Credit risk models: why they failed in the credit crisis

Credit risk models have played a key part in the global credit crisis. The main shortcomings of these models are examined and a new causal framework is proposed to build deductive credit default models that have predictive capabilities.¹

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THE GLOBAL CREDIT CRISIS has occurred as major parts of the credit market have failed to function normally leading to failures of financial institutions³ because they were unable to obtain funding from the market. The first part of the market to fail was the US sub-prime mortgage market. Subsequent failures of other parts⁴ of the market suggest that the problems were more fundamental than simply the mispricing of some mortgage-backed securities.

Credit market failure
In his seminal paper, Akerlof (1970) identified two ingredients for market failure: low-quality products (e.g. ‘lemons’ in the used car market) and asymmetric information when buyers are less informed than sellers. Both these ingredients are present in the credit market crisis in mortgage-backed securities.

Minsky (1992) anticipated⁵ that the flawed incentives of the mortgage securitisation process would create loans of low credit quality, which now have a variety of names: ‘sub-prime’, ‘Alt-A’, ‘non-conforming’. This insight was recently confirmed⁶ officially by the US Government (Paulson 2008). The securitisation process also led to asymmetric information, because not all information about the loans the mortgage brokers had at loan approval was transmitted to the buyers of the mortgage-backed securities (MBS), as the crisis subsequently proved. At the time, the existence of asymmetric information was difficult to demonstrate because buyers relied on prices set by credit rating agencies that were presumably fully informed about the approved loans.
Once money was lost from MBS, withdrawal from the market by investors gave rise to a modern version of a ‘run on the banks’ in the financial system. The failure of the market to provide credit might not have been so evident or debilitating for the economy, if the dependence on credit from the market had not been so great. With 50% of the US$14.4 trillion (Federal Reserve Bulletin 2008) in outstanding mortgages in the United States being intermediated through securitisation at the end of the third quarter 2007 (35% through traditional institutions and 15% through governments and individuals), the disruption to market function was significant.

When the market temporarily becomes illiquid due to uncertainty following an initial shock from unexpected news, it normally recovers quickly and trading resumes around new consensus price levels. However, in this crisis, market recovery did not occur quickly, highlighting the existence of an asymmetric information problem. After several months of the crisis, we still seem to be a long way from a solution to this problem.

Many parts of the credit market have remained closed to new lending, suggesting that something still more serious has affected the market. It seems that having more information on the mortgages is insufficient to unlock the market, since we need to translate individual loan data to prices for securities with credit risk. This appears to be beyond the capabilities of the credit risk models that are currently in use.

In March 2008, in his testimony before the US House of Representatives, Charles Prince, then the chair and CEO of Citigroup, one of the largest banks in the world, admitted that the credit risk models used at Citigroup and in the industry were wrong. In early May 2008, Standard and Poor’s announced (Shenn 2008) that it would stop rating the ‘market segment does not allow meaningful analysis’.

In his famous critique on macroeconomic policy making, Robert Lucas (1976) pointed out the limitations of econometrics for guiding economic policy. We believe his basic argument applies also to economics and finance theory generally and we sketch here an outline of his argument. Econometrics is based on inductive methods and is mainly concerned with the estimation of a general statistical model from empirical data:

\[ y_{t+1} = F(y_t, x_t, \theta, \varepsilon_t). \]  

The Lucas critique

What’s wrong with the credit risk models? Most credit risk models, like much in economics and finance, are based on the assumption of market equilibrium (Blaug 1998), which has not been adequately supported by empirical evidence in the real world (Coase 1998). The basic shortcoming of these models can be discussed firstly within a general critique of econometrics.

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Given a history up till time \( t \) for a vector of dependent variables \( y_t \), a vector of independent ‘forcing’ variables \( x_t \), a vector of independent and identically distributed random shocks \( \varepsilon_t \), and a set of environmental factors \( \theta \) representing public policy and decision rules, the objective of econometrics is to determine the model \( (F, \theta) \), where \( F(.) \) is a function and \( \theta \) is a set of parameters. In credit risk models, \( y_t \) would be default rates and recovery rates, \( x_t \) could be risk factors measured by accounting ratios or other characteristics of the borrower, and \( \theta \) is the set of environmental factors and individual behaviours which are implicit in the model.

Given a set of historical data \( \{y_t, x_t\} \), we can, in principle (though not necessarily easily) determine a model \( (F, \theta) \) through statistical data-fitting. The presumption in econometrics is that \( (F, \theta) \) is structurally stable and does not vary with different sets of data of the ‘forcing’ variables \( x_t \). In his critique, Lucas (1976, p. 25) points out: ‘Everything we know about dynamic economic theory indicates that this presumption is unjustified’. In other words, given another set of data \( \{y', x'\} \), it will often lead to another model \( (F', \theta') \). In empirical research, we often find significant differences between ex-post and ex-ante model results. In essence, a given \( (F, \theta) \) is a description of a state of the world; this state will not change structurally only if the world is in a state of equilibrium. An econometric model describes an historical state specified by \( (F, \theta) \) which is estimated from the empirical data. This historical state may not be an equilibrium state and may not continue into the future if environmental conditions change due to economic policy or other factors.

The Lucas critique is robust against any further developments in econometrics as defined by equation (1), as new research merely leads to more sophisticated models \( (F, \theta) \) and it will not be of use for forecasting and policy evaluation of actual economies (Lucas 1976, p. 39). The world we experience is structurally unstable relative to econometric models or equilibrium states, where large deviations of several standard deviations should not be a surprise. Our world is inhabited by ‘black swans’ (Taleb 2007) and distributions with ‘fat tails’. In one example from the credit crisis, delinquency rates were sometimes several standard deviations higher than can be expected from credit risk models.
Credit risk models

There are two recognised approaches to credit risk models: reduced form models and structural models. Most credit risk models in use are reduced form models, which are usually a linear subset of the general econometric model given by equation (1). Hence the Lucas critique applies to them and they are not generally valid. Expansion of $F(.)$ about an equilibrium state $\theta$ in a single period model leads to

$$y_{t+1} = c_0(\theta) + c_1(\theta)x_t + x'c_2(\theta)x_t + ... + \epsilon_t.$$  \hspace{1cm} (2)

The third term on the right-hand side is a nonlinear quadratic term where $c_2(\theta)$ is a square coefficient matrix dependent on the state $\theta$ and $x_t$ is the transpose of $x_t$. These second order and higher order terms are ignored in linear models of default or recovery risks, because equilibrium fluctuations are assumed to be small. It has become a highly simplified form of the general econometric problem (1), where standard linear regression methods can be used.

One may argue that there are equilibrium environments where $F(.)$ is approximately linear and $\theta$ are stable and this approach can be used to exploit available market information for pricing and hedging (Jarrow and Protter 2004). This appears to be true in the halcyon days of the credit market when the economy was growing steadily and credit default rates were low; the market was in a temporary quasi-equilibrium state. The models were useful in predicting credit defaults. Once the market started to move from this state, the estimated models ceased to be valid because the regression coefficients $c_0(\theta)$ and $c_1(\theta)$ were changing. New models can be estimated only when $c_0(\theta)$ and $c_1(\theta)$ stop changing and sufficient data have been collected in a new quasi-equilibrium state.

The main shortcoming of the econometric approach in the reduced form models is the typical reliance on large amounts of statistical data from a quasi-equilibrium state. The approach cannot even be used to make short-term forecasts in rapidly changing environments such as a credit crisis. Such inductive models failed to predict what would happen when they were most needed. The problems with using inductive methods alone have been well recognised historically. In a letter to Keynes, Alfred Marshall wrote, ‘You talk of the inductive and the deductive methods: whereas I contend that each involves the other...’ There is a need to integrate inductive and deductive methods in economics, as inductive methods alone cannot provide non-equilibrium predictions.

Inductive and deductive methods have been used in an integrated epistemology (see Figure 1) in the natural sciences leading to solid advances in human knowledge. The ultimate objective of this epistemological process is the creation of deductive models which could predict accurately empirical data. Predictability (Blaug 1998, p. 29) is ‘the ultimate test of whether our theories are true and really capture the workings of the economic system independent of our wishes and intellectual preferences’. Only deductive models can make predictions based on limited amount of data or assumptions.

![Figure 1: An epistemology of science](image-url)

Relatively little of economics and finance has gone through the whole epistemological loop in Figure 1. Most has been trapped either to the lower-left part of the loop in purely econometric studies or to the upper-right part of the loop in equilibrium theory formalism as discussed by Blaug (1998). Reduced form models as a subset of the general econometric model have been trapped in the lower-left part of the loop. Structural models have perhaps covered more parts of the loop, as they are deductive and have been applied to empirical data.

Structural models originated from Merton (1974), who applied equilibrium theory of option pricing to corporate debt. Strictly speaking, his model is not a credit default theory, but a theory of risk premium determination based on the assumption that traders will eliminate arbitrage opportunities in a bond market at equilibrium. There is a subtle but important distinction: it is an equilibrium theory about bond prices if the bonds can default. The theory identifies the expectation of loss from insolvency with the expectation of default. The Merton model has been interpreted (Kealhofer 2003) as causal and deductive. However, this paper will show that the Merton model is not applicable generally to many areas of credit risk, including markets for unsecured loans and markets without securities trading.

Essentially, the Merton model estimates the probability that the stochastic insolvency variable

$$x_v = \frac{\text{Assets}}{\text{Liabilities}}$$  \hspace{1cm} (3)

falls below unity, indicating the borrower has negative equity. The variable is stochastic because the value of the firm fluctuates according to some stochastic process while the amount of outstanding bonds (liabilities) is assumed fixed. If we assume the stochastic process to be a standard random walk of a Gaussian process, we obtain enclosed-form solutions of the Black and Scholes option pricing formulae. Over time the model has had various extensions (e.g. the KMV model), but recently Kealhofer (2003, p. 42) concluded: ‘Implementation of the model in practice has
proven to be more difficult than originally anticipated. These difficulties are likely to be due to inappropriate or incomplete default causality in the Merton model.

The basic idea that insolvency is the cause of default in the Merton model is not sufficiently general, because other possible causes exist. Insolvency may be a necessary, but not sufficient, condition for default of secured loans. There are probably many individuals and corporations that are technically insolvent but still able to stave off default because they continue to make the necessary debt payments. In other words, liquidity or the ability to service loan commitments is also a decisive factor in a default. Below are two examples in which liquidity or the ability to service loans is critical in understanding credit default.

In the aftermath of the Asian financial crisis in 1997, average property prices in Hong Kong SAR (Fan and Peng 2005) dropped 60–70% over a six-year period from 1998 to 2003, and as many as 30% of residential mortgage loans had negative equity. While property prices were dropping continuously throughout the period, the loan delinquency ratio rose at first from slightly above 2% to a peak of more than 7% in 1999. But thereafter, delinquency rates dropped continuously to less than 3% by the end of 2003, as property prices continued to fall. This contradicts the underlying assumptions and the subsequent predictions of the Merton model.

The second example is the Grameen Foundation (Yunus 2006), which makes very small loans to poor villagers who have no assets as collateral. Actual experience over several years showed that the default rates averaged less than 2% per annum, due to the ability of villagers to service the loans by making small business profits. The Merton model is inapplicable to Grameen microcredit and to the whole class of unsecured loans, such as credit cards and other consumer credit.

Clearly, the Merton approach suffers from incomplete causality for all types of loans; we need to also include the causal effects arising from an entity’s cash flows in a more complete theory (even for the traded bond market). When assessing corporate health from financial account data, for example, a more complete theory would pay attention to the profit and loss statements, as well as to the balance sheet statements – which are the only statements a Merton model would consider.

A new causal framework

In a new approach to credit risk (Sy 2007), we assume that the primary cause of credit default is loan delinquency due to insufficient liquidity or cash flow to service debt obligations. In the case of unsecured loans, delinquency is assumed to be a necessary and sufficient condition. In the case of collateralised loans, delinquency is a necessary, but not sufficient condition, because the borrower may be able to refinance the loan from positive equity or net assets to prevent default. In general, for secured loans, both delinquency and insolvency are assumed necessary and sufficient for credit default.

We introduce a liquidity model which estimates the probability that the stochastic delinquency variable

\[ x_s = \frac{\text{Cash flow to service loan}}{\text{Loan payment}} \]  

falls below unity. The variable is stochastic because circumstances can change in random ways to affect the ability of the borrower to service loan obligations. This new approach is viewed as a framework rather than a theory because there are arbitrary numbers of ways to model cash flow depending on the circumstances of the borrower and the information available to quantify liquidity. Hence the framework permits many possible theories and models.

Once the stochastic process controlling the evolution of the delinquency variable is specified, we can determine its probability distribution at a later time \( t \) and from this calculate the probability for delinquency where \( x_s \leq 1 \). As a simple example, assuming a standard Gaussian process, the probability distribution at a later time is described by a ‘distance to delinquency’ variable:

\[ z_s = \frac{\ln(x_s) + (\mu_s - \frac{1}{2} \sigma_s^2) t}{\sigma_s \sqrt{t}} \]  

The probability of delinquency is given by \( N(-z_s) \) where \( N(.) \) is the standard normal cumulative probability function. Two parameters, the drift rate \( \mu_s \) and the volatility, \( \sigma_s \), can be used to describe future conditions and risk.

A similar discussion applies to the insolvency variable \( x_i \) and an analogous expression for \( z_i \) can be written by replacing subscripts in equation (5). We reject the equilibrium assumptions of the Merton model as too restrictive, since we are concerned with other non-traded markets as well as traded bond markets. In general, we have an evolution of the insolvency variable described by two parameters: the drift rate \( \mu_i \) and the volatility \( \sigma_i \). In the Merton model the drift rate is replaced by a riskless interest rate due to the absence of arbitrage at market equilibrium.

In the case of secured loans, the two causal stochastic variables for delinquency and insolvency may be correlated, a priori. If we assume Gaussian processes then the default probability is determined by a bi-variate normal probability density function, with a given correlation coefficient (Sy 2007).

In the uncorrelated case, we have a product of two independent uni-variate normal probability density functions, with a set of four parameters: \( \mu_s, \sigma_s, \mu_i, \sigma_i \). The probability of default is then given simply by \( N(-z_s)N(-z_i) \). In the case of the Hong Kong SAR mortgage market (Fan and Peng 2005) referred to above, we would have \( N(-z_i) \) being essentially equal to one. For this case and for the cases of Grameen microcredit and unsecured loans, the probability of default is determined by \( N(-z_s) \), which is the probability of delinquency.

The puzzle of the Hong Kong SAR housing market has been resolved (Sy 2007) by showing that the falling
interest rate environment of the period made loans more easily serviceable, leading to low probabilities of delinquency. With reasonable selected values for the parameters: \( \mu, \sigma_x, \mu_y, \sigma_y \), we are able to reproduce the main observed features of the Hong Kong SAR property market between 1997 and 2003, when interest rates and property prices were both falling.

Similar models can be applied to any property market, provided we can model the factors affecting the cash flow situation of the borrower. We are particularly interested in the Australian market.

**Australian residential mortgages**

To illustrate the application of the causal framework, we assess residential mortgage default risk using a simple model for typical households with wage earners. For the delinquency variable in (4), we assume a loan serviceability ratio (LSR) defined by

\[
x_s = \frac{\text{After tax income} - \text{Living costs} - \text{Other payments}}{\text{Mortgage payment}}
\]

The insolvency variable in (3) is assumed to be the reciprocal of the loan-to-value ratio (LVR). The loan approval process captures the relevant data from the borrower to provide estimates of LSR and LVR at origination for each loan.

Given microeconomic and macroeconomic assumptions about how wages, inflation, consumer credit usage, interest rates and property prices are likely to change in the period ahead, we can estimate the model parameters \( \mu_x, \sigma_x, \mu_y, \sigma_y \) to predict how LSR and LVR will evolve over time. From their time-dependent probability distributions, we can calculate the probability of default, loss given default and expected loss for any given loan, for any time ahead.

In 2006, Australian Prudential Regulation Authority (APRA) collected data on 112,000 housing loans approved by the 44 largest lenders worth $27.6 billion in loan commitments. A statistical report has recently been published by APRA (2008). We also found, in other studies and datasets, that increases in house prices running well ahead of wage increases had led to decreased serviceability of many loans. At the same time, lower lending standards relative to traditional criteria facilitated increased housing lending to more and more households.

We define 'traditional' loans as those satisfying the criteria:

- debt service to gross income ratio not exceeding 30%;
- loan-to-value ratio not exceeding 80%;
- loan approval directly by lending institution, rather than through mortgage brokers; and
- full documentation, rather than low-documentation.

Traditional loans from our sample have a median LSR of 2.5 and have low probabilities of default (as calculated from our model) even though interest rates were rising in the 18 months since approval. The standard variable rate from the Reserve Bank of Australia (RBA) increased from 7.8% to 9.45% in April 2008. This was counterbalanced by average property prices continuing to rise over the period. Data from the Australian Bureau of Statistics show the weighted average index of eight capital cities for established homes rose from 109.3 to 128.1 in December 2007.

The non-traditional loans have a lower median LSR of 1.6, leading to higher probabilities of default due to increased difficulties in servicing the mortgages in the same environment, particularly at higher values of LVR (though the average LVR of the sample was around 70%). The parameters \( \mu_x, \sigma_x, \mu_y, \sigma_y \) used in Figure 2 have respective values: 12%, 20%, 11% and 25%. The values have been estimated (RBA statistical data) from actual changes in average wage, inflation, mortgage interest rates and property prices since September 2006. The calculation predicts what would happen to non-traditional housing loans since September 2006, if the assumed environmental conditions remained constant over the forecast period.

**FIGURE 2:** Australian residential mortgages

The Merton model would have predicted falling default rates because of rising property prices, contrary to our predictions and actual experience. The example selected is not meant to indicate anything general about Australian mortgages, as this would require a comprehensive study of the contents of all housing loan portfolios. It is selected to illustrate the ability of our deductive model to make predictions based on limited general assumptions about the environment in the period ahead. An inductive method cannot be used to model an anticipated new environment, particularly if it has no historical precedence, since there is no empirical data available to estimate the new model and old models would be inappropriate.

Credit risk models need to be based on causal frameworks. Only through an understanding of the causality of the credit default process can we build deductive models that are capable of making predictions in a changing environment.

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Notes

1. The lack of predictive ability in current economics (Blaug 1998) is
   catastrophic damage to the financial system and the real economy.
2. J.M. Keynes (1925) wrote: 'It is dangerous to apply to the future
   what is based on past experience unless one can distinguish
   between broad reasons for what it was and narrower reasons
   for the past experience
3. Early examples of failure include Northern Rock in UK, IKB
   Deutsche Industriebank in Germany, Bear Stearns in the US
   and RAMS in Australia. All were either bailed out by government
   or taken over by much larger entities.
4. Other parts of the market include other non-conforming mortgage
   markets, the municipal bond market and auction-rate securities
   market, to name a few.

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