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## Session 27 PD

### Quantitative Methods Used in Managing Credit Risk

**Track:** Risk Management, Investment

**Moderator:** ANTHONY DARDIS

**Panelists:** RISHI KAPUR  
UGUR KOYLUOGLU<sup>†</sup>  
PERRY D. MEHTA<sup>‡</sup>

*Summary: The panel describes and discusses methods that are currently used for quantifying credit risk. Attendees learn about basic concepts in credit risk quantification, procedures for evaluating an individual credit risk and techniques for portfolio credit risk measurement.*

**MR. ANTHONY DARDIS:** We have a very distinguished panel and a topic that I think is of interest to all actuaries as credit risk comes into virtually every modeling exercise that we do. For the content of the session, we will look at some basic concepts. We will try to give an overview and background to bring people up to speed on some basic ideas. Then we will get into some detail, looking at both credit risk from a portfolio perspective and also credit risk for individual securities.

Credit risk quantification comes into many different aspects of actuarial work. Certainly in terms of modeling it tends to be critical to have a good feel for your credit risk exposures. It comes into both cash flow testing and into more advanced asset/liability management modeling, right through to capital management. It is a growing subject area. More and more actuaries are paying close attention to it.

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Note: All handout materials are available through the link on the table of contents.

It is also an area where we can learn a lot from other institutions. In the banking environment, credit risk is clearly an area that has had a lot of attention focused on it for a number of years. Some of the techniques being used there are certainly worth looking very carefully at, and, with the far-reaching accounting and regulatory changes that are taking place, maybe by necessity we are going to have to start doing that very soon, if we haven't already.

Our first speaker this afternoon will be Rishi Kapur from Swiss Re. Rishi will be talking about sources of credit risk and will be presenting an exposure framework. Rishi is head of financial risk management for Swiss Re. He is responsible for the identification, measurement and management of financial risks across the Swiss Re group. Prior to joining Swiss Re, Rishi worked for Oak Hill Platinum Partners, a hedge fund based in upstate New York set up by former employees of Long-Term Capital Management. Rishi is an FSA, a Fellow of the Canadian Institute of Actuaries (FCIA) and a chartered financial analyst (CFA).

Our second speaker will be Perry Mehta from Ernst & Young. Special thanks go to Perry who is standing in for Peter Davis from Ernst & Young. Perry will be discussing current practices and challenges that face us in the credit risk management area. Perry is a senior manager in the financial services advisory practice of Ernst & Young. His focus includes credit risk management, modeling and economic capital methodologies. Perry has been with Ernst & Young for just seven months, previously working with the Charlotte branch of the Federal Reserve Bank of Richmond, where he reviewed credit risk models at large commercial banks for regulatory and economic capital. Perry has a Ph.D. in finance from Temple University, Philadelphia, where he taught undergraduate and MBA courses.

Our final speaker this afternoon will be Ugur Koyluoglu of Mercer Oliver Wyman. Ugur will be looking at credit risk portfolio management. Ugur is a director in Mercer Oliver Wyman's finance and risk practice area. He has worked with more than 100 banks, insurers, financial conglomerates and regulators in North America, Europe and emerging markets. He has contributed significantly to the development of the firm's intellectual capital but also to the financial services industry's intellectual capital in this area. He has written a number of papers, approximately 40 papers in journals alone. His most cited work, *Reconcilable Differences*, which was published in *Risk* magazine in October 1998, has information that has been incorporated into the development of Basel II's formula for minimum capital requirements.

**MR. RISHI KAPUR:** You might wonder what a market risk guy is doing talking about credit risk. The credit world and the market world are combining into one. As credit risk becomes more of a traded risk in the financial markets, the methodologies and metrics used to identify, measure and manage that risk are becoming very similar to the way equity, interest rate and foreign exchange risks have traditionally been measured. That is why I spend a lot of time focusing on the quantitative credit risk side. Essentially the only thing that is considered pure credit

risk these days is fundamental credit analysis and providing ratings to individual counterparties. Everything else has converged into one big financial market risk area.

As mentioned earlier, I am going to talk briefly about the sources of credit risk that occur in Swiss Re. Some of you might be amazed at the wide variety of sources of credit risk that occurs in the organization. I will talk briefly about how we try to define the exposures. The other participants are going to talk a lot about modeling, but before they do that, we can focus on the basic groundwork of figuring out what your exposure is to individual counterparties. This is the foundation that you need to get right before you move into the modeling aspects.

Kapur slide 3 defines credit risk. There are two things I would like to focus on here. The first is economic value in the second bullet point. We look at credit risk, not just from a perspective of whether somebody is not able to pay their obligations, but also how the economic values of our positions change. For example, perceived changes in credit quality of a counterparty is a big factor to us, even though the counterparty may be fairly top-notch. The other point I would like you to focus on is that in Swiss Re, a lot of the credit risk actually occurs as a byproduct of taking other risks. Sometimes we take credit risk for the sake of taking credit risk. Other times we take credit risk embedded within our insurance products. The challenging aspect is that the identification of credit risk frequently has to be done by people who are not credit risk professionals. Our insurance underwriters have to look at deals to be able to identify whether there may be some credit risk and then get the right people involved.

Kapur slide 4 details the sources of credit risk within Swiss Re. It is a pretty comprehensive and large list of how Swiss Re sources credit risk from across the globe. On the life reinsurance business, some of the biggest credit risks arise from corporate bonds, which are in the second part of point 5 under "funded credit." It shows that while corporate bonds can be a big credit risk, for us they are a fairly small portion of the overall credit risk. Some of the toughest sources of credit risk that we have to deal with are in the credit derivatives area. We have some very traditional forms of taking credit risk—trade credit, surety business—but some of the places where we spend the most amount of time are collateralized debt obligations (CDOs), CDOs of CDOs, CDOs of CDOs of CDOs and it never really ends. I will talk a little about how we look at risk for those areas. Somehow, at the end of the day, we have to combine the credit risk coming from the CDO<sup>n</sup> products with those traditional trade credit products in one aggregate framework for modeling purposes. That remains a big challenge for us.

I divided some of the credit measures that we use into two categories for ease of understanding. I will go through some of them in more detail later. We have what are known as transactional issuer-based exposure methods. These are methods that we use to track how much exposure we have to an individual counterparty or how much credit exposure is coming from a particular transaction for pricing

purposes. These methods are not very useful. These methods could be used in a portfolio context as well, but they tend to be more bottom-up additive measures.

Then there are the portfolio-based methods, which come out of the portfolio modeling that is done. An example is credit value at risk, which is just a credit version of the financial market value at risk. Another example is shortfall, which is also known as conditional tail expectation. We do a lot of stress tests for credit. We would look at what happens if credit spreads were to widen (as they did in the fall of 1998, for example) and what the impact would be on our portfolio.

There are also a couple of other things that are relatively new, called basis risk and implied correlation risk. I will not go into that in too much detail, but they are coming out of some highly structured credit products like the CDOs. These are risks that are typically not in linear products, like corporate bonds. This is, again, more of an emerging area of credit risk, and we do spend a lot of time on developing those risk measures and getting a handle on how much credit risk these products are contributing.

Kapur slide 6 has some definitions. The first one, the potential credit exposure (PCE), is used for credit limits. What is the worst that could happen? What is the worst amount that we could lose for a particular counterparty, assuming everything goes wrong? Often this number tends to be extremely large, but this is currently what we use in order to allocate limits to counterparties to see how much credit risk we are willing to take from them. We would not necessarily manage to that number, but that is a number that we track, and ultimately that is the number that goes to senior management. We also have things like net credit exposure (NCE) and estimated credit exposure (ECE). The ECE is the number that we use for modeling purposes. It is our best-guess estimate of how much outstanding credit exposure we would have to a counterparty.

I will give some examples later as to how these three measures relate to each other. Sometimes they are the same. Sometimes they are quite different, depending on the nature of the underlying product. The ECE then goes into our portfolio modeling. It is important to note that that ECE number is not weighted by probabilities of default. A recovery rate is just an estimated exposure that we would have to a particular counterparty.

We have also been looking at things like maximum anticipated credit exposure (MACE). One of the problems is that on some of our products (e.g. certain kinds of derivatives), in theory, there is an unlimited amount of credit exposure we have to a counterparty. Now that may be a scary concept to some (that we do not know how much a counterparty may owe us), but it is the nature of the business that we do. So, what we have chosen to do is to look at, say, a 90<sup>th</sup>-percentile confidence level to decide how much exposure we would have to a counterparty and set some limits according to that. It is a relatively new measure with which we are working,

but it is designed to get around some of the limitations of products where there is, in theory, unlimited amounts that a counterparty could owe us.

Next on the list is value on default (VoD). Again, this is mostly applicable to CDOs. If a particular counterparty were to default, how much would we lose? Either we would have to pay some money out, or the mark to market of the remaining transactions that we hold would change. The sum of those two changes is called VoD risk.

The one item on the list that with which you should be quite familiar is essentially the credit equivalent of interest rate risk (CRO1s). This asks, if credit spreads were to change by one basis point, what will be the impact?

These are some of the tools that we use to manage and track our exposure on individual transactions to our counterparties. Different people in the organization will use different features. Some of the larger exposure numbers, like PCE, NCE and ECE, are used by the portfolio modelers. The traders on the front desk will tend to use things like CRO1s and VoDs because it is a mark to market change, and that is what they are concerned about on a day-to-day basis. Traders especially use CRO1s and VoDs to hedge the exposure that we have to a specific counterparty.

Again, the implied correlation and basis risk are related to each other in the sense that recently there have been a lot of credit index-based products that are traded in the market. So, a lot of times when you have credit exposures, you go out in the market, and you hedge. It's almost like hedging your equity exposure with the Standard & Poor's (S&P) 500. It's just a credit version of it, and, of course, that creates things like basis risk between your actual portfolio and the market indices. This is a key concern for us because we want to make sure that even if our portfolio appears hedged on an overall basis, that we are actually taking into account this basis risk, because this basis risk does vary over time. Especially when you're focused in a mark to market environment as opposed to an amortized environment, changes in this basis do affect you on a day-to-day basis.

Next I will discuss the difference between PCE, ECE and losses (Kapur slide 9). There is no NCE here because it is the same thing. For corporate bonds and loans, the PCE and the ECE are the same. You have lent somebody \$100; you have a \$100 bond. The maximum they could owe you is \$100. On an estimated basis as well, the potential exposure is \$100, but so is the estimated exposure. It does not move up or down unless the bond has some sort of an amortizing notional. There is not that much difference between PCE and ECE, but that is how the PCE and ECE end up relating to the losses. This is typically the case for linear instruments.

Let us move to the trade credit risk, which arises when people export goods. They go to their local bank and take that receivable, and they get the money back from the local bank. The local bank ends up collecting the money from the foreign bank, and the foreign bank's client is the actual counterparty to whom you exported your

goods. So, you export goods to somebody in another country, but you get money from your local bank. There is some credit risk there between the banks and a credit risk between the foreign bank and the foreign buyer of the goods.

PCE is, in theory, the maximum amount we could lose to a particular counterparty, but then you tend to have what is known as "retention of policyholders." So, essentially the policyholder or the bank tends to take a first layer of the loss. That ends up reducing our exposure. We track that as the net credit exposure (NCE). Further to that, even though we allocate a certain limit to a particular counterparty, the actual usage of limit is a function of how much has been exported to a particular buyer, and, therefore, it is not always the full amount. Historical usage patterns are used to estimate the amount of the limit that is actually taken at any given point in time. ECE is based on usage factors and on retention of the policyholders. The ECE number is used for modeling purposes. In cases of default, you may have some recoveries, and then you have some losses.

Kapur slide 11 summarizes the various kinds of exposures that we have (on the top) and the kind of metrics that we use (on the side). You will see that the simplest ones to deal with are the trade credit business, the financial guarantee business and the contingent capital counterparty risk business. When you start moving into traded instruments, which are either on a funded (e.g. corporate bonds) or an unfunded (e.g. simple credit default swaps) basis, you tend to look at things like CRO1s or deltas—basically sensitivities to individual names. If spreads were to move by one basis point, what would be the impact? We're in a market environment. These are not buy-and-hold instruments, so you have to worry about these things.

The most complicated tends to be credit risk coming from a portfolio of credit names. The products might be funded or unfunded. In these situations, you have to move beyond traditional measures and move to things like VODs, the correlation risk and basis risk. For those of you who are somewhat familiar with the equity market, there is a concept of a delta and a gamma, which are first-order and second-order market risks. The CRO1s are essentially a first-order market risk in the credit world, and the VODs are essentially a second-order market risk in the credit world. You can see now how the terminology from the traditional financial markets area is percolating into the credit world. You are looking at these concepts that you are very used to dealing with in financial markets, but applying them to credit just creates its own set of complications.

That is essentially how we track our exposures. Now I will pass it on to Perry to talk about some of the modeling issues and how we end up using these exposures to get a better sense of capital that we need to allocate to business.

**MR. PERRY D. MEHTA:** Tony and my colleague, Peter Davis, were kind enough to send me the other presentations over the weekend. When I looked at them, I could

place my own ideas in context. I will delve into somewhat more detail relative to Rishi's material, and I believe Ugur will explore some concepts even further. Rishi's presentation has provided an excellent overview of some of the key exposure metrics. I will explore them further within our time constraints. You can view this as a 30,000-foot flyover with the occasional deep dive into some interesting areas.

My background, as Tony outlined in the beginning, is more in the commercial banking world, but I have become very involved with the broker-dealer and insurance worlds since I joined Ernst & Young. I have noticed that, as Rishi rightly pointed out, a lot of these risks, whether they're market or credit, are being unified, in that the metrics and approaches to addressing them are very similar. Even though a lot of what I say will resonate for those of you who have backgrounds in commercial banking, I will also relate how it is relevant to the broker-dealer world, to the insurance world and, for that matter, for all financial institutions.

My goal is to look at the key parameters that have evolved in these converging methodologies on portfolio credit risk. The three that I am going to focus on—probability of default (PD), loss given default (LGD) and exposure at default (EAD)—are also three key inputs into the brave new world of regulatory capital modeling for commercial banks. For those of you who are familiar with Basel II, the big new proposal with which your banking affiliates are grappling, these are three of the four key parameters that go into the capital calculation. Getting to those parameters is a preliminary challenge in itself, and that's what I am going to talk about. Also, I would like to share along the way what I have learned from my regulatory days and through Ernst & Young on what the current practices are in the financial world.

Rishi outlined a set of exposure types. I think I have some of the same ones, but I have grouped them slightly differently (Mehta slide 1, page 2). I have investments and on balance sheet credit extensions, what you might call the direct credit on the left side, and then contingent and counterparty exposures on the right. There are reasons for grouping them the way I have done here. Let me talk briefly about this grouping. The very first set of exposures are on-balance-sheet investments. Typically what you're likely to see in your firms in the insurance industry include these categories, which are by no means complete. One of the things that the convergence in the financial services industry is going to lead to is concerns about a level playing field. Things that I might bring to your attention about regulatory capital requirements or economic capital methodologies in the banking and broker-dealer worlds may be something that you are interested in because they may influence your regulatory capital requirements, too.

The first thing that strikes someone with a banking background like mine when they see on-balance-sheet investments is that they are very unlike traditional direct credit—originated loans, for instance—in that typically they're on the trading book, not the banking book, and they are subject to value-at-risk-type methodologies. You do a distribution of losses and take a percentile—say, the 99<sup>th</sup>—that you want

to have your confidence level at and decide you'll hold as much capital as will be enough to cover losses 99 percent of the time (or whatever the desired percentile is). That percentile may come from a certain capital coverage goal. It may come from a rating agency objective, desired rating, etc.

But when something is in the trading book, it is subject to one set of management approaches where value at risk, market risk management, is a very common measure, and they have to have certain characteristics to qualify for this approach to management. One of the key things there is that they have to be actively traded and marked to market, frequently. You do not see that happen a whole lot with direct credit extensions, certainly not in the banking world. Right now this simple concept—trading book versus banking book, the set of requirements that qualifies you for one over the other—is a subject of considerable discussion with some of our clients.

There are a lot of institutions attempting to make that separation. The reason is that there is a perception, probably largely true, that there are two benefits to the trading book. The first is that you hold less capital, which might seem strange because in the trading book you're holding capital for deterioration in quality not just default, whereas the perception is that for originated credits you're holding capital only for default. Second, some of the control requirements relating to validation and documentation are far more onerous in the banking book world than they are in the trading book world. This is one big distinction. What I'm going to focus on with PDs, LGDs and EADs is certainly most applicable to the banking book but, as I will point out a little later, is being contemplated for trading-book-managed exposures as well.

Counterparty exposures, again, arise mostly with things that are on the trading book—over-the-counter derivatives—but you still have some commonality in the credit risk measures with the traditional banking book. Credit risk measures are used for setting exposure limits, estimating credit loss reserves, pricing extensions of credit, allocating capital and measuring performance. I believe that most of you have a great familiarity with them. Likewise, the benefits of credit risk modeling are more sensitive capital allocation, more forward-looking reserves, pricing that is actually more aligned with risk and, finally, performance measures.

I would like to emphasize the notion that risk is for unexpected losses and not for expected losses. A few years ago, when I was outlining the then-new notions of economic capital and Basel II-based regulatory capital, this is a picture I presented to my regulatory colleagues (Mehta slide 1, page 4). It's a set of charge-offs over time at two banks. We will call them A and B. I would ask the audience the question: Which one has more credit risk? Many of them would choose Firm B because it has bigger charge-offs for the most part. When you look at the most recent trend in charge-offs, there is a slight decline in recent years with Firm A. But when you calculate economic capital against them you find, all else being the same, that Firm A actually has more credit risk economic capital. Why is that? What is it



about these two charge-off pictures that suggests that Firm A has more risk even though it has lower levels of losses? The key point here is that risk is not associated with the level of loss—that is the expected loss, or the predictable component of loss, you hold reserves against it—but capital is held against the unexpected component of loss.

The greater the variability around losses, the greater is the required capital. A distinction needs to be made here between level and volatility, and here we simply have another way of presenting the same notion. Mehta slide 2, page 5 shows two loss distributions. We'll call them two different firms—C and D. They both have the same mean (that's the thin vertical line), but one is clearly more spread out and has a fatter tail than the other. Firm D clearly will require more capital.

Mehta slide 2, page 6 is a picture of what really underlies our notion of capital. Just as I had outlined for market risk, you can have a value-at-risk for credit. Imagine that this is a distribution of credit losses; that's the curve there. I have taken a couple of percentile points. There is the 99.9<sup>th</sup> percentile. This is what regulatory capital will be set to for commercial banks. Many institutions for internal capital measures will use a stricter percentile measure. The 99.97<sup>th</sup> percentile seems to correspond (at least in recent years) to the AA rating—three-basis point default rate. The key takeaway here is that when you take a loss distribution, reserves are meant to cover expected losses. Capital is meant to cover the variability, the "spread-outness" of those losses.

Mehta slide 1, page 7 shows a couple of notes from the Basel II guidance for banks and the "consolidated supervised entity" (CSE) for broker-dealers published by the SEC. Both of them reinforce a couple of things. The first point here is that, under Basel, insurance subsidiaries of banking entities bear the full entrepreneurial risks, and they should be considered in the group-wide accounting of risks. Banks with insurance affiliates could well be subject, under level-playing-field rules, to some of the same guidelines. Insurance companies will be subject to the same guidelines that banks are. What the CSE guidance says (there are about 60 references to the Basel rules) is that broker-dealers will also be subject to the same capital rules that banks are. In other words, it is probably appropriate to expect that regulatory requirements for banks, insurance companies and broker-dealers will converge over time, to the extent that they address similar types of exposures.

These are the three measures on which we're going to spend some time. PDs are also known as expected default frequency (EDF), a notion that came out of Moody's KMV (MKMV). They essentially mean the same thing, although how they are measured varies. LGD, loss in the event of default and severity all mean the same thing. EAD and loss equivalent exposure (LEE) are sometimes measured as a usage amount of an unfunded commitment. So, there is a contingent exposure out there, like a \$100 line of credit, of which \$20 is drawn. How much do you expect of the remaining \$80 to be drawn until a default occurs or over the next year, whichever is earlier? That is your measure of usage, which leads to an EAD.

How do banks essentially get at PDs? Mehta slide 1, page 8 shows a couple of mappings that we have seen. The first one is from a bank; the second one is from an insurance affiliate. The first one is based on a derivation of internal ratings for all credit exposures. I am not going to go into methodologies for internal rating, but one approach certainly is to look at an external agency rating like you see on the right side and map it to an internal rating. The external agency ratings have default histories. You can take average actual default frequencies for each of those to arrive at a PD measure, but there are a lot of issues surrounding this seemingly straightforward calculation of a PD. The first arises when you use a reference data source to drive your PDs. For instance, if you are using agency ratings, your reference data source is composed of all of those bonds or loans or credits that are rated by their agency. How similar are the bonds and loans in that reference data set and your own exposures? Your population may be quite different. One thing is that your definition of default might differ from that of the rating agency. Are you making adjustments for it, either in the rating assignment or in translating the rating to a PD?

With some of the modeling that we confront for portfolio credit risk are conceptually simple issues such as this one (the similarity of the reference data set to your own exposures). I will talk about some other issues relating to internal controls and validation, but they are all very run-of-the-mill, not rocket-scientist-type issues for the most part. Another has to do with your definition of default. When we are talking about default definition, we have to mention what Basel II has. One of the things in Basel II is the so-called "silent" default. What happens when you have a credit exposure that's collateralized, the obligor doesn't pay and goes into default (at least technical default)? You liquidate the collateral and are able to cover your outstanding without any loss whatsoever. Would you record that as a default, and would you record the liquidation value of the collateral as a recovery in your firm? Well, if the answer is no, you have a lot of company. Unhappily, that goes fundamentally against the regulation. The regulation says that when the obligor doesn't pay, that is a default. You have to count it as a default, and you have to measure your default frequencies accordingly. That will change your estimate of PD. Likewise, the dollars you get back from liquidating the collateral have to be considered recovery. That will influence your estimates of LGD. Definitions do matter a lot.

Here is another key regulatory requirement that is a major challenge for just about every single one of our clients. This is an example right out of an insurance affiliate. It has bonds by a certain obligor that are officially in default, selling 20 cents on the dollar. That same obligor has an originated credit with a banking affiliate. The regulation requires that that second obligation, that loan with the banking affiliate, be considered as having defaulted. It does not happen, because they have different IDs. They are booked in different systems. Then it is hard to unify some of these data elements. It is really complex to deal with this seemingly simple-sounding challenge. For anybody who has dealt with legacy systems and merged companies, I think you know exactly what we're talking about here.

The regulation for banks, again, requires a long-term-average measure of a PD, long-term-average or unconditional or a through-the-cycle measure, as opposed to something that is cyclical or conditional or point-in-time. Having a long-term measure certainly helps in having a stable value for your capital. If the PD for a given credit exposure is changing frequently, then your capital requirement against that credit will also be extremely volatile, and that is undesirable. That can exacerbate credit cycles. Just when the economy is tanking, your credit requirement blows up at precisely the time that you do not want it to, making the credit cycle dip even worse. So, one understands the need for a more stable PD measure for economic capital or for regulatory capital purposes. But imagine an institution that takes that pro forma economic capital measure and uses it to price credit—set the interest rate on loans, for instance. Will you want a long-term stable measure there? When the economy is booming and everybody else is lowering the rates they charge their AA and A customers, do you want to hold your rates at the same level? When the economy is tanking and everybody else is tightening credit and raising rates, do you want to hold rates at the same level you did during a booming economy? The concern is that what you would use for internal pricing and internal management purposes probably needs to be different and more sensitive to economic cycles than the measures for economic capital.

Is there anything wrong with using multiple approaches like this? The difficulty comes through the Use Test. The regulators not only specify a long-term-average measure, they also have the Use Test, which says: do not just calculate this for capital purposes; we want to see you use these measures in internal management in your actual day-to-day processing.

Let me go on to some of the key issues surrounding LGD. I will quickly outline one or two key issues with exposure default. There are definitional issues. Clearly, with LGD, the definition of default matters. If you have restructured credit at a substantial credit loss, the regulators say that you have to call that a default and the amount of charge you take will be a loss. The restructured loan will be a completely new loan. These loss amounts will influence your LGD estimates.

Additionally, the loss has to be a true economic loss, not a mere accounting artifact. What does that mean? That has to include direct and indirect costs associated with working out a defaulted credit. You would have administrative expenses, legal expenses and overheads. I've not seen a lot of institutions that are able to allocate these costs credit by credit. Many institutions are able to aggregate them across business lines, but that's not enough. They have to be allocated to each single individual credit for which you're holding capital.

Let's talk about the discount rate for recovery cash flows. First of all, even the data on recovery cash flows for many financial entities is a challenge. When a credit defaults or is in distress, it typically goes into a workout group, a special assets group (SAG). Those folks do not have any incentive to retain recovery data. Their goal is to squeeze the last possible dollar they can from the exposure. Their goal is

not data maintenance. Recovery data is going to be a key challenge, let alone time-stamped recovery data, because what you are expected to do with this recovery information, especially if you have multiple cash flows coming from the obligor during workout, is to discount them to a present value.

One of the biggest, hottest discussions that I have had in my regulatory tenure was: What is the appropriate discount rate for those recovery cash flows? Should it be the original rate on the loan? That rate reflected a certain amount of risk, but now that credit has defaulted. Isn't the amount of risk a little different now? Well, is the amount of risk more or less? Basel demands that whatever rate you use cannot be less than the rate you would charge to an equivalent customer to originate a similar kind of credit, but what if your belief was that those recovery cash flows have a degree of certainty that exceeds the degree of certainty associated with the original cash flows? Shouldn't the rate be less? This is a big discussion point, but as far as actual practice is concerned, it's a major challenge just getting at the recovery cash flow data.

For LGDs, whether it is bonds or originated credits (this is truer actually of originated credits), if you look at a distribution in a given risk category, it tends to be bimodal. LGDs are either very, very low—usually when there's a large amount of collateral, e.g., with secured credit—or very, very high for the entirely unsecured credits. Any time you apply an average to something that is bimodally distributed, you know that the actual realization of the LGD is never going to be the mean that you took. Most often it is either very high or very low; it's never in the middle. How do you address this problem? It's a clear sign that the volatility in the LGD distribution needs to be considered.

Every time we have looked at exposure methodologies or usage methodologies with our clients, they quote the two standard studies: Asarnow and Marker, who did a study at Citibank, published in 1995; and Araten and Jacobs at Chase, who did a study of exposures. They had similar results. They both found that the key determinant of how much usage you can expect to see right before default is the obligor's credit rating. They found that there is a very tight distribution of the usage amounts, ranging from just slightly over 40 percent to just slightly over 65 percent. Both of these studies found the same thing. There's an inverse relationship between credit risk and usage. The better credits actually have the higher usage, and the rationale for this is that the poorer credits are more strongly monitored and restricted in the amount of usage they have when they are near distress. Very few entities that we know have attempted to look at other sources of risk and other drivers of usage.

There have been attempts to correlate these with product type, geography and industry, but there simply isn't enough data. Data is one of the biggest issues in large-scale portfolio credit-risk modeling. With PDs it is hard enough not having enough defaults, but at least with a PD calculation, your universe is all of your credits. The denominator, if you will, is the total number of credits you have. The

numerator is the number of defaulted credits within a given segment, risk, bucket, industry or whatever your desired segmentation is. With LGD or EAD, the denominator is the number of defaulted credits. An even smaller universe makes data gathering an even bigger challenge.

Validation is another big one. How can you back-test something where you have already pointed out you expect three chances out of 10,000 of failure? So, every 10,000 years we'll see three chances of failure for a given bank. That is an exceedingly long time horizon, certainly much longer than you would have for market risk where you have variability in days as opposed to years and insufficient actual default data to do any kind of back-testing. So, regulators permit additional types of validation (e.g., developmental evidence, benchmarking).

The correlation of default occurrence with loss magnitude is an area where there is an increasing amount of research. When defaults are high, the amount of losses associated with those defaults is also high. We don't see much modeling, at least in our clients, of this issue. What we have seen is approximate, "back-of-the-envelope" approaches to addressing this correlation.

I would like to stop here and recap three key inputs into any kind of portfolio credit risk model—PD, LGD and EAD. (Basel also specifies a fourth, effective maturity). Modeling them you certainly will see a lot of technical issues, rocket-scientist-type issues. I know Ugur is going to talk about a few of those, but very many of the concerns and challenges that are associated with modeling are run-of-the-mill issues relating to data availability, data cleanliness and ability to back-test. With that, I would like to pass it on to Ugur for a more technical discussion on modeling.

**MR. UGUR KOYLUOGLU:** My presentation is going to focus on credit risk portfolio models, just portfolio modeling, part of credit risk quantification. I have been working on this very topic since 1997, and I had the chance to think about key problems and I wrote a couple of articles on this topic. Before I dive into credit risk portfolio modeling concepts, I want to know whether you ever use a credit risk portfolio model or you have ever tried to or develop or have implemented credit risk portfolio models. If you can, just let me know by raising your hands. Then I can pace my presentation and go deeper into the technical matters.

Both Rishi and Perry gave great introductions to key topics in credit risk quantification. Koyluoglu slide 3 sort of summarizes all of them and also explains what I am going to focus on hereafter. If you think about it, the industry standard approach is basically a frequency, severity and correlation approach. You want to know what the likelihood of default is at a given time horizon. It could be one year, five years or whatever. That is usually calibrated based on rating agency experience, internal data or vendor models (MKMV's Credit Monitor, RiskCalc, etc.). LGD is another one that is difficult to deal with, but there is also publicly available information from rating agencies for the products that you buy and sell on the investment side to calibrate LGD as well.

Exposure-at-default (EAD) is difficult to quantify for some products, but then you think about the corporate bond portfolios, all the mortgage-backed, asset-backed, etc., you know your marked-to-market, hence EAD if things go bad right now. So, although coming up with a perfect answer that you are fully comfortable with in these three dimensions is difficult, it is achievable. There are several institutions that have achieved it and put these in place on the insurance world. The part that I am going to focus on is the portfolio dynamics. How do we bring in the correlations across our obligors? Let these be different bonds or different industries, different geographies, different countries: How can we bring them together so that we can get the cumulative loss or change in value distribution? I am going to focus on loss only. Although credit migration and value distribution are very important, especially for a life insurance portfolio, due to time limitations I'll just talk about losses driven by default.

Portfolio models allow us to calculate credit value at risk, economic capital and diversification benefits. These are just some of the key outputs of such models. You will get all sorts of additional statistical information. In this example (Koyluoglu slide 4), I picked up a portfolio with very high concentrations backing up a product. Because of these concentrations, the portfolio distribution is not smooth. We see all these concentrations in the form of jumps in the distribution. This is the cumulative loss for this sub-portfolio on the horizontal axis, and the probability density is drawn in the graphics. Obviously you get more output from the portfolio model, and you can talk about the averages, standard deviations and any confidence level or any other risk metric from that output.

Once we have that information, this could be used for identifying risk concentrations. Then you might say, "Hey, look, if I really close this exposure, and, instead of having too much of such-and-such bonds, if I just diversify it across industries, perhaps I need to hold less risk capital." The information that you have can also be used for limit setting, asset selection and strategic steering of the portfolio. You can reflect this approach into industry evaluation, rich-cheap analysis for bonds. You can also apply these findings for better pricing.

I am sure you are familiar with these topics. Let me walk you through the correlation modeling part (Koyluoglu slide 6). This is interesting because there isn't one way of doing it. The people who have been using credit risk portfolio models probably have gone through a model selection process. A model selection process is a little different from vendor selection because different vendors provide different models coming from different schools. I have tried to group them into three in this table. The first of these three approaches is a micro-economic approach coming from a Merton model. The Merton model assumes that a firm would default when the value of assets is less than the value of its liabilities. So, it is really a micro approach. We need to think about it firm by firm and the correlations across different firms in this model.

The second one is more econometric. It is also cause for default, but the cause is not linked to an individual firm. Rather, it is pegged through macroeconomy. Here the default rate is explained by macroeconomic indicators. These could be gross domestic product (GDP), unemployment rate, monetary policy or equity-indexed returns.

The last one is more actuarial. You do not care about the reason for default. All you care about are the statistics of default. From the statistics of default we look at the implied correlations in the data and incorporate that into modeling.

Back in 1997, these three models were seen as competing alternatives in the banking industry. There were a couple of studies in 1998, revealing that these models are reconcilable. One such study is a paper I have co-authored. It is entitled "A Generalized Framework for Credit Risk Portfolio Models." The paper shows that although these modeling techniques are very different, the differences can be reconcilable under a generalized framework. I am going to walk you through the ideas behind that.

The first model, micro view, needs asset correlation between any two companies in your corporate bond portfolio. In the second one, you need the regressions to market economy so that you can forecast the future default rate environment for different ratings. In the last one, you need a default rate and the default rate volatility for each of those ratings, so that we can put the correlation into the framework. If you have MKMV PortfolioManager in place, you are basically following a Merton-based approach. RiskMetrics' CreditManager does the same thing, more or less. Algorithmics PC-RE does this. If you go to CreditSuisse First Boston's Web site, you can download CreditRisk+ free of charge, and that is the actuarial model. All of these models in practice have their own pros and cons, and they are coming from different sciences. The first one is from finance. It is sort of developed by Stanford professors and Stanford Ph.D.s. The second one is econometrics. The last one is actuarial, applying a simple finding from the casualty actuarial discipline.

The question for you is: Which one works best for your portfolio or application? Most life insurers follow the first approach, Merton-based. However, say you have time and could have your hands on multiple models even within the same sort of group. If you run different models for the same portfolio, you might be puzzled with the output because the results are different. The differences in results obviously make different recommendations about credit risk management.

Let us put the results of three models on a slide for illustration (Koyluoglu slide 7). The question is: Do we have enough capital for our portfolio of risks? Model A says, yes, we have enough capital. This is available capital minus economic capital, and the first model says that we are significantly over-capitalized. The second one says that we are under-capitalized. The third one says that we are modestly over-capitalized. Then we look at loan level. Does this loan or does this bond concentrate my portfolio or diversify my portfolio, compared to the average? One says that it is

about the average. The other one says that it is concentrating. The third one says that it is diversifying. Which one is telling me the truth? I'm making decisions. If you are on the investment side, you buy and sell these things. If you are a loan officer on the credit lending side, these are important questions to address. What is driving the differences? How can we build comfort around the results? What is the sensitivity of results with respect to parameters or methodological assumptions? I have seen industry practitioners dealing with these key questions.

Let us step back and divide the problem into pieces. The main question is: What is driving the differences in the results? I am going to have three sets of pieces of that question. Is it the underlying methodologies? Instead of MKMV's PortfolioManager, if I use CreditRisk+, will I get the same results, or are they really very different? One uses asset correlations; the other one uses default data. The answer to that is that the differences can be reconcilable, indeed, and the math is in the paper. There are other studies backing that up as well. For example, there are papers by Michael Gordy and Chris Finger. It is not really the methodologies in general. Obviously there are some specific parts that are different in these models, but it is not the basic methodology that is driving the differences.

The difference is in the parameters. I am not talking about PD, LGD and EAD. The results will be different even if you put the same PD, LGD and EAD into the models. I am talking about the correlation parameters, and these are difficult to quantify. Because they are difficult to quantify, there is some uncertainty around it, and traders have realized that uncertainty. Correlation is being traded now in the market as long and short due to just that uncertainty.

How about detailed assumptions? Obviously detailed assumptions are important, and they might affect results. We are going to look at some of the detailed assumptions. While the methodological parts can be reconciled by math, the parameter problems and the model assumptions are, in my opinion, eternal issues. The other paper on the table outside is a survey of these "eternal challenges."

Let us look at the reconciliation. It is not that complicated. These models have three components. One of them is the joint default behavior, correlation modeling. The other one is the solution in which all bonds are treated as if they are independent. The last one is a sort of convolution, or aggregation, and pulls all of these together.

If you look at Merton-based models, MKMV or RiskMetrics, you will realize that if all obligors, if all corporate bond issues are independent, for a homogeneous portfolio we would have ended up with a binomial distribution. The aggregation is usually done in these models by using Monte Carlo simulation. If you look at the actuarial approach, CreditRisk+, for the independent default behavior case, they use a Poisson distribution. In terms of aggregation, they use a sort of closed form solution. Poisson and binomial distributions are limiting distributions to each other when the default rate is small and we have a large number of obligors. That is our



case. There is no difference in terms of the second component. In terms of the third component, there are also no differences. We can aggregate using simulation, or, if you have a closed form solution, you just use a closed form solution. Basically, in the actuarial approach, in CreditRisk+, you take the Poisson distribution and let it go through a gamma kernel. Hence you end up with negative binomial, an analytically closed solution. It is that simple.

If there are conceptual differences in terms of components, it is in the first part—how you put the correlation into the framework. The first one uses asset correlations, the second one uses regressions to macroeconomy and the third one uses default rate volatility.

Koyluoglu slide 11 was the slide that we used to explain the reconciliation back then, and it founded a lot of applications. For example, Basel II's formula can be linked to this chart. Leaving the crowded part of the graph aside, let's look inside of the x and y axes. Here, x-axis is my economy. To the right is good economy. To the left is bad economy. The y-axis is conditional default rate. In a good economy we have small default rate, and in a bad economy, we have high default rate. The transformation function just links these two to each other. You don't need to be a rocket scientist to think about the inside. We accept that there exists this monotonously decaying relationship in between default rate and macro economy.

The econometric approach directly models this. It says that all right, I have the default rate information, now I can really define and observe macroeconomy by using some indicators, and why don't I do the regression and come up with this transformation function? A logistic curve is usually chosen for the regression.

In terms of the actuarial approach, there is no transformation function because it doesn't care why there is default. It immediately starts from the default rate distribution. If you believe that there is a relationship in between conditional default rate and macroeconomy, if the x-axis is random because x and y are tied through your transformation function, then y-axis is also random. They imply each other whenever you have a transformation function or a regression and random macroeconomy. Macro view then implies that you have a default rate distribution in your analysis, or actuarial view implies that there is a transformation function. This is the reconciliation in between those two (Koyluoglu slide 12), and the Merton-based approach can also be reconciled to this framework, as explained in the paper "A Generalized Framework for Credit Risk Portfolio Models."

When you harmonize the parameters of these modeling approaches, you end up with pretty much the same thing. The graphic on the far lower right really shows you what I was showing a page ago for Merton-based approach, econometric approach or actuarial approach. That shows that as the economy gets favorable, to the right, you will have less default, and you can see that. This relationship also implies a default rate distribution, and all of them, as you can see, are highly skewed distributions. This example is based on Moody's average default rates. The

average default rate is about 110 basis points with volatility and is 90 basis points in this example. To do this, we just harmonized the parameters. You can start from Merton framework. You can start from default rates. You can start with macroeconomy. You can come up with the parameters in each of the different paradigms. This finding is a big relief, and, if you're thinking about banking industry's acceptance of these models, it is somewhat resting on that relief.

However, if you are a naïve user of these models, even with the same PD, LGD and EAD, you will end up with different results. This was studied in the other paper, "Devil in the Parameters." In this table (Koyluoglu slide 14), we look at results from CreditManager, PortfolioManager and CreditRisk+. The left table is a high credit quality portfolio; say that this is investment grade portfolio. The right table is a low credit quality portfolio. As we have the same PD, LGD and EAD, we are ending up with the same expected loss, and the expected loss is only eight basis points of our exposure for the high credit quality portfolio. Unexpected loss is one standard deviation, and we found different results. Even when we use two Merton-based approaches, we end up with different results. When we look at economic capital (in this example it's defined at the 99.90<sup>th</sup> percentile), we have differences. These differences are pretty significant, especially the differences between CreditRisk+ and the others, which are larger. Likewise, when you look at the low credit quality portfolio, you see a similar set of results. If you are a single portfolio model user, you might be making some decisions that another portfolio model user with a different model would not make. Who is right then? In order to answer that question, you need to dig into what is really driving these differences.

In addition to looking at everything at the portfolio level, you can also look at things at the bond level. We defined a concentration indicator to analyze bond level results (Koyluoglu slide 15). If it is greater than zero, then this bond concentrates the portfolio. If it is less than zero, then it's diversifying the portfolio compared to average. Again, we ran PortfolioManager and CreditManager, and here are the results for all bonds of 360 exposures. The results indicate that the models have consensus for 80 percent of the portfolio. They agree that 70 of these bonds are concentrating the portfolio and 239 bonds are diversifying the portfolio. However, there is disagreement for the other 51 bonds; one model says that it's diversifying; the other one says that it is concentrating.

Now, if we then turn ourselves to look at the assumptions under the spotlight, we see weaknesses and differences. Perry emphasized a couple of them. I am just going to mention two of them due to limitation of time.

One of the weaknesses is that loss and default correlation are assumed to be the same thing. Loss and default are two different things. When you think about loss, you need to consider LGD and EAD. So, as your default rate changes, if the recovery rate changes (that's what you observe in junk bond markets), then there is a correlation between PD and recovery rate. There is a correlation between a PD and severity, which is 1 minus recovery rate. This is usually ignored in models. For

example, in PortfolioManager, there is no correlation between PD and LGD. Moreover, there is also systemic variation of LGD. So LGD of one default is sort of correlated to LGD of another one. This is also usually ignored in these vendor solutions. You need to consider those if you want to have a realistic model.

One of the important differences is how the parameters inside these tools are set. Let's consider CreditManager and PortfolioManager. These shouldn't be that different, but they are. Methodologically, they are coming from slightly different versions of the Merton-based model. Also, historically, KMV was one of the sponsors of CreditManager. However, there are a lot more details in the methodological assumptions. PortfolioManager comes with its own correlation structure as a black box. CreditManager of RiskMetrics has a by-default correlation structure; however, it also gives you the flexibility to play with the correlation structure. These correlation structures are different. It should be noted that CreditRisk+ comes as a totally open box and you need to come up with all the parameters.

In the quantification of the correlations in all of those, there is parameter risk. Unfortunately, on the banking side, the researchers and the practitioners have not yet paid enough attention to parameter risk, standard error concepts due to length of data, frequency of data, relevance of data, etc. as much as in property and casualty (P&C) and life. This is another weakness, and credit risk practitioners should pay attention to that.

Then there is the model risk. That is also typically ignored. There are all sorts of assumptions that come with a Merton-based approach. People might ignore model risk, and you might want to stress this.

If you look at these correlations, they change from time to time, and the timing is important. We have done some work to investigate this, and it is in the paper entitled "Eternal Challenges."

Based on all sorts of numerical studies, Basel II simplifies the correlation framework. For regulatory purposes, the asset correlation is bounded by 24 percent and decays with poorer rating and smaller size (Koyluoglu slide 19). In the calibration of this, as far as I know, because it's not that clearly documented, regulators have used MKMV's PortfolioManager. Different banks also contributed with various studies. This is the agreed correlation curve. But behind the curve is just Merton model and Merton model assumptions, with their weaknesses and strengths.

We wanted to calculate asset correlations from default data. We looked at the default rate volatility and then figured out the implied asset correlations, as in the way we reconciled the differences in methodology. When you look at the correlation in the default markets, you'll find out that the implied correlation in the default markets is much less than what anyone who uses the Merton model would say.

These numbers are all calibrated from Moody's data. What we found out is that for really good ratings, maybe it's not 24 percent; perhaps 20 percent is a more reasonable level. For sub-investment grade, maybe 12 percent is not really the minimum; perhaps we can go even lower to the 6 percent or 7 percent level. In short, default market data indicates that there is less correlation than the industry thinks.

The next thing that we introduce in our analysis is the parameter risk. The bar lines that you see are the results of our calculations as a result of Monte Carlo simulations of default rates, considering parameter uncertainty. As we looked at these uncertainty bounds, we see that the correlation level Basel II is reasonable. We expect regulation to be a little conservative, and this considers parameter risk in an embedded way.

Maybe I didn't do a good job of explaining this slide, but it is explained in detail in the paper. I tried to summarize about 50-60 pages of research. I hope that these will be the key takeaways for you. If you have already made a decision about your portfolio model and the vendor, that is fine. You shouldn't really question whether it was suitable for your portfolio or not, because all of these models are modeling the same thing but coming from different angles.

In general, this was just to deepen your understanding of what is going on and the underlying methodologies. However, if you have time for research, I think you should dedicate 90 percent of your time to the estimation of the parameters and doing all sorts of sensitivity tests around that. There are also parameter benchmarks on the banking side that you might want to use in the calibration of your model. If you are going to make very big decisions based on the outputs of these models, it's also worth it to look at some of the detailed assumptions for the model workings or for the parameters. As you look at these detailed assumptions, you will realize that there are some sensitivities that really need attention.