (same as for the independent case above).

$$1 - \gamma = E \left[\sum_{k=0}^{\tau} \binom{n}{k} \left(1 - \prod_{t=1}^T \left(1 - \Phi \left(\frac{\Phi^{-1}(p) - S_T \sqrt{\rho}}{\sqrt{1-\rho}} \right) \right) \right)^k \left(1 - \left(1 - \prod_{t=1}^T \left(1 - \Phi \left(\frac{\Phi^{-1}(p) - S_T \sqrt{\rho}}{\sqrt{1-\rho}} \right) \right) \right) \right)^{n-k} \right]$$

Solving for p below:

$$1 - \gamma = \frac{1}{N} \sum_{i=1}^N \left[\sum_{k=0}^{\tau} \binom{n}{k} \left(1 - \prod_{t=1}^T \left(1 - \Phi \left(\frac{\Phi^{-1}(p) - S_T \sqrt{\rho}}{\sqrt{1-\rho}} \right) \right) \right)^k \left(1 - \left(1 - \prod_{t=1}^T \left(1 - \Phi \left(\frac{\Phi^{-1}(p) - S_T \sqrt{\rho}}{\sqrt{1-\rho}} \right) \right) \right) \right)^{n-k} \right]$$

Low Portfolio Default Probability Example

Input Variables	Values	Symbols
Confidence Level Required	80%	gamma
Total Obligor	500	n
Number of Defaults	10	r_
Asset Correlation	15%	rho
Year-to-year Correlation	30%	Theta
Number of Years	5	TheYears
Number of Simulations	100	BigN

Output Solutions

Function: LowDefaultProbability(Gamma, n, r_, rho, Theta, TheYears, BigN)

Low PD = **0.81%**

Note, that this example is over a 5-year period (no longer just one year of default outcomes), hence the lower PD estimate.

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