Credit Risk and Macroeconomic Dynamics

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Abstract

Credit risk is the dominant source of risk for commercial banks and the subject of strict regulatory oversight and policy debate. This paper provides an overview of the *conditional* credit risk modeling approach set out in detail in Pesaran, Schuermann, Treutler and Weiner (2003). Asset value changes of a credit (loan) portfolio are linked to a dynamic global macroeconometric model, allowing macro effects to be isolated from idiosyncratic shocks from the perspective of default (and hence loss). The approach can be used, for example, to compute the effects of a hypothetical negative equity price shock in South East Asia on the loss distribution of a credit portfolio held by a commercial bank over one or more quarters. It is shown that the effects of such shocks on expected default are asymmetric and non-proportional, reflecting the highly non-linear feature of the credit risk model. The proposed modeling approach has broad application potential in credit risk management and the pricing of risky assets such as credit derivatives.

1 Introduction

Credit risk is the dominant source of risk for commercial banks and the subject of strict regulatory oversight and policy debate (BIS (2001a,b)). Credit risk is typically defined as the risk of loss resulting from failure of obligors or borrowers to honor their payments. The business conditions of those borrowers are tied to the business cycle; in an expansion demand is strong, business is good; during a recession, keeping a business profitable is more challenging. So it should come as no surprise that the credit risk profile of a commercial bank is tied to the business cycle through its borrowers. Then why have U.S. banks been able to weather the current economic storm so well? Fifteen of the twenty largest U.S. bankruptcies since 1980 occurred in the last two years (BankruptcyData.com). Corporate bond defaults have seen record high and debt recoveries record low levels. Nevertheless U.S. banks are reporting strong profits and remain well capitalized. One

*Any views expressed represent those of the author only and not necessarily those of the Federal Reserve Bank of New York or the Federal Reserve System.

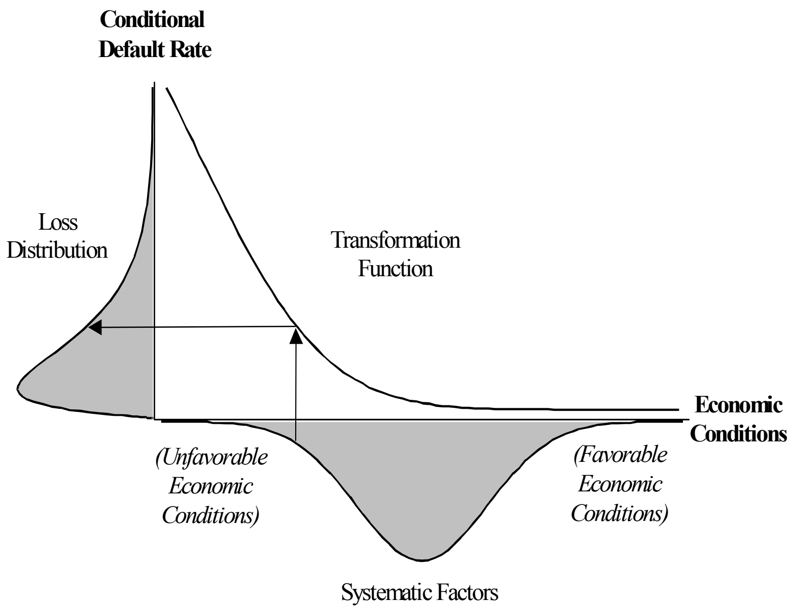

Figure 1: A General Framework for Credit Risk Models

answer may very well be: better (credit) risk management through the use of tools such as credit risk models and credit derivatives (Boland (2003)). Our focus will be on the former.

A bank's risk profile can be summarized through its loss distribution, i.e. the distribution of losses that may result in many different states of the world. Credit portfolio models aim to generate precisely that distribution, often through simulation, so that a bank may, among other things, set the level of capital it needs to hold to withstand losses to a certain degree of confidence, i.e. a tail region in the loss distribution.

Most credit portfolio models link the portfolio loss distribution to states of the world; they differ in how specifically they are linked (see Figure 1).[1] However, with only one exception this linkage is to a single, unobserved systematic risk factor. The basic idea of our approach, described in detail in Pesaran, Schuermann, Treutler and Weiner (2003) – hereafter PSTW – is to make this linkage more concrete. We will tie a bank's credit exposures to underlying international macroeconomic factors and thereby distinguish default (and loss) due to systematic versus idiosyncratic (or firm

[1] For detailed a comparison of the different credit risk models, see Koyluoglu and Hickman (1998), Gordy (2000), Saunders and Allen (2002) and Allen and Saunders (2002).

specific) shocks. Here we start with a simple problem: the development of a conditional loss model using only publicly traded firms. We make the probability of default, PD, a function of observable macroeconomic variables but keep loss given default, LGD, exogenous (yet random).

The first step in developing such a model is to build an economic engine reflective of the environment faced by an internationally active bank. This is done in Pesaran, Schuermann and Weiner (2003) – hereafter PSW – using recent advances in the analysis of cointegrating systems,[2] where we develop a global vector-autoregressive macroeconometric model (GVAR). Because of the integrated nature of the model, we can analyze how a shock to one specific macroeconomic variable affects other macroeconomic variables, even (and especially) across countries. The model allows for interaction amongst the different economies through three separate but interrelated channels:

1. Direct dependence of the relevant macro-factors on their region-specific foreign counterparts and their lagged values;

2. Dependence of the region-specific variables on common global exogenous variables such as oil prices and possibly other variables controlling for major global political events;

3. Non-zero contemporaneous dependence of shocks in region i on the shocks in region j, measured via the cross-region covariances.

Thus, for instance, we are able to account for inter-linkages between equity market movements in South East Asia and output in Germany.

We examine the credit risk of a fictitious corporate loan portfolio and its exposure to a wide range of risk factors in the global economy. In a simple Merton-type credit portfolio model, credit risk is modeled as a function of correlated equity returns of the obligor companies. These equity returns are linked to correlated macroeconomic variables using an approach structurally similar to the Arbitrage Pricing Theory (APT). Once we pin down the link between equity returns and macroeconomic variables, we derive the overall credit loss distribution of a sample portfolio through Monte Carlo simulation.

The plan for the remainder of the paper is as follows. Section 2 introduces a structural model of firm default and develops the conditional credit risk model. Section 3 presents empirical results of the 11-region GVAR model including the impact of shock scenarios on a credit portfolio, and Section 4 concludes.

[2] See especially Garratt, Lee, Pesaran and Shin (2001) and Pesaran and Shin (2002).

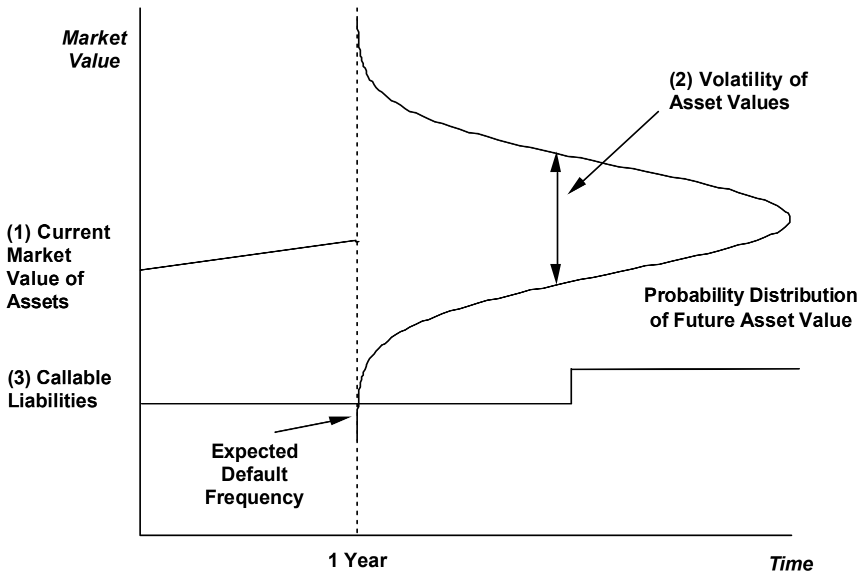

Figure 2: The Merton Asset-Based Model of Default

2 A Structural Model of Firm Default and Conditional Credit Risk

Our primary goal is to build up the loss distribution of the credit portfolio of a financial institution such as a bank, first unconditionally, and then with explicit conditioning on macroeconomic factors. The unconditional distribution is intended to be "business cycle-neutral" and provides a benchmark loss distribution which is applicable in the very long run and integrates out the differential effects of business cycle variations (boom, bust, expansion, recession, etc.) on losses.

Consider a simple structural approach to modeling changes in the credit quality of a firm. The basic premise is that the underlying asset value evolves over time (e.g. through a simple diffusion process), and that default is triggered by a drop in firm's asset value below the value of its callable liabilities. Following Merton (1974), the shareholders effectively hold a put option on the firm, while the debtholders hold a call option.[3] If the value of the firm falls below a certain threshold, the shareholders will put the firm to the debtholders. The concept is shown schematically in Figure 2.

[3] Through put-call parity, one could also conceptualize this as shareholders holding a call option on the firm's assets, while the debtholders' pay-off is isomorphic to writing a put option.

Thus there are two aspects which require modeling: (i) the firm's performance or return process, and (ii) the default threshold. Following an approach which is structurally similar to Ross's (1976) Arbitrage Pricing Theory (APT), a firm's change in value (or return) is assumed to be a function of changes in the underlying macroeconomic variables (the systematic component) and the firm-specific idiosyncratic shocks. In any given time period, the probability of default for firm j in region i will be correlated, through the influence of common macro effects (or systematic risk factors) in region i, and globally, with the probability of default of other firms in the bank's portfolio. However, not all macro factors will affect all firms in the same way.

We follow a typical adaptation of the Merton model by using asset returns and their volatility instead of total value of assets and their volatility. But since asset returns and their volatility are difficult to observe directly, we use equity returns and their volatility as proxies.[4]

We denote the return of firm j in region i over the period t to $t+1$ by $r_{ji,t+1}$ and assume that conditional on the information available at time t, Ω_t, it can be decomposed as

$$r_{ji,t+1} = \mu_{jit} + \xi_{ji,t+1}, \tag{1}$$

where μ_{jit} is the (forecastable) conditional mean, and $\xi_{ji,t+1}$ is the (non-forecastable) innovation component of the return process. Following the standard Merton model we shall assume that

$$\xi_{ji,t+1} \mid \Omega_t \sim N(0, \omega^2_{\xi,ji}). \tag{2}$$

The GVAR model provides the link between changes in macroeconomic variables (in region i and globally) in μ_{jit}. The expected or forecastable portion of firm return, μ_{jit}, is comprised of firm-specific fixed effects (i.e. the "alphas" in an APT context), effects of regional fixed and time trend effects, macroeconomic factor loadings, and the effects of the global exogenous variable (oil prices in our application).

The unexpected component, $\xi_{ji,t+1}$, is influenced by three different types of shocks: a firm's own shock, macroeconomic shocks, and the global exogenous shock. Note that although the firm in question operates in country/region i, its probability of default could be affected by macroeconomic shocks worldwide.

The main advantage of using the GVAR as a driver for a credit portfolio model is that it provides the (conditional) correlation structure among macroeconomic variables of the global economy. When generating loss distributions, this allows us to account for the state of business cycle and

[4] Arguably equity returns are even preferred since they allow for non-constant liabilities within the Merton framework.

the interdependencies that exist in the global economy in a relatively parsimonious and internally consistent manner.

The second aspect of the credit risk model is the default threshold with respect to which the default state can be defined. In the Merton model default occurs if the value of the firm j in region i at time t falls below a given threshold value, c_{ji}. We can characterize the separation between a default and a non-default state with an indicator variable $I\left(r_{ji,t+1} < c_{ji}\right)$ such that

$$\begin{aligned} I\left(r_{ji,t+1} < c_{ji}\right) &= 1, \text{ if } r_{ji,t+1} < c_{ji} \Longrightarrow \text{ Default,} \\ I\left(r_{ji,t+1} < c_{ji}\right) &= 0, \text{ if } r_{ji,t+1} \geq c_{ji} \Longrightarrow \text{ No Default.} \end{aligned} \tag{3}$$

We may then denote the probability of default of company j in region i at time t as $PD_{jit} = \Pr(r_{ji,t+1} < c_{ji} \mid \Omega_t)$.

Conceptually it is useful to anchor the default process by fixing the default threshold, for instance at the end of the sample period, thereby allowing the loss distribution to shift in response to macroeconomic factors. Figure 3 illustrates the general idea. The right of the two bell-shaped curves represents the return distribution as calculated from the historical average over, say, several decades, and thus can be regarded as "unconditional" in that it represents an average state of the economy. Conditional on a certain state of the economy, however, the mean return may shift. The illustrative example in Figure 3 shows the given state of the economy shifting the obligor company closer to default, where the conditional distance from default is given by the solid curve; the tail area to the left of the origin has increased. This area represents the conditional probability of default given a "bad" state of the economy.

In the Merton default prediction model, accounting data (book value of callable liabilities), the market value of equity and the volatility in the market value of equity are used to derive PD_{jit}.[5] We do the inverse: using an existing measure of expected default probability, we determine the critical value c_{ji}. This default measure can be obtained from public sources of firm risk ratings provided by rating agencies such as Moody's or Standard & Poor. Both of these rating agencies give solvency standards for the rated institutions and their publicly issued debt (bonds) in the form of a credit grade, which may then be converted to a probability of default (e.g. $PD(\mathcal{AA}_t)$, the (annual) probability of default for an '$\mathcal{AA}$' rated firm), using historical data on bond defaults.

[5] This approach, for example, is taken by KMV to generate what they call *EDF*s (expected default frequencies) at the firm level.

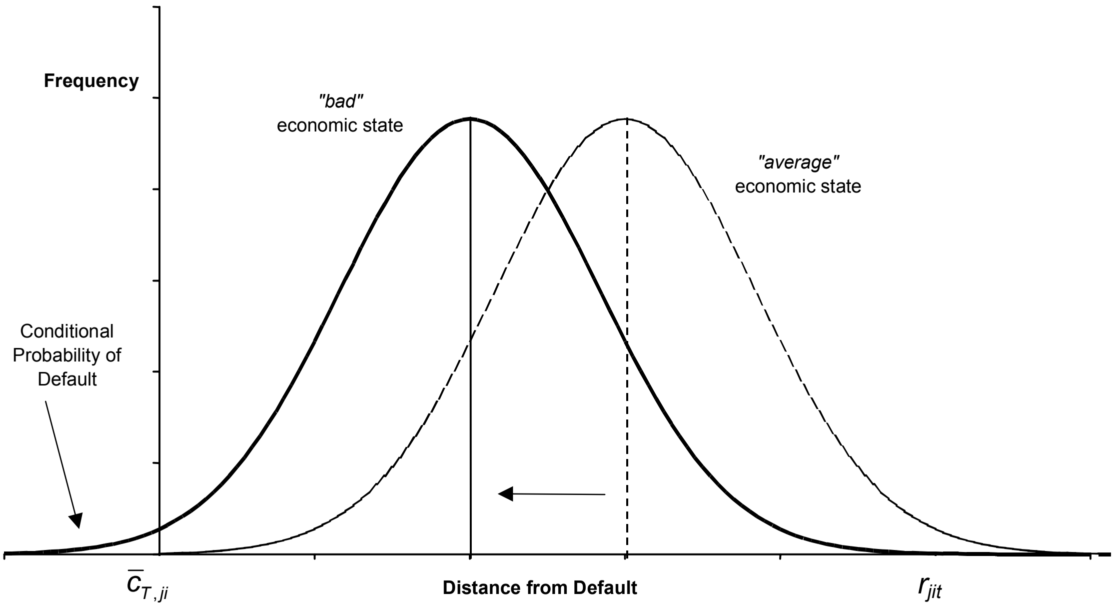

Figure 3: Distance from Default Conditional on the State of the Economy

3 Simulated Conditional Loss Distributions

3.1 The Global Macro Model

We estimate a global quarterly model over the period 1979Q1-1999Q1 comprising a total of 26 countries which are grouped into eleven country/regions. The output from these countries comprise around 70% of world GDP. The seven key economies of the U.S., Japan, China, Germany, U.K., France and Italy are modeled as regions of their own while the other 19 countries are grouped into four regions - Latin America, South East Asia, Middle East and the rest of Western Europe. Region specific models are cointegrating and can allow for the presence of long-run relationships such as the purchasing power parity, uncovered interest parity and the Fisher equation. The U.S. dollar is used as the numeraire exchange rate and its value in terms of the other currencies is determined outside the U.S. model. The endogenous variables for individual countries are $y_{it} = \ln(GDP_{it}/CPI_{it})$, $p_{it} = \ln(CPI_{it})$, $q_{it} = \ln(EQ_{it}/CPI_{it})$, $m_{it} = \ln(M_{it}/CPI_{it})$, $e_{it} = \ln(E_{it})$,

$\rho_{it} = 0.25 * \ln(1 + R_{it}/100)$ where

$GDP_{it} =$	Nominal Gross Domestic Product of country i during period t, in domestic currency
$CPI_{it} =$	Consumer Price Index in country i at time t, equal to 1.0 in a base year (say 1996)
$M_{it} =$	Nominal Money Supply in domestic currency
$EQ_{it} =$	Nominal Equity Price Index (not available for China and the Middle East)
$E_{it} =$	Exchange rate of country i at time t in terms of US dollars
$R_{it} =$	Nominal rate of interest per annum, in per cent

In total, there are 63 region-specific domestic macroeconomic variables or factors. Estimating an unrestricted VAR in all these 63 variables will not be feasible. To overcome this problem the domestic variables in the region-specific models are related to the foreign variables using trade weights, and each sub-model is estimated assuming that the foreign variables are weakly exogenous. The estimated models are then re-combined to solve for all the 63 endogenous variables in the global economy. PSW provide the estimation details and tests of the validity of the weak exogeniety assumption.

3.2 Credit Loss Results

Using methods described in Lando and Skodeberg (2002), we obtain quarterly PD estimates using ratings histories for firms rated by Moody's from January 1, 1979 to March 31, 1999. We then analyze the effects of economic shocks on a hypothetical sample of large-corporate loan portfolio comprised of 119 companies, dispersed over 10 regions, with a current face value of $1bn.[6] The estimated global model serves as the economic engine for generating a conditional loss distribution of a credit portfolio using stochastic simulation. Sampling takes place along three lines: correlated random draws of macroeconomic factors; draws of firm-specific risk components; and draws of stochastic loan loss severities.

We generate loss distributions for two different horizons: one-quarter and four-quarters ahead. A one-year horizon is typical for credit risk management and thus of particular interest. For each horizon we examine the impact of several shock scenarios:[7]

- a –2.33 σ shock to U.S. equity, corresponding to a quarterly drop of 14.28%
- a +2.33 σ shock to real German output corresponding to a quarterly rise of 2.17%

[6] We restricted ourselves to major, publicly traded firms which had a credit rating from either Moody's or S&P.

[7] 2.33 σ corresponds, in the Gaussian case, to the 99% Value-at-Risk, a typical range in risk management.

- a –2.33 σ shock to S.E. Asian (SEA) equity corresponding to a quarterly drop of 24.77%

In addition we present a symmetric positive shock to S.E. Asian equity prices – but the impact on losses will not be symmetric.

We generated 50,000 simulations for each scenario over two time horizons: one quarter and four quarters. The simulated expected loss results together with the unexpected counterparts (*S.D.*) are summarized in Table 1.

Table 1

Simulated Mean and Standard Deviation of Losses for One-Quarter and Four-Quarters Ahead (in Basis Points Exposure)

Shock Scenarios	One-Quarter Ahead		Four-Quarters Ahead	
	Mean	S.D.	Mean	S.D.
-2.33σ U.S. Equity	4.37	12.57	8.71	17.33
-2.33σ SEA Equity	3.24	11.15	7.53	16.47
Baseline	2.45	9.52	6.43	15.05
+2.33σ German Output	2.38	9.37	6.40	14.98
+2.33σ SEA Equity	2.14	8.77	5.87	14.22

The U.S. equity price shock seems rather severe at first: expected loss is nearly double than what is expected under the baseline (no shock) scenario while unexpected loss (i.e. the loss standard deviation) is about one-third higher. By the time one moves to the tail (99% and beyond) of the loss distribution (Figure 4), the absolute differences are less pronounced.

For the baseline, there is a 1% chance of losing about 49.7bp of the face value of the portfolio after one quarter, while conditional on the -2.33σ U.S. real equity price shock the loss is closer to 53.8bp. The two loss scenarios diverge further out in the tail such that at the 99.7% level, with a loss of about 55.7bp for the baseline and 68.0bp for the U.S. equity price shock scenario, only to converge again past the 99.8% level (and re-diverge past about 99.9%).[8] This nonlinearity is a direct consequence of the nonlinearity of the credit risk model which can only be uncovered in the loss distribution through simulation. The positive German output shock has little bearing on the loss distribution, either in terms of expected and unexpected loss, or even the shape of the loss

[8] As simulations for far tail events are increasingly less reliable the further out into the tail one goes, the numbers should be interpreted with some care.

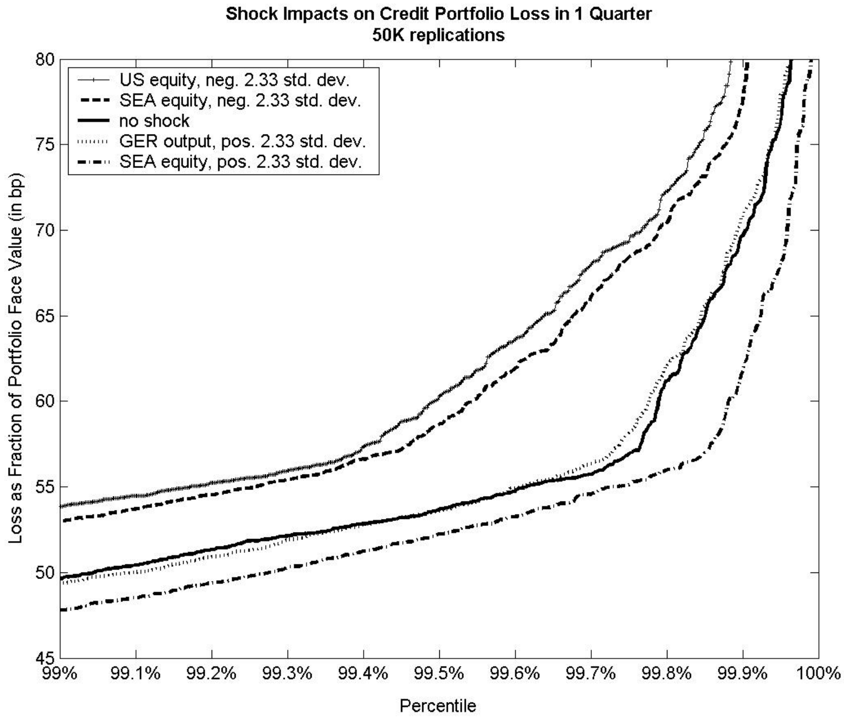

Figure 4: Shock Impacts on Credit Portfolio Loss in One Quarter

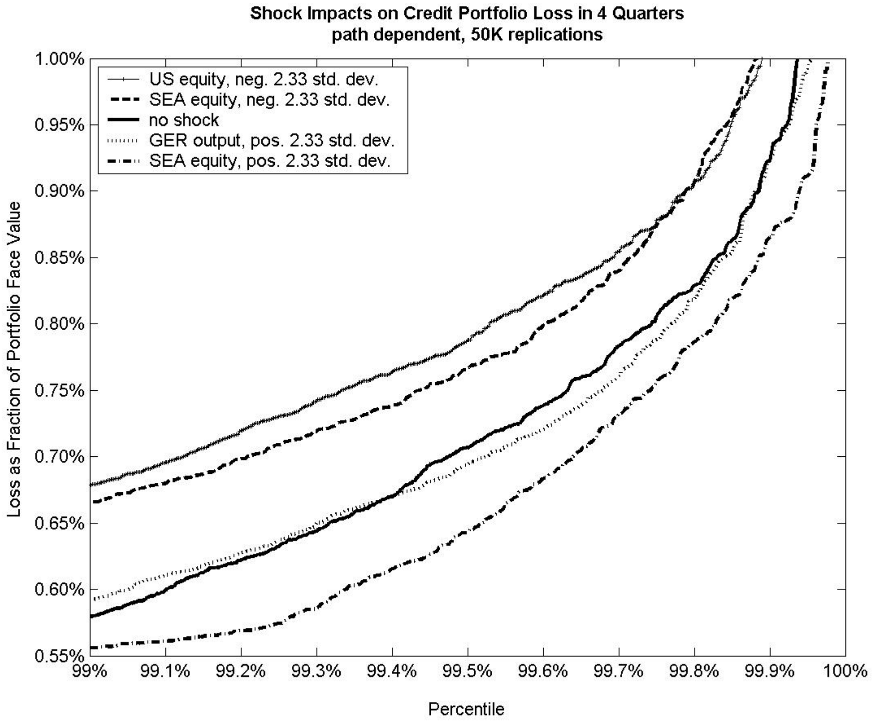

Figure 5: Shock Impacts on Credit Portfolio Loss in Four Quarters

distribution itself. In fact, the positive shock to S.E. Asian real equity prices is more beneficial. Thus from the perspective of, say, a German risk manager, given this portfolio, positive shocks to German output are less cause for excitement than positive shocks to S.E. Asian equity prices.

Symmetric shocks do not translate to symmetric loss outcomes. The loss curve in Figure 4 for the negative S.E. Asian equity shock lies further above the baseline than the positive equity shock curve lies below it. This also is a result of the nonlinear credit loss model.

The four quarter loss distribution was generated sequentially one quarter at a time, with defaulted firms in each replication being eliminated from the portfolio for the second quarter simulations, and so on. Mean and standard deviation of the annual simulated loss distributions are presented in the second set of columns in Table 1. The loss distributions for the baseline and the four shock scenarios are displayed in Figure 5.

The expected loss for the U.S. equity shock scenario is now about one-third higher than the baseline at the four quarter horizon, and the pattern of the loss curves are broadly in line with the curves for the one-quarter losses, except that the loss distributions for the favorable shocks are now relatively closer to the baseline distribution. The four-quarter is also somewhat smoother then the one-quarter loss distribution, lacking the "elbow" in the 99.7 to 99.8% range.

4 Concluding Remarks

In this paper we provide an overview of the conditional credit risk modeling approach set out in PSTW in some detail. Asset value changes of a credit (loan) portfolio are explicitly linked to a dynamic global macroeconometric model which allows us to isolate macro effects from idiosyncratic shocks from the perspective of default (and hence loss). The first step in developing such a model is to build an economic engine reflective of the environment faced by an internationally active global bank. Our macroeconometric model, which builds on recent advances in the literature on the analysis of cointegrating systems, allows for interaction amongst the different economies. Thus, for instance, we are able to account for inter-linkages between equity market movements in South East Asia and output in Germany.

Using a simple Merton-type credit portfolio model, we model credit risk as a function of correlated equity returns of the obligor companies. These equity returns are linked to correlated macroeconomic variables using an approach structurally similar to the Arbitrage Pricing Theory (APT). We then use the estimated macroeconometric global model to generate a conditional loss distribution of a credit portfolio using stochastic simulation. Finally we analyze the impact of a shock to a set of specific macroeconomic variables (domestic or foreign) on that loss distribution. We find that symmetric shocks do not result in symmetric loss outcomes due to the nonlinearity of the credit risk model. This nonlinearity manifests itself in other ways: proportional shocks do not result in proportional loss outcomes.

The applications for our conditional approach are potentially wide and numerous. They include the pricing of credit instruments such as collateralized debt obligations (CDOs) and credit derivatives, credit portfolio management, and bank risk and capital management.

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