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How good is your information?

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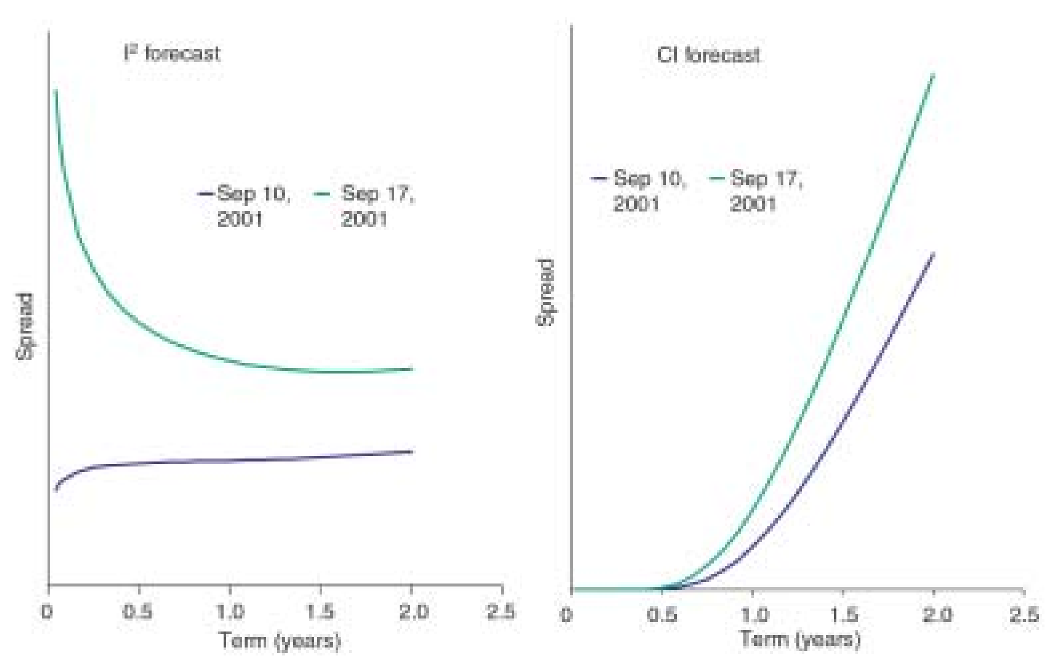
Most investment decisions are based on incomplete information. This disquieting fact, whose origins range from the complex nature of our economic environment to sneaky corporate practices, flies in the face of the assumptions that underlie many credit models. Nevertheless, a framework to model credit in the context of incomplete information is of surprisingly recent vintage – see, for example, Duffie & Lando (2001), Giesecke (2001) and Cetin *et al* (2002).

There are two main quantitative approaches to analysing credit risk. First is the structural approach, which models the cause of default. The second is the reduced-form approach, which directly models the conditional default rate, and which is often preferred for pricing.

For the purpose of measuring default risk, neither approach explicitly accounts for the fact that investors rely on information that is imperfect. The framework described below directly addresses this issue by giving a common perspective on reduced-form and structural models. This perspective leads to previously unrecognised hybrid models that incorporate the best features of both traditional approaches while avoiding their shortcomings.

The I^2 model and reduced-form models assume default is like falling blindfolded off a cliff; it cannot be anticipated

1. Term structures of credit spreads forecasted by the I^2 and CI models before and after September 11, 2001



Giesecke & Goldberg (2003a) describe a structural reduced-form hybrid default model based on incomplete information. This model, hereafter denoted I^2, is a first-passage time model: it assumes that a firm defaults when its value falls below a barrier. First-passage time models are widely used since they take account of the empirical fact that default can occur at any time.

All first-passage time models require descriptions of both firm value and a default barrier. What distinguishes the I^2 model from traditional first-passage time models is that it assumes investors do not know the default barrier. The importance of modelling uncertainty about the default barrier is highlighted by high-profile scandals at firms such as Enron, Tyco and WorldCom, and by the 919 US accounting restatements reported by the General Accounting Office in the past four years. In these cases, public information led to poor estimates of the default barrier.

Short spreads

Let's examine the effect of incomplete information on model output. Figure 1 shows model forecasts of United Airlines' term structure of credit spreads just before and then after the September 11 attacks. As markets re-opened, equity dropped abruptly, generating jumps in the credit spreads forecast by both the I^2 and a traditional first-passage time model that is based on complete information (CI).

Even after the drop, the credit curve generated by the CI model becomes flat and tends to zero at short maturities. This is not the result of unusual model inputs; rather, it comes from an implicit CI model assumption that default can be anticipated. The CI model and many other structural models assume that the distance to default is known. This has unintended consequences, such as producing a forecast that, in the next instant, makes United Airlines and the US government equally credit risky.

The I^2 model and reduced-form

models contain the opposite assumption: default is like falling blindfolded off a cliff; it cannot be anticipated. As a consequence, the I² forecasts positive short-term spreads when the possibility of default is imminent. It acts like a reduced-form model, as it can be fit to the positive short spreads that are pervasive in the market.

Leverage

Leverage, which is the ratio of a firm's debt to its value, is a key input to most structural credit models. The I² and CI models are not exceptions. However, the I² model incorporates the history of a firm's leverage, not just its current value. This makes it more reactive.

The height of the default barrier, which is its largest possible value, is based on the maximum historical leverage ratio. When a firm first hits a historically high leverage ratio, short-term forecasts jump up, since the model allows that the distance to default might be arbitrarily small. When the leverage ratio falls from its historical high, the distance to default acquires a positive lower bound, and short-term forecasts jump down. The greater reactivity of the I² model relative to the CI model is illustrated in figure 2.

Intelligent calibration

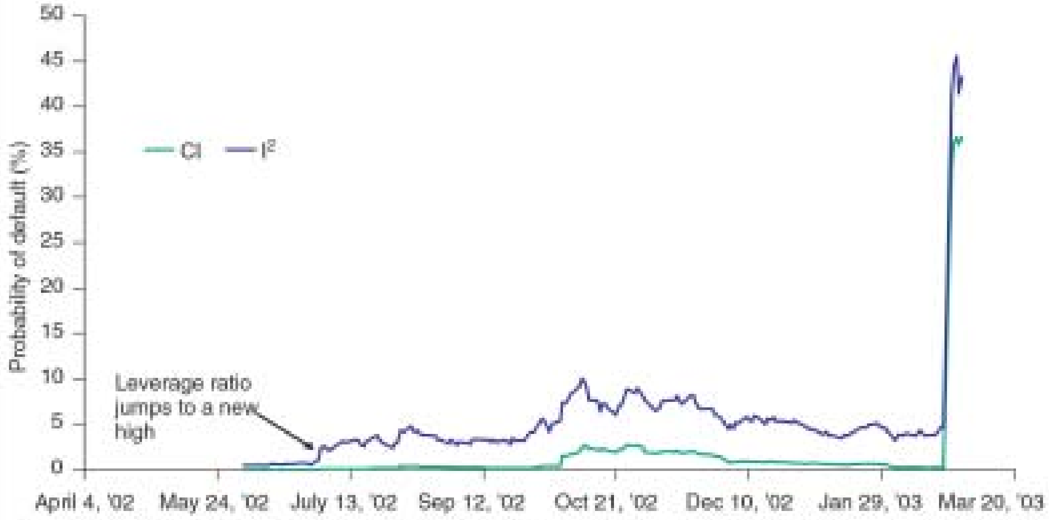
Both the expected default barrier and the uncertainty around it can be calibrated to available information in the I² model. Imagine that a firm is believed to be in good financial health, but that a particular analyst thinks otherwise. The analyst can increase the forecasts to line up with his views by raising the expected value of the barrier. He can also adjust the variance of the default barrier to the level of his confidence in reported levels of the firm's liability.

In figure 3, we illustrate the impact of changing these two parameters on one-year default forecasts for US-based pharmaceutical research company Pfizer. Since Pfizer seems to be in good financial health, the probability forecasts are relatively low and are plotted on a logarithmic scale for readability.

Model evaluation

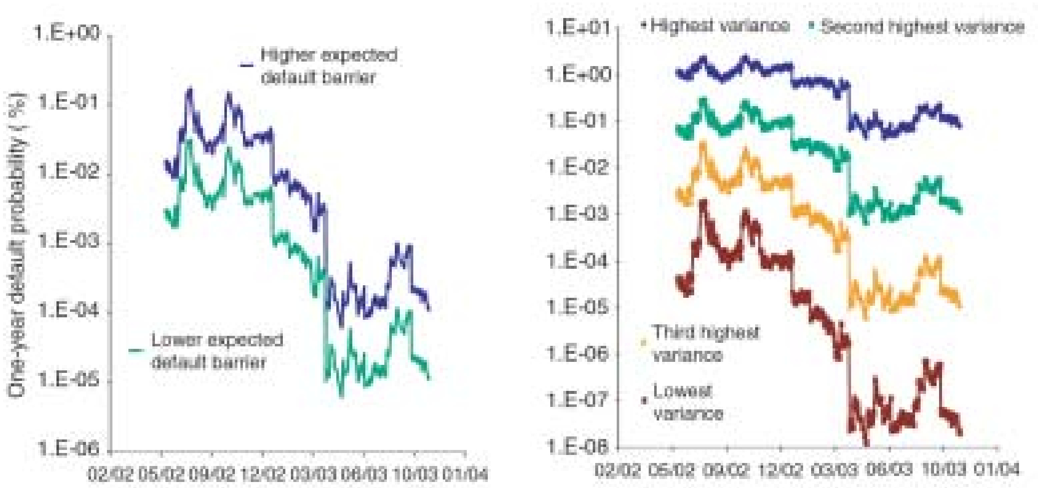
Default forecasting models make two types of errors. A false negative, which is often perceived as the more dangerous of the two types, is an actual default not forecasted by the model. If the model forecasts default but the firm survives, the error is called false positive. In fact, false positives are also very dangerous, since they undermine the power of correct forecasts.

2. One-year default probabilities for Royal Ahold, second-half 2002



In February 2003, Netherlands-based Royal Ahold, the largest Dutch food retailer, admitted overstating $500 million in earnings and to other 'accounting irregularities'. The early reaction time of the I² model relative to the CI model is evident

3. Default barrier can be calibrated in the I² model



The uncertainty around the default barrier is fixed but the expected value changes. A manager with a more conservative view can raise the level of the default barrier, and the model forecasts a correspondingly higher level of default

The expected default barrier is fixed and the uncertainty around the default barrier changes. A manager with a less confident outlook can increase the uncertainty around the barrier

Consider a model that forecasts default for every firm. This model has no false negatives: it correctly identifies every default but, due to the abundance of false positives, is useless.

The ideal is to minimise both types of errors. Thus, a sound model evaluation should include the power ratio of true positives – where the model forecasts an actual default – to false positives.

To evaluate the power ratio of the I² model, the default probability forecast over a given horizon must be converted to a binary forecast. This is achieved by labelling forecasts below a fixed cutoff as 'no default' and forecasts equal to or above the cutoff as 'default'. The cutoff is varied since it is arbitrary. The resulting receiver operating characteristic (ROC) curve, or power curve, is a standard statistical test of decision-making tools.

ROC tests of the I² model, the CI model and agency ratings are illustrated in figure 4. Here, true positives are plotted against false positives as the cutoff varies.

"By recognising that the level of default is unknown, the I² model incorporates the strengths of the structural and reduced-form models while avoiding their shortcomings"

Lisa Goldberg, Barra

Beyond default forecasts

Reliable default probability forecasts are a valuable investment decision tool. They can be used to screen portfolio assets or to indicate which securities to hedge in a synthetic index. But default probability is only one of several factors needed to price securities or to evaluate credit risk.

Defaultable security prices incorporate a credit risk premium, which is the extra compensation required by investors for taking a credit risk, as well as market estimates of post-default recovery. Incomplete information models provide a way to incorporate both of these ideas.

Giesecke & Goldberg (2003b) extend the I^2 model to price defaultable securities. This extension takes into account the abrupt drops in security values that accompany default. It also includes a decomposition of the credit risk premium into two economically meaningful components. The first is associated with the variation in firm value prior to default. The second comes from the jumps in prices that happen at default.

The two components of the credit risk premium and implied recovery rates can be disentangled and extracted from market prices of defaultable securities. Thus, they can be integrated into portfolio risk forecasts and hedged separately.

The big picture

In the I^2 model, incomplete information comes into play through an unobservable default barrier.

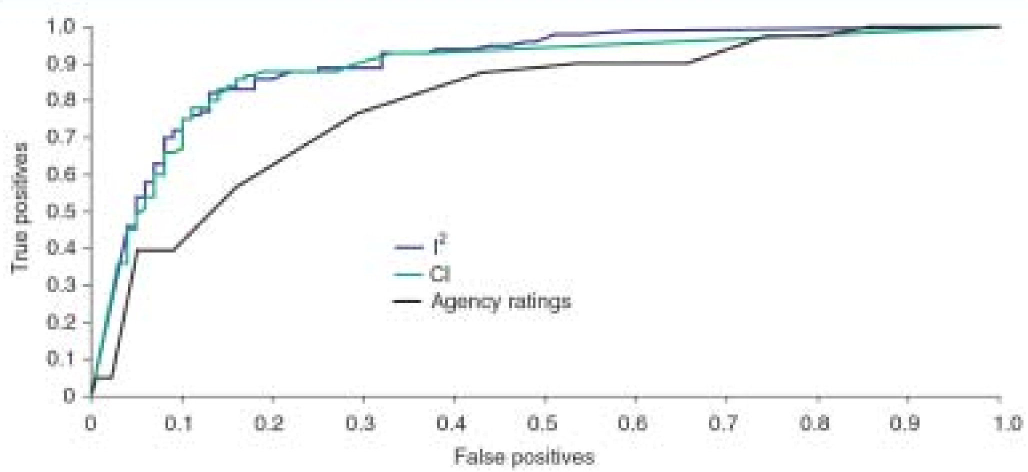
However, there are other possibilities. Duffie & Lando (2001) combine a known default barrier with noisy estimates of firm value in a first-passage time model. Alternatively, we can move away from the first-passage time definition of default. Suppose a firm defaults when its value remains below an unknown barrier for a fixed period of time. This paradigm has been explored theoretically but awaits implementation. It may lead to a host of interesting new results.

By recognising that the level of default is unknown, the I^2 model incorporates the strengths of the structural and reduced-form models while avoiding their shortcomings. It is a simple, economically reasonable model that reacts quickly to new information and accounts for the short-term uncertainty inherent in the market.

The I^2 model extends to give pricing formulae for defaultable securities and a breakdown of the credit risk premium. It paves the way to estimation of market-wide credit factors that can be included in portfolio risk models, and provides insight into the power of the incomplete information approach. □

Lisa Goldberg is vice-president, credit research at risk management firm Barra in Berkeley, California. Email: lrg@barra.com

4. ROC curves comparing model performance



The slope of the curve at any point is the power ratio for the cutoff that determines the point. A steeper curve indicates a more powerful model. Both the I^2 and CI models have greater predictive power than agency ratings. The I^2 and CI models are extremely close, demonstrating that the reactivity and flexibility of the I^2 model do not come at a price of diminished forecasting power

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