Chapter 14
Stress Testing

INTRODUCTION

In this chapter, we will zoom in on stress testing. Stress testing is an activity that is done once the PD, LGD, and EAD models have been built. Its purpose is to analyze how credit risk models behave under adverse internal or external circumstances. We will discuss various ways of doing stress testing such as sensitivity-based stress testing, historical scenario–based stress testing, and hypothetical scenario–based stress testing.

Purpose of Stress Testing

An obvious question is: "Why do we need stress testing?" An answer you will often get is because it is required by regulators. However, besides regulatory value, stress testing is also valuable from a business perspective. First, it can be used to help set pricing and product features. The output of a stress testing exercise can be helpful to determine the spread above the risk-free rate when pricing loans. It also allows for the capture of the impact of exceptional but plausible loss events. Value-at-risk (VaR) models, as discussed earlier, typically reflect everyday market behavior. Stress testing looks into the tail of the loss distribution to study the impact of abnormal markets. It also allows for a clearer picture of the risk profile of the firm. It is especially important here to comprehensively aggregate the risks across various credit and noncredit portfolios.

Types of Stress Tests

In Exhibit 14.1 you can see a taxonomy of stress testing approaches, as introduced by the Monetary Authority of Singapore in 2002.

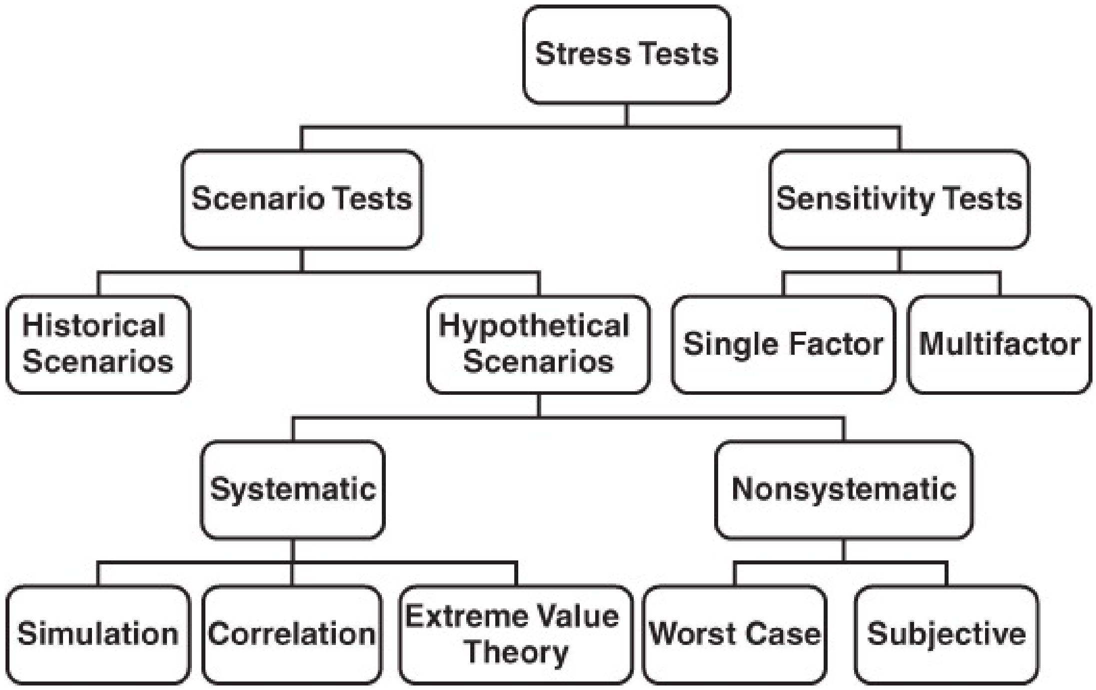

Exhibit 14.1 Types of Stress Tests

A high-level distinction can be made between scenario-based and sensitivity-based stress testing. A single-factor sensitivity test analyzes the impact of varying a single variable. A multifactor sensitivity test varies multiple variables simultaneously, ideally by taking into account the correlation between them. A scenario test can be historical, whereby the impact of a historical adverse event is reenacted. It can also be hypothetical when a new scenario is devised. This can be done in a systematical way using correlation, simulation, and extreme value theory. It can also be done in a nonsystematical way by assuming a worst-case scenario or by using expert-based input.

Sensitivity-Based Stress Testing

The idea of sensitivity-based stress testing is to gauge the impact of changing variables. This is a static approach that does not take into account external effects, such as macroeconomic information. Single-factor sensitivity tests have proven to be very popular for market risk. Some examples are a yield curve shift by 100 basis points or a decrease in the GBP/USD exchange rate of 5 percent.

In credit risk, a single-factor sensitivity stress test can be conducted at each of the levels of the credit risk model architecture, as we discussed earlier. At level 0, the data can be stressed. For example, an income drop of 10 percent, an increase in the loan-to-value ratio of 20 percent, a rise in unemployment of 5 percent, and so on. At level 1, the scores can be stressed. For example, assume all application and behavioral scores drop by 5 percent. At level 2, the ratings and PD can be stressed. For example, downgrade every obligor one notch, such that an AAA-rated obligor becomes an AA-rated obligor, an AA-rated obligor an A-rated obligor, and so on. Also, the PD can be multiplied with a stress factor.

The advantage of sensitivity-based stress tests is that they are very easy to understand. They are also typically used in the starting phase of a stress testing exercise. Their key shortcoming is that it is difficult to defend the connection with changes in economic conditions. A multifactor stress test analyzes multiple variables simultaneously. When conducted appropriately, it takes into account the correlation between the selected variables such that it will quickly become a scenario test.

Scenario-Based Stress Testing

The next approach to stress testing is scenario-based testing. The idea here is to work out an adverse shock event and gauge the impact on the various parameters. Typically, the source of the shock and the parameters affected are well defined. Scenarios can be defined in several ways, such as portfolio driven versus event driven, or historical versus hypothetical. Defining a scenario usually involves a trade-offbetween realism and comprehensibility.

Portfolio-Driven versus Event-Driven Scenario Stress Testing

Portfolio-Driven Stress Testing

In the portfolio-driven approach, you can start from portfolio characteristics. To start, it is crucial to ask what the risk parameter changes that result in a portfolio loss are. This question should be decomposed across the various levels of the credit risk model architecture. For example, at level 2 a key parameter is the PD, at level 1 you can think of application and behavioral scores, and at level 0 you can then further consider data characteristics such as debt ratio, income, unemployment, and credit bureau score. A next step is then to define events or scenarios that bring about adverse changes in any of these data variables.

Event-Driven Scenario (Reverse) Stress Testing

An event-driven approach works the other way around. It starts from identifying an event or a risk source that causes adverse changes in financial markets. From there onward, how these changes affect the risk parameters and corresponding portfolio loss are studied. This is also referred to as bottom-up or reverse stress testing.

Historical versus Hypothetical Scenario Stress Testing

Historical Scenario Stress Testing

In historical scenario stress testing, historical stress scenarios are analyzed and reenacted in the current portfolio. Since you can rely on actual past events, fewer qualitative judgments are needed by the business experts. Note, however, that the future does not always resemble the past; thus this approach might be less suited to the current situation due to changes in either portfolio or strategy, or both.

Historical recession scenarios are sometimes also referred to as black swan events. Europeans thought black swans did not exist until they were discovered in Australia. Like black swans, economic downturns that came as a surprise include:

- European sovereign crisis, 2010/2011
- Subprime and U.S. credit crisis, 2008/2009
- Enron/WorldCom, 2002
- September 11, 2001
- Dot-com bubble burst, 2000
- Russian credit crisis, August 1998
- Asian currency crisis, summer 1997

Hypothetical Scenario Stress Testing

When no historical scenario is appropriate, hypothetical scenario stress testing might be considered. The idea here is to model a scenario that has not yet happened. In contrast to historical stress testing, the scenario should be forward looking and focus on the vulnerabilities of the portfolio and/or firm. Since you have no historical events to rely on, this will require more qualitative judgment from the business expert. Historical data can be useful to analyze relationships and correlations, which can then be extrapolated in the hypothetical scenario. Ideally, the scenario should also include dynamic projections of firm revenue, income/losses, and other balance sheet figures. Note that these scenarios are more labor intensive but also likely to be relevant. They should also be defined in a comprehensive way by taking into account corporate banker behavior toward stress events. Examples here are adjusting the underwriting standards or marketing programs, cutting dividends, or raising capital.

When defining hypothetical scenarios, you should first thoroughly analyze the various factors that may cause stress. A first example is a macroeconomic downturn, such as successive periods of gross domestic product (GDP) contraction. Other examples are deterioration in reputation, an adverse change in competitive position, failure of a market counterparty, or illiquidity conditions.

Various types of hypothetical scenarios can be considered. First is the worst-off scenario. The idea is to look at the most adverse movement in each risk factor. Obviously, this is a very conservative scenario and not that plausible since it ignores the correlations between the various risk factors. Note that it is commonly applied.

Second is a subjective scenario. Here, expert-based input is used to qualitatively define the stress scenario. The quality of the scenario will then depend on the experience of the expert. Also, simulations can be used to analyze the behavior of the loss distribution under stressed conditions.

Ideally, the simulations should be backed by appropriate correlation analysis. The idea here is to stress some factors and use the correlation matrix to simulate values of the rest. A popular example concerns the correlation between PD and LGD, or default and loss rates. It is important to understand that correlations are time varying and may be different during stress and nonstress periods. Expert input may come in handy to adjust the empirically observed correlations. Also, the asset correlation values as reported in the Basel Accords can be useful.

Finally, extreme value theory can also be used for stress testing. Typically, the loss distribution is assumed normal or lognormal. It has been shown in earlier research that under extreme stress, the tail of the distribution is fatter than normal. The theory of stochastic processes then allows for identification of suitably extreme distributions for stress testing.

Post-GFC Stress Testing

Since the global financial crisis (GFC), prudential regulators have mandated that stress tests must be conducted by banks to gauge their capital resilience against central bank–prescribed macroeconomic scenarios. For example, in the United States the Federal Reserve Bank requires the following stress tests:

- Dodd-Frank Act supervisory stress test (DFAST)
- Comprehensive Capital Analysis and Review (CCAR) stress test

In Europe, the European Banking Authority (EBA) has conducted several European Union–wide stress tests for the largest banking institutions. In addition, various national regulators have conducted tests for their countries (e.g., the Financial Services Authority and the Bank of England in the United Kingdom). Similar examples exist for Australasian economies with prominent examples in Australia (Australian Prudential Regulation Authority), Singapore (Monetary Authority of Singapore), and China (China Banking Regulatory Commission).

Exhibit 14.2 shows a number of U.S. domestic macroeconomic scenarios for some of the key variables describing the economic activity under the DFAST “baseline,” “adverse,” and “severely adverse” scenarios for 2015 (Federal Reserve System [2015]).

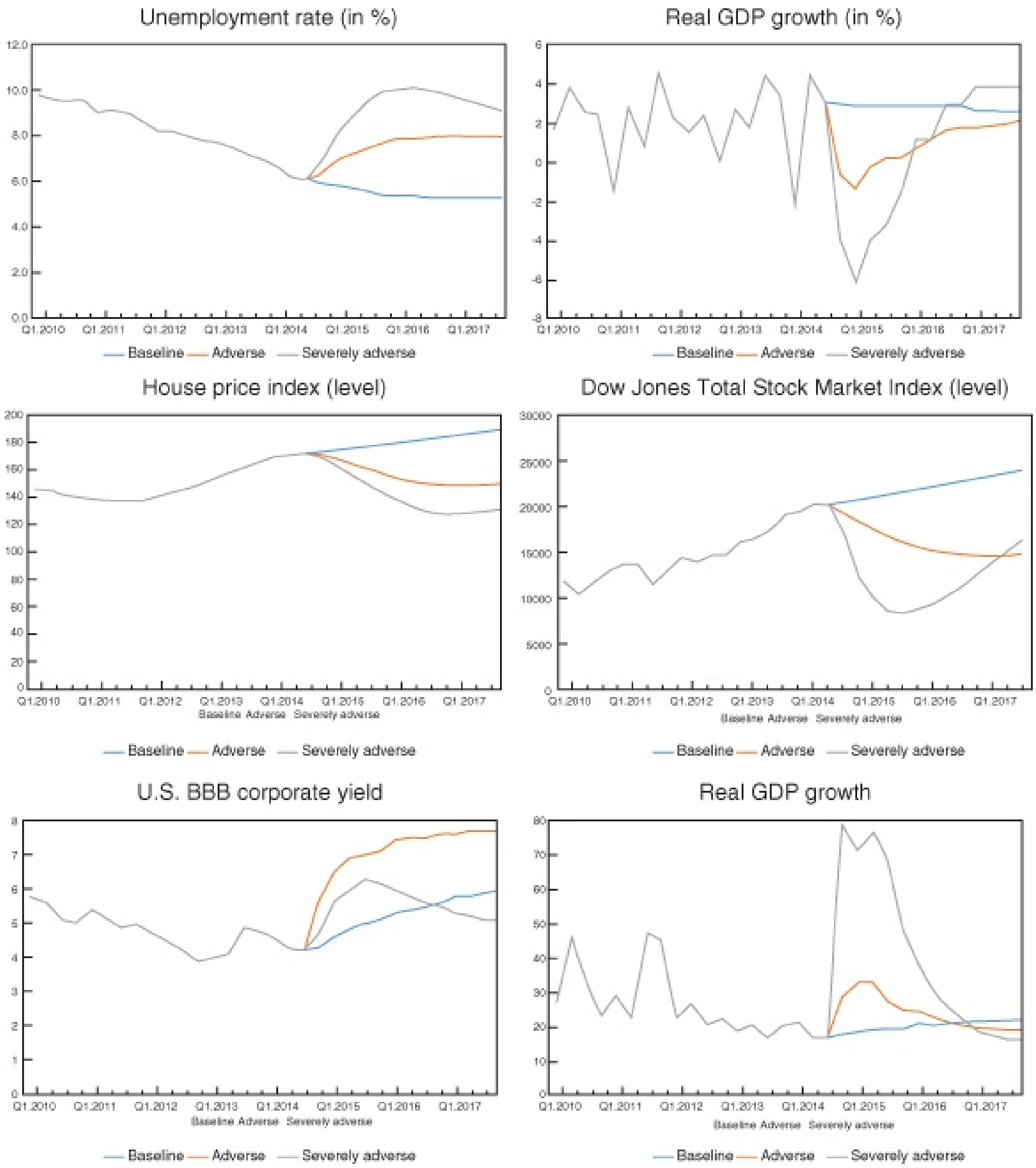

Exhibit 14.2 DFAST "Baseline," "Adverse," and "Severely Adverse" Scenario

These stress scenarios ("adverse" and "severely adverse") are generally based on initial economic shocks that revert to (and in some instances exceed) the "baseline" scenarios in later periods.

These stress tests require banks to demonstrate that the ultimate parent companies (bank holding companies) have adequate capital to sustain the various stress-test scenarios and that capital distributions (i.e., dividends and share repurchases) do not put the banks at substantial risk. While the analysis is performed in both qualitative and quantitative ways, the assessment of credit risk losses is a key consideration and the conditioning of bank PD, LGD, and EAD models on these macroeconomic stress tests is an important undertaking.

Not meeting minimum compliance standards has major business implications such as restrictions on remuneration of stakeholders and increased regulation. A major component of stress testing is the analysis of the impact of macroeconomic stress scenarios on the performance of the lending book. In this chapter, we discuss approaches to implementing stress tests in line with current requirements. In addition, we analyze the impact of risk realizations that exceed current requirements but may be of interest for economic consideration, for example, in order to meet bank investor expectations.

Challenges in Stress Testing

Various challenges arise when undertaking stress testing. An initial challenge relates to the various regulatory authorities that impose stress testing. A key concern is the often-observed discrepancies in terms of severity of the imposed stress tests. A more homogeneous and consistent definition of stress testing would be much welcomed.

Stress testing is also more developed for market risk than for credit risk. Market risk stress testing is typically conducted on a daily basis, whereas credit risk stress testing usually occurs less frequently. Ideally, to generate a corporate-wide view on the impact of a stress testing scenario, both market risk and credit risk should be integrated. Unfortunately, this is still far away for most financial institutions. One of the key difficulties here concerns the time horizon and confidence levels adopted, which are typically not identical. Hence, both market and credit risk stress testing scenarios are typically difficult or even impossible to integrate.

Given its strategic impact, it is of key importance to also actively engage senior management in defining and interpreting the stress tests conducted. In credit risk, many institutions are increasing the frequency of stress testing from annually to quarterly. There appears to be a greater consensus in the industry that a stress event corresponds to a once-in-25-years event.

Stress Testing Governance

From a governance perspective, it is important to appropriately and unambiguously define the following items:

- The scope and aim of the stress tests, such as business versus regulatory
- The ownership of the stress test
- The various contributors, reporting lines, frequency of tests, and committees

Once finalized, the stress testing results should also be presented to senior management and the board of directors, who should ensure that the necessary training and coaching are available. Also, accompanying strategies and actions should be foreseen, if necessary. Finally, the outcome of the stress testing exercise should be publicly disclosed and documented.

INTEGRATION WITH THE BASEL RISK MODEL

Financial institutions often provide a capital buffer in excess of regulatory capital. The capital buffer is based on the assessment of risks that are not included in the Basel capital calculations (e.g., risks other than credit risk, market risk, and operational risk) and other assessment techniques that complement a portfolio's risk model such as stress testing (e.g., risk measurements in excess of Basel requirements).

The Basel Committee on Banking Supervision ([2006]) has formulated the following stress testing requirements for financial institutions:

> A bank must have in place sound stress testing processes for use in the assessment of capital adequacy. These stress measures must be compared against the measure of expected positive exposure and considered by the bank as part of its internal capital adequacy assessment process. Stress testing must also involve identifying possible events or future changes in economic conditions that could have unfavorable effects on a firm's credit exposures and assessment of the firm's ability to withstand such changes. Examples of scenarios that could be used are:

1. Economic or industry downturns,
2. Market-place events, or
3. Decreased liquidity conditions.

Berkowitz (2000) and others have questioned the use of stress tests as they should be part of the loss distribution and provide no further informational value. Hence, stress testing has to be interpreted in conjunction with the portfolio risk model and related level of conservatism as capital is assigned to higher percentiles of the portfolio loss distribution.

Furthermore, recent stress testing requirements are based on very precisely defined macroeconomic scenarios and include soft (not measurable) and hard (measurable) information. As such, the level of detail placed in this single evaluation exceeds the efforts for scenarios in a portfolio loss distribution and may provide information that is not part of the risk model. The capital that banks hold then becomes:

$$\text{Minimum capital} = \max(\text{regulatory capital, stress test capital, economic capital})$$

In what follows, we discuss the capital allocation under the Basel regulation and stress testing. Economic capital considerations are generally institution-specific. For example, some banks may target a minimum credit rating to limit their interbank funding costs. There are many, often offsetting, underlying considerations, which are beyond the scope of this book, and we do not provide further guidance on these matters.

Risk Model under Basel Regulations

The Basel Committee on Banking Supervision (2006) expects financial institutions to provide sufficient Tier I and Tier II capital to cover future worst-case credit portfolio losses. These worst-case losses are based on conservative assumptions for a set of parameters such as the probability of default (PD), asset correlation ρ, loss given default (LGD), and exposure at default (EAD):

- Stress of PDs: PDs are based on a one-factor nonlinear model where the factor equals the 99.9th percentile of a systematic standard normally distributed variable and the sensitivity is based on the so-called asset correlation.

- Stress of asset correlations: Asset correlations can be interpreted asa measure of the sensitivity of PDs to the business cycle and therefore have a major impact on the stress of the PDs. The Basel Committee on Banking Supervision has provided conservative estimates (sometimes in dependence with PD) for these parameters.
- Stress of EADs and LGDs: EADs and LGDs are modeled based on an economic downturn condition.

Exhibit 14.3 shows a typical credit portfolio loss distribution. The expected loss is covered by loan loss provisions that are already deducted from the capital account. The unexpected loss (in excess of the expected loss) is covered by regulatory capital. The stressed loss (in excess of the unexpected loss) is covered by the capital buffer.

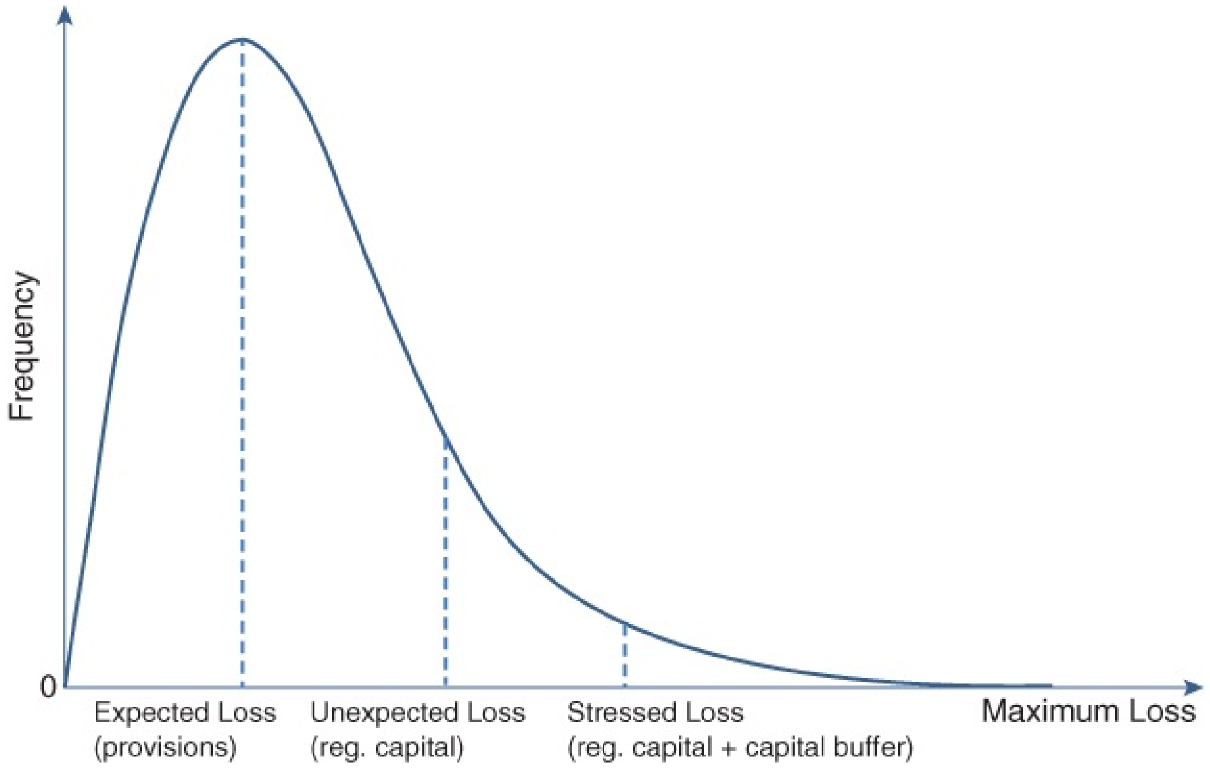

Exhibit 14.3 Expected Loss, Unexpected Loss, and Stressed Loss

The Basel Accord introduces different types of capital regulations, which can be categorized into standardized (ratings-based) and internal ratings based approaches:

- Standardized approach: In this approach credit risk exposures are categorized into risk buckets, and risk weights are assigned. Risk buckets are generated by ratings provided from certified credit rating agencies (CRAs). Outstanding asset exposures are multiplied by risk weights, and the risk-weighted assets are computed. Off-balance-sheet exposures are converted into the asset equivalents, which are then risk weighted.
- Internal ratings based (IRB) approach: The capital requirement is computed using a portfolio model based on risk parameters assuming an infinitely granular credit portfolio and independence between the risk parameters. The risk parameters are default probabilities (PDs), asset correlations, loss rates given default (LGDs), exposures given

default (EADs), and the maturity for loans and together with some other characteristics for securitizations (for details, we refer to Rösch and Scheule [2012a]). The risk parameters are stressed conditional on economic downturns. As mentioned previously, the conditioning on economic downturns is explicitly formulated in the case of EAD and LGD and implied in the case of PDs and asset correlations by the formulation of a worst-case default rate and provision of conservative asset correlation values.

Furthermore, risk mitigation by guarantees, collateral, and netting is considered. For the rest of this section, we focus on the risk model implied by the IRB approach. Here, regulatory capital is calculated as follows:

$$\text{Regulatory capital} = (\text{WCDR} - \text{PD}) * \text{DEAD} * \text{DLGD} * \text{MA}$$

with the worst-case default rate (WCDR) and the maturity adjustment (MA) for corporate exposures. No maturity adjustment is applied for retail loans. DEAD is the downturn exposure at default, and DLGD is the downturn loss rate given default.

We do not discuss the maturity adjustment further, as it applies only to corporate loans and is a function of the PD and the maturity of a loan. The intention is to allocate a slightly higher capital amount for longer-maturity corporate financial instruments.

The difference between WCDR and PD implies that regulatory capital is based on unexpected losses, that is, losses that exceed their expected level based on the default probability. Basel follows this approach, as expected losses are deducted from the capital base via loan loss provisioning and hence the remaining capital is required for covering unexpected losses.

Note that the regulatory capital for credit risk is converted to risk weights by multiplication of $1/cr$ with capital ratio cr to aggregate the risk-weighted assets for credit risk with those for market risk and operational risk:

$$\begin{aligned}\text{RWA}_{\text{credit, market, operational}} &= \text{RWA}_{\text{credit}} + \text{RWA}_{\text{market}} + \text{RWA}_{\text{operational}} \\ &= \frac{\text{capital}_{\text{credit}}}{cr} + \frac{\text{capital}_{\text{market}}}{cr} + \frac{\text{capital}_{\text{operational}}}{cr}\end{aligned}$$

The capital and risk-weighted assets (RWA) for market risk and operational risk are subject to other models and required computations. Given a capital ratio underlying these computations of 8 percent, the multiplier $1/cr$ is 12.5 or 1,250 percent for the conversion of risk-based capital into risk-weighted assets.

Asset Correlations and Worst-Case Default Rate

The worst-case default rate (WCDR) is a central element in the Basel risk model and an example of a stress test for the default probability. We refer to the default models presented in our credit portfolio risk chapter. The asset return A_{it} of borrower i ($i = 1,\ldots,I$) in time period t ($t = 1,\ldots,T$) is a latent process of a systematic risk factor F_t that is specific to the time period under consideration, and an idiosyncratic factor ϵ_{it}. Both are random and independent from each other and over time.

$$R_{it} = -\sqrt{\rho}X_t + \sqrt{1-\rho}\epsilon_{it}$$

The sensitivity to the systematic factor is $\sqrt{\rho}$. We chose a negative sign for consistency with the Basel formula but this is irrelevant as X_t follows the standard normal distribution. The sensitivity to the idiosyncratic factor is $\sqrt{1-\rho}$. A default event occurs if the asset return R_{it} falls below a threshold c_{it} . The probability of default (PD) given a standard normal distribution of the random variables is:

$$PD_{it} = P(D_{it} = 1) = P(R_{it} < c_{it}) = \Phi(c_{it})$$

Φ is the cumulative density function of the standard normal distribution. This probability corresponded to an unconditional default probability with regard to the unobserved systematic risk factor X_t and is estimated with discrete-time or continuous-time approaches as discussed in the default probability chapters. The default probability conditional on the realization of the systematic risk factor is:

$$WCDR = P(D_{it} = 1|x_t) = P(R_{it} < c_{it|X_t}) = \Phi\left(\frac{c_{it} + \sqrt{\rho}X_t}{\sqrt{1-\rho}}\right)$$

with $c_{it} = \Phi^{-1}(PD_{it})$. The Basel Committee specifies the asset correlation ρ and the realization x_t of X_t as the worst in 1,000 economic scenarios (i.e., as X_t is standard normal: $x_t = \Phi^{-1}(0.999)$). The following well-known equation results for the worst-case default rate under the IRB approach:

$$WCDR = P(D_{it} = 1|x_t) = P(R_{it} < c_{it}|x_t) = \Phi\left(\frac{\Phi^{-1}(PD_{it}) + \sqrt{\rho}\Phi^{-1}(0.999)}{\sqrt{1-\rho}}\right)$$

We have discussed in the default correlations and credit portfolio risk chapter how to estimate default and asset correlations. In the Basel regulations, prudential regulators currently do not allow banks to estimate this parameter. Instead, they specify the asset correlation as a constant value (15 percent for mortgages and 4 percent for revolving loans) or as a function of the default probability for corporate and other retail loans. The asset correlation for standard corporate loans is computed as follows:

$$\rho = 0.12\frac{1-exp(-50PD)}{1-exp(-50)} + 0.24\left(1 - \frac{1-exp(-50PD)}{1-exp(-50)}\right) \approxeq 0.12(1+exp(-50PD))$$

and for other retail exposures:

$$\rho = 0.03\frac{1-exp(-35PD)}{1-exp(-35)} + 0.16\left(1 - \frac{1-exp(-35PD)}{1-exp(-35)}\right) \approxeq 0.03(1+exp(-35PD))$$

The rather complicated smoothing function implies that the asset correlation is a declining function in terms of the default probability from 24 percent (PD of zero) to 12 percent (PD of one) for corporate loans and a declining function in terms of the default probability from 16 percent (PD of zero) to 3 percent (PD of one) for other retail loans. The thinking behind this is that high-PD companies are primarily exposed to idiosyncratic risk and to a lesser degree systematic risk. Researchers have found mixed empirical evidence on both the levels of asset correlations and their link to PDs. The following program computes and plots the asset correlations in relation to the PDs:

```
DATA graph;
DO PD=0 to 0.1 by 0.001;
ac_corporate=0.12 *(1-EXP(-50*PD))/(1-EXP(-50))
+ 0.24*(1-(1-EXP(-50*PD)/(1-EXP(-50))));
ac_mortgage=0.15;
ac_revolving=0.04;
ac_retail=0.13 *(1-EXP(-35*PD))/(1-EXP(-35))
+ 0.16*(1-(1-EXP(-35*PD)/(1-EXP(-35))));
OUTPUT;
END;
RUN;
ODS GRAPHICS ON;
AXIS1 ORDER=(0 to 0.1 BY 0.02) LABEL=('PD');
AXIS2 ORDER=(0 to 0.25 BY 0.05) LABEL=('Asset correlation');
SYMBOL1 INTERPOL=SPLINE WIDTH=2 VALUE=TRIANGLE C=BLUE;
SYMBOL2 INTERPOL=SPLINE WIDTH=2 VALUE=CIRCLE C=RED;
SYMBOL3 INTERPOL=SPLINE WIDTH=2 VALUE=CIRCLE C=GREEN;
SYMBOL4 INTERPOL=SPLINE WIDTH=2 VALUE=SQUARE C=BLACK;
LEGEND1 LABEL=NONE SHAPE=SYMBOL(4,2) POSITION=(BOTTOM OUTSIDE);
PROC GPLOT DATA=graph;
PLOT ac_corporate*PD ac_mortgage*PD ac_revolving*PD ac_retail*PD
/ OVERLAY LEGEND=legend1 HAXIS=AXIS1 VAXIS=AXIS2;
RUN;
ODS GRAPHICS OFF;
```

Exhibit 14.4 is the resulting figure produced by PROC GPLOT,

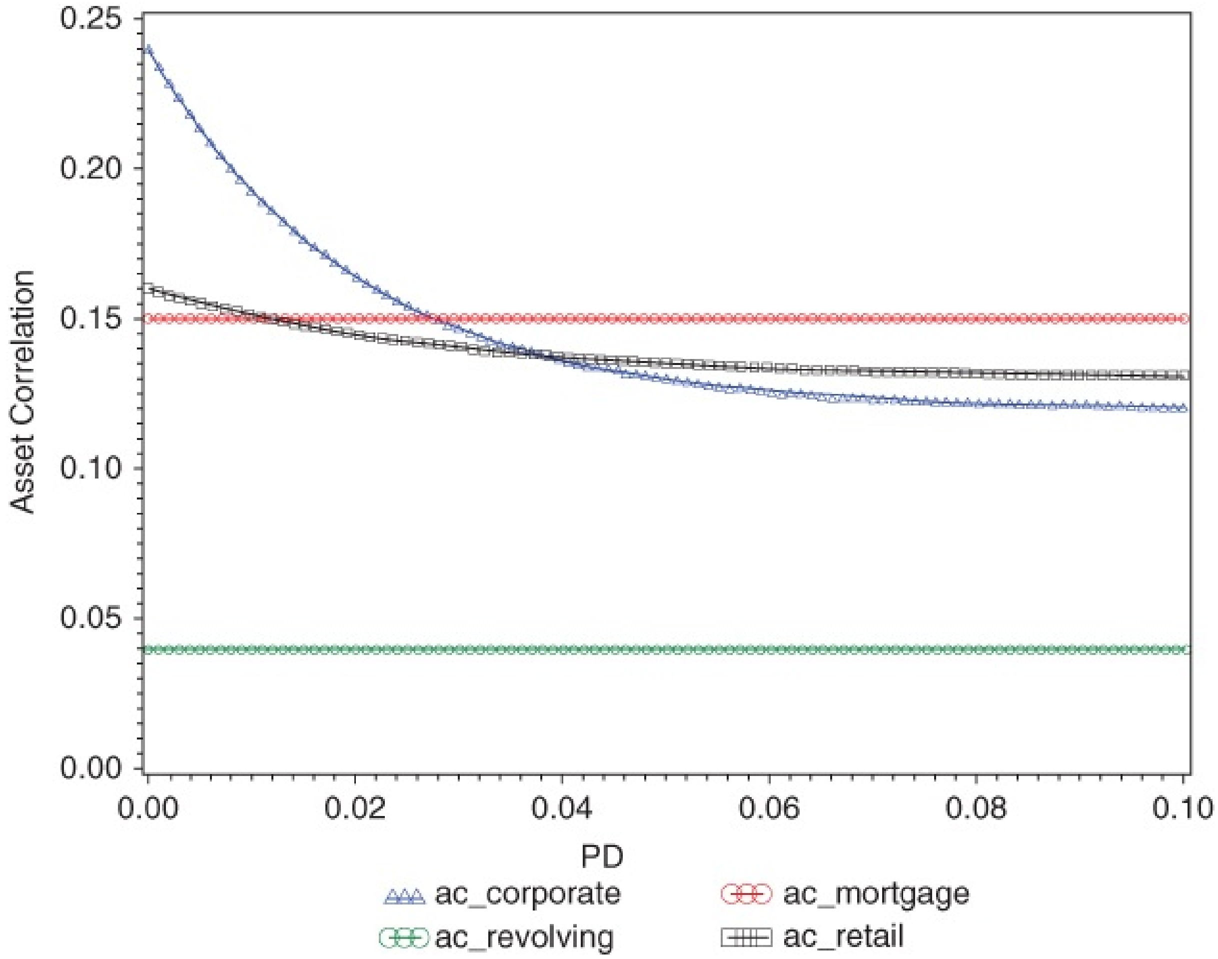

Exhibit 14.4 Asset Correlations

High sensitivities to the systematic risk imply high worst-case default probabilities (i.e., conditional PDs conditional on a 1 in 1,000 economic scenario) and eventually high capital requirements. The following code computes worst-case default rates in relation to the input PD and plots this relationship:

```
DATA graph;
SET graph;
wcdr_corporate=PROBNORM((PROBIT(PD)+SQRT(ac_corporate))
/SQRT(1-ac_corporate));
wcdr_mortgage=PROBNORM((PROBIT(PD)+SQRT(ac_mortgage))
/SQRT(1-ac_mortgage));
wcdr_revolving=PROBNORM((PROBIT(PD)+SQRT(ac_revolving))
/SQRT(1-ac_revolving));
wcdr_retail=PROBNORM((PROBIT(PD)+SQRT(ac_retail))
/SQRT(1-ac_retail));
RUN;
ODS GRAPHICS ON;
AXIS1 ORDER=(0 to 0.1 BY 0.02) LABEL=('PD');
AXIS2 ORDER=(0 to 0.2 BY 0.05) LABEL=('WCDR');
SYMBOL1 INTERPOL=SPLINE WIDTH=2 VALUE=TRIANGLE C=BLUE;
SYMBOL2 INTERPOL=SPLINE WIDTH=2 VALUE=CIRCLE C=RED;
SYMBOL3 INTERPOL=SPLINE WIDTH=2 VALUE=CIRCLE C=GREEN;
SYMBOL4 INTERPOL=SPLINE WIDTH=2 VALUE=SQUARE C=BLACK;
```

```
LEGEND1 LABEL=NONE SHAPE=SYMBOL(4,2) POSITION=(BOTTOM OUTSIDE);
PROC GPLOT DATA=graph;
PLOT wcdr_corporate*PD wcdr_mortgage*PD wcdr_revolving*PD wcdr_retail*PD
/ OVERLAY LEGEND=legend1 HAXIS=AXIS1 VAXIS=AXIS2;
RUN;
ODS GRAPHICS OFF;
```

Exhibit 14.5 is the resulting figure produced by PROC GPLOT.

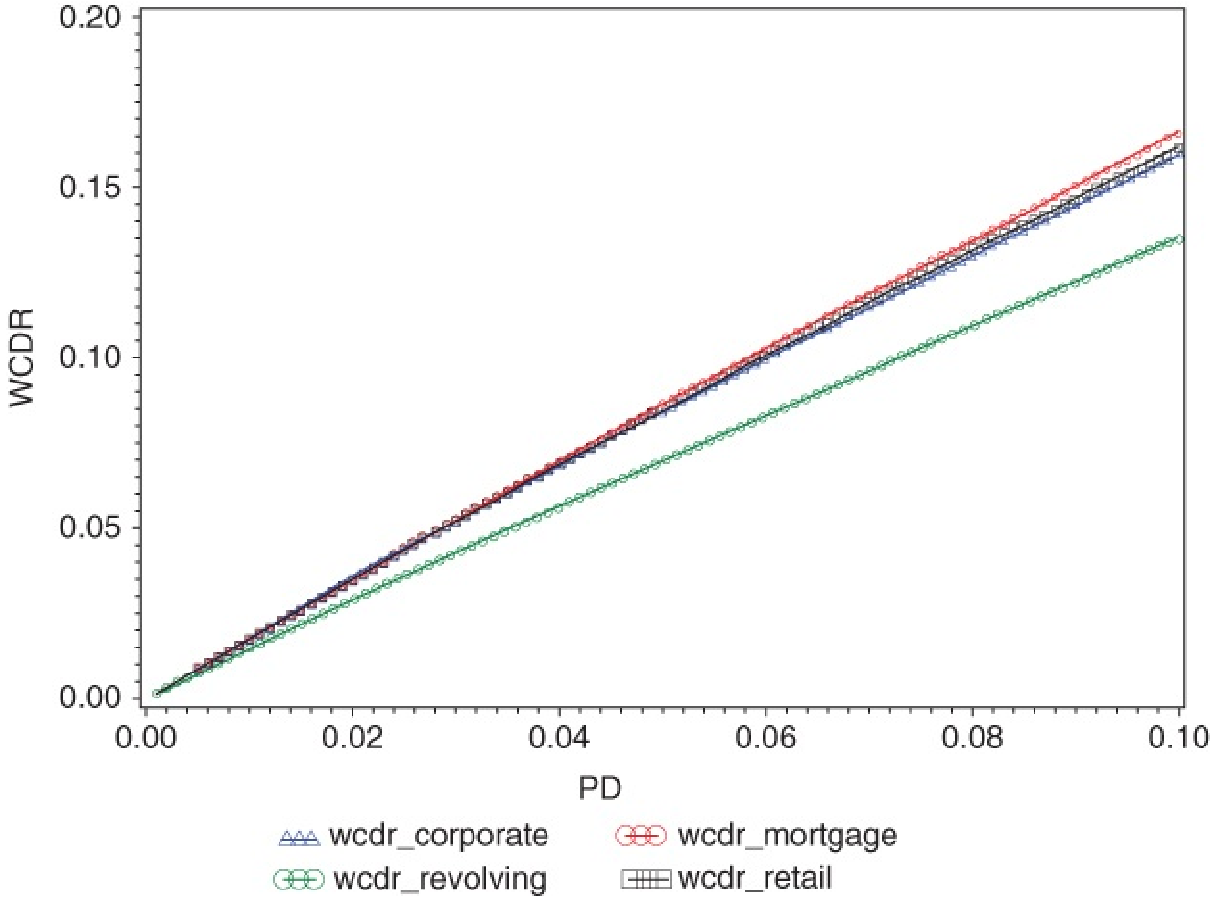

Exhibit 14.5 Worst-Case Default Rate

The following code computes the resulting unexpected losses and hence capital (based on an EAD of one, an LGD of one, and a maturity adjustment of one) and plots this relationship:

```
DATA graph;
SET graph;
DEAD=1;
DLGD=1;
MA=1;
capital_corporate=(wcdr_corporate-PD)*DEAD*DLGD*MA;
capital_mortgage=(wcdr_mortgage-PD)*DEAD*DLGD;
capital_revolving=(wcdr_revolving-PD)*DEAD*DLGD;
capital_retail=(wcdr_retail-PD)*DEAD*DLGD;
RUN;
ODS GRAPHICS ON;
AXIS1 ORDER=(0 to 0.1 BY 0.02) LABEL=('PD');
AXIS2 ORDER=(0 to 0.08 BY 0.02) LABEL=('Capital');
```

```
SYMBOL1 INTERPOL=SPLINE WIDTH=2 VALUE=TRIANGLE C=BLUE;
SYMBOL2 INTERPOL=SPLINE WIDTH=2 VALUE=CIRCLE C=RED;
SYMBOL3 INTERPOL=SPLINE WIDTH=2 VALUE=CIRCLE C=GREEN;
SYMBOL4 INTERPOL=SPLINE WIDTH=2 VALUE=SQUARE C=BLACK;
LEGEND1 LABEL=NONE SHAPE=SYMBOL(4,2) POSITION=(BOTTOM OUTSIDE);
PROC GPLOT DATA=graph;
PLOT capital_corporate*PD capital_mortgage*PD capital_revolving*PD
capital_retail*PD
/ OVERLAY LEGEND=legend1 HAXIS=AXIS1 VAXIS=AXIS2;
RUN;
ODS GRAPHICS OFF;
```

Exhibit 14.6 is the resulting figure produced by PROC GPLOT.

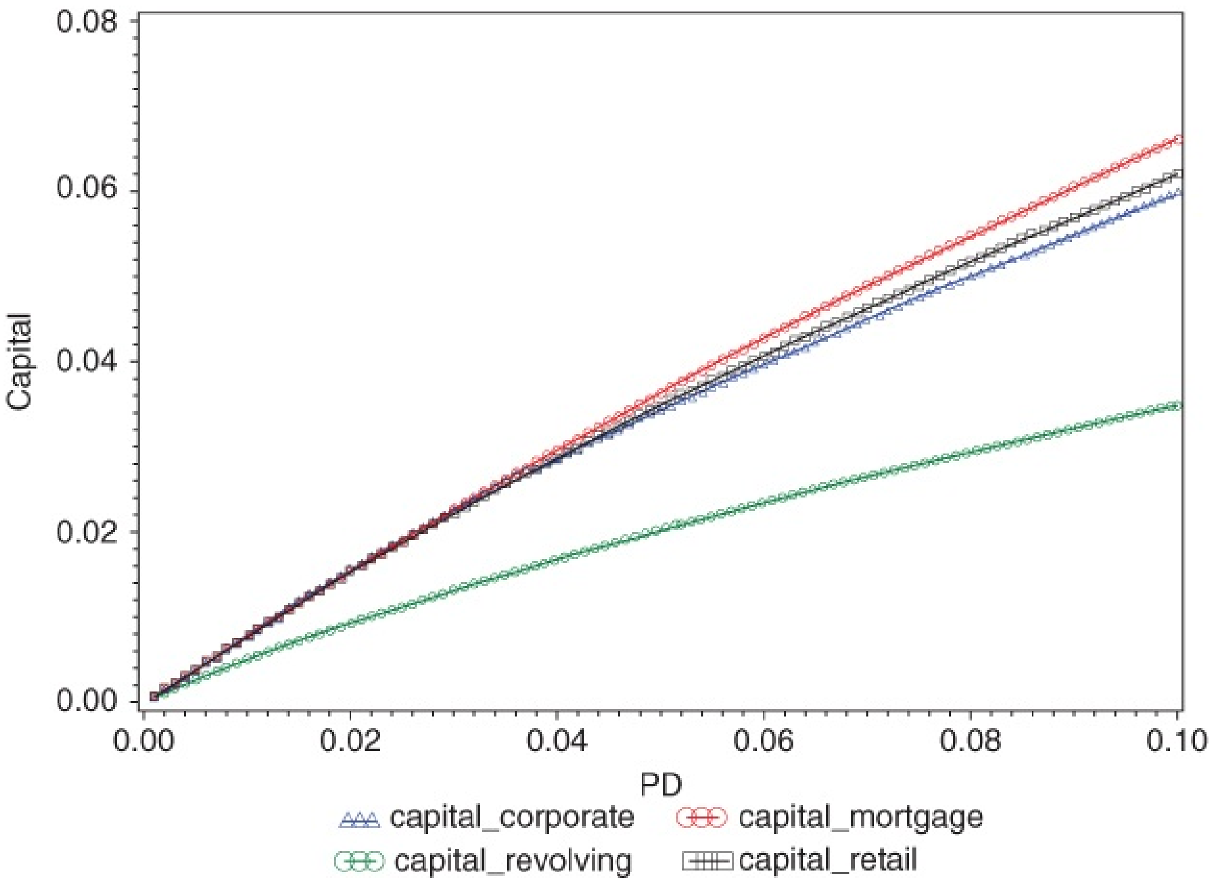

Exhibit 14.6 Unexpected Loss (Capital)

Downturn LGD

The Basel Committee on Banking Supervision (2006) requires a downturn loss rate given default (downturn LGD) as an input for LGD in the regulatory capital computations:

> A bank must estimate a LGD for each facility that aims to reflect economic downturn conditions where necessary to capture the relevant risks. This LGD cannot be less than the long-run default-weighted average loss rate given default calculated based on the average economic loss of all observed defaults within the data source for that type of facility. In addition, a bank must take into account the potential for the LGD of the facility to be higher than the default-weighted average during a period when credit losses are substantially higher than average.

In short, there are two key ideas presented here: The LGD should be higher than the long-run default-weighted average loss rate given default, and it should be an economic downturn LGD. We will discuss both in more detail in what follows.

Averaging LGD

There are various ways of calculating an average LGD. A time-weighted LGD first calculates the LGD for the individual years of observation and then averages those. A default-weighted LGD is calculated by dividing the total losses by the total number of defaults. An exposure-weighted LGD weighs each default by its EAD, whereas a default count LGD assigns an equal weight to each default. Based on this, an average LGD can be computed in four possible ways. In Exhibit 14.7 you can see the four possible average LGDs.

Exhibit 14.7 Options for Averaging LGD

	Default Count Averaging	**Exposure-Weighted Averaging**
Default-Weighted Averaging	**Option 1**: Each default has equal weighting. Defaults from all years are grouped into a single cohort.	**Option 2**: The weighting of each default is determined by the exposure at default. Defaults from all years are grouped into a single cohort.
Time-Weighted Averaging	**Option 3**: Each default has equal weighting within the annual cohort average. The average is calculated as the average of annual averages.	**Option 4**: The weighting of each default within the annual cohort average is determined by the exposure at default. The average is calculated as the average of annual averages.

Economic Downturn LGD

Various approaches to specify the downturn LGD are common in industry:

- Basel foundation approach: The Basel Committee on Banking Supervision (2006) specifies within the internal ratings based (IRB) approach a benchmark loss rate given default as follows: $DLGD = \begin{cases} 75\% & \text{for all subordinated claims} \\ 45\% & \text{for corporate senior unsecured loans} \\ 10\% & \text{for real estate secured loans} \end{cases}$
- Office of the Comptroller of the Currency (OCC) proposal: The U.S. Department of the Treasury, Federal Reserve System, and Federal Deposit Insurance Corporation (2006)

proposed a linear relationship between the downturn LGD and the expected LGD (ELGD). The formula implies a floor of 8 percent and a cap of 100 percent:

$$DLGD = 0.08 + 0.92 \times ELGD$$

- Historical approach: Financial institutions may apply the expected loss rate given default of selected historical downturn periods.

Historical Approach

The expected LGD may be computed for a risk segment as the average LGD over time. The correct computation is often controversial. In particular, the second and third approaches lead to different outcomes for financial institutions in different economies. Economies that have experienced a severe economic downturn in recent history are likely to have a higher downturn LGD than economies that have not.

Rösch and Scheule ([2010, 2012b]) show how to estimate downturn LGD based on two econometric techniques. In the first approach, downturn LGD is estimated by restricting the LGD data to downturn periods (i.e., periods where the loss rate is below the median). In the second approach, downturn LGD is estimated based on the Basel worst in 1,000 economic scenarios and the estimated correlation between the default and recovery processes. Similar principles apply to downturn EAD.

Here, we show two simple examples to determine downturn LGD. In the first example, a bank may allocate the maximum average LGD observed in its history to a risk segment j:

$$DLGD_j = \max_t (LGD_{jt})$$

In the second example, downturn LGD is computed by constructing a table as depicted in Exhibit 14.8.

	Segment 1	Segment 2			Segment K	Periods with Decreasing Default Rates
Period 1: (year with highest DR)	AVG LGD (period 1, segment 1)	AVG LGD (period 1, segment 2)	…	…	AVG LGD (period 1, segment K)	
Period 2: (2 years with highest DR)	AVG LGD (period 2, segment 1)	AVG LGD (period 2, segment 2)	…	…	AVG LGD (period 2, segment K)	
…						
…						
…						
Period $n-1$: (all years except with lowest DR)	AVG LGD (period $n-1$, segment 1)	AVG LGD (period $n-1$, segment 2)	…	…	AVG LGD (period $n-1$, segment K)	
Period n: (all years)	AVG LGD (period n, segment 1)	AVG LGD (period n, segment 2)	…	…	AVG LGD (period n, segment K)	
Reference	**Calibrated LGD1**	**Calibrated LGD2**			**Calibrated LGDK**	

Exhibit 14.8 Example for Computing the Downturn LGD

Let us assume we have K LGD ratings or segments. Assume period 1 is the year with the highest default rate, period 2 is the two years with the highest default rate, and so on. We can then calculate the average LGD for each of the cells in the table. If the averages reported within each of the columns are relatively similar, then it can be concluded that there is no PD-LGD correlation and no downturn calibration is needed. However, if the averages do vary substantially, then a correlation is present, and a downturn LGD can be obtained by only including the first one, two, or more rows.

STRESS TESTING APPLICATIONS IN SAS

Rösch and Scheule ([2007, 2008]) show that the following uncertainties may be considered by a bank in its stress testing analysis:

- Scenario stress testing
- Parameter uncertainty

In light of the presence of a risk model and the Berkowitz critiques, stress testing results in capital increases only if a stress test produces a more severe outcome than the risk model. Examples that will increase the required capital are:

- A stress test of the PD that exceeds the worst-case default
- A stress test of the asset correlations that exceeds the Basel asset correlations
- A stress test of the LGD that exceeds the downturn LGD
- A stress test of the EAD that exceeds the downturn EAD

Scenario-Based Stress Testing

We start off with the DFAST "severely adverse" scenario for GDP (gdp_time) and unemployment rate (uer_time). We include these macroeconomic variables in a probit model for the PD next to the idiosyncratic FICO score and the idiosyncratic and time-varying current LTV ratio:

```
PROC LOGISTIC DATA=data.mortgage DESCENDING;
MODEL default_time = FICO_orig_time
LTV_time GDP_time uer_time/ LINK=PROBIT;
STORE OUT=model_probit;
RUN;
```

The parameter estimates show that the GDP growth rate reduces the credit risk (PD) whereas the unemployment rate increases the risk (see Exhibit 14.9).

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	−0.9135	0.0363	633.3864	<.0001
FICO_orig_time	1	−0.00239	0.000050	2,288.8365	<.0001
LTV_time	1	0.00851	0.000179	2,269.6179	<.0001
gdp_time	1	−0.0546	0.00173	996.4997	<.0001
uer_time	1	−0.0260	0.00218	142.3360	<.0001

Exhibit 14.9 Probit Model

We will now estimate the PDs for all loans in time period 60 for the baseline scenario by generating a data set that includes only observations for this period and scoring the data set using PROC PLM:

```
DATA mortgage_base;
SET data.mortgage;
WHERE time=60;
KEEP FICO_orig_time LTV_time gdp_time uer_time;
run;
PROC PLM SOURCE=model_probit;
SCORE DATA= mortgage_base out= probabilities;
RUN;
```

We then convert the predicted scores into baseline PDs (PD_time_base) and Basel worst-case default rates. Next, we overwrite the baseline economic scenarios by the DFAST severely adverse scenarios in the first quarter in 2015: GDP growth of –6.1 percent and an unemployment rate of 8 percent. Note that the actual values for the period included a GDP growth of 2.84 percent and an unemployment rate of 5.7 percent.

```
DATA probabilities;
set probabilities;
PD_time_base=PROBNORM(predicted);
PD_time_wcdr=PROBNORM((PROBIT(PD_time_base)+SQRT(0.15))/SQRT(1-0.15));
gdp_time=-6.1;
uer_time=8;
run;
```

We then compute the cumulative frequencies for the resulting baseline PDs and worst-case default rate:

```
proc sort data=probabilities;
  by PD_time_base;
run;
data probabilities;
set probabilities nobs=totalobs;
PD_time_base_pcs = _n_ / totalobs;
PD_time_wcdr_pcs = _n_ / totalobs;
run;
```

We estimate the PDs for all loans in time period 60 for the severely adverse economic scenario by generating a data set that includes only observations for this period and scoring the data set using PROC PLM:

```
PROC PLM SOURCE=model_probit;
SCORE DATA= probabilities out= probabilities2;
RUN;
```

We then convert the predicted scores into stressed PDs (PD_time_stress) and compute the cumulative frequencies for the resulting stressed PDs:

```
DATA probabilities2;
SET probabilities2;
PD_time_stress=PROBNORM(predicted2);
RUN;
PROC SORT DATA=probabilities2;
  BY PD_time_stress;
RUN;
DATA probabilities2;
SET probabilities2 NOBS=totalobs;
PD_time_stress_pcs = _N_ / totalobs;
RUN;
```

We use PROC GPLOT to plot the cumulative distribution functions for the baseline PDs, worst-case default rates, and stressed PDs. We see that the worst-case default rates are substantially higher than the baseline PDs and that the stressed PDs are substantially higher than the worst-case default rates.

```
ODS GRAPHICS ON;
AXIS1 ORDER=(0 to 0.1 BY 0.02) LABEL=('PD');
AXIS2 ORDER=(0 to 1 BY 0.25) LABEL=('Frequency');
SYMBOL1 interpol=SPLINE WIDTH=2 VALUE=TRIANGLE C=BLUE;
SYMBOL2 interpol=SPLINE WIDTH=2 VALUE=CIRCLE C=RED;
SYMBOL3 INTERPOL=SPLINE WIDTH=2 VALUE=SQUARE C=BLACK;
LEGEND1 LABEL=NONE SHAPE=SYMBOL(4,2) POSITION=(BOTTOM OUTSIDE);
PROC GPLOT DATA=probabilities2;
PLOT PD_time_base_pcs*PD_time_base PD_time_wcdr_pcs*PD_time_wcdr
PD_time_stress_pcs*PD_time_stress /
OVERLAY LEGEND=legend1 HAXIS=axis1 VAXIS=axis2;
RUN;
ODS GRAPHICS OFF;
```

In Exhibit 14.10, a stress is more pronounced the farther the cumulative distribution function moves to the right. A bank performs similar analyses for a large number of macroeconomic stress scenarios covering multiple future periods for the various credit risk parameters. Similarly to stressing PDs, other risk parameters such as asset correlations, LGDs, and EADs can also be stressed. All stressed parameters will be aggregated into cumulative losses. The cumulative losses from the loan portfolios will be aggregated with the bank risk exposures (e.g., the trading book and operational risk exposure). The aggregated loss will then be compared with existing loss levels. Alternatively, a bank may compute the capital level that is required to sustain such a severely adverse economic scenario.

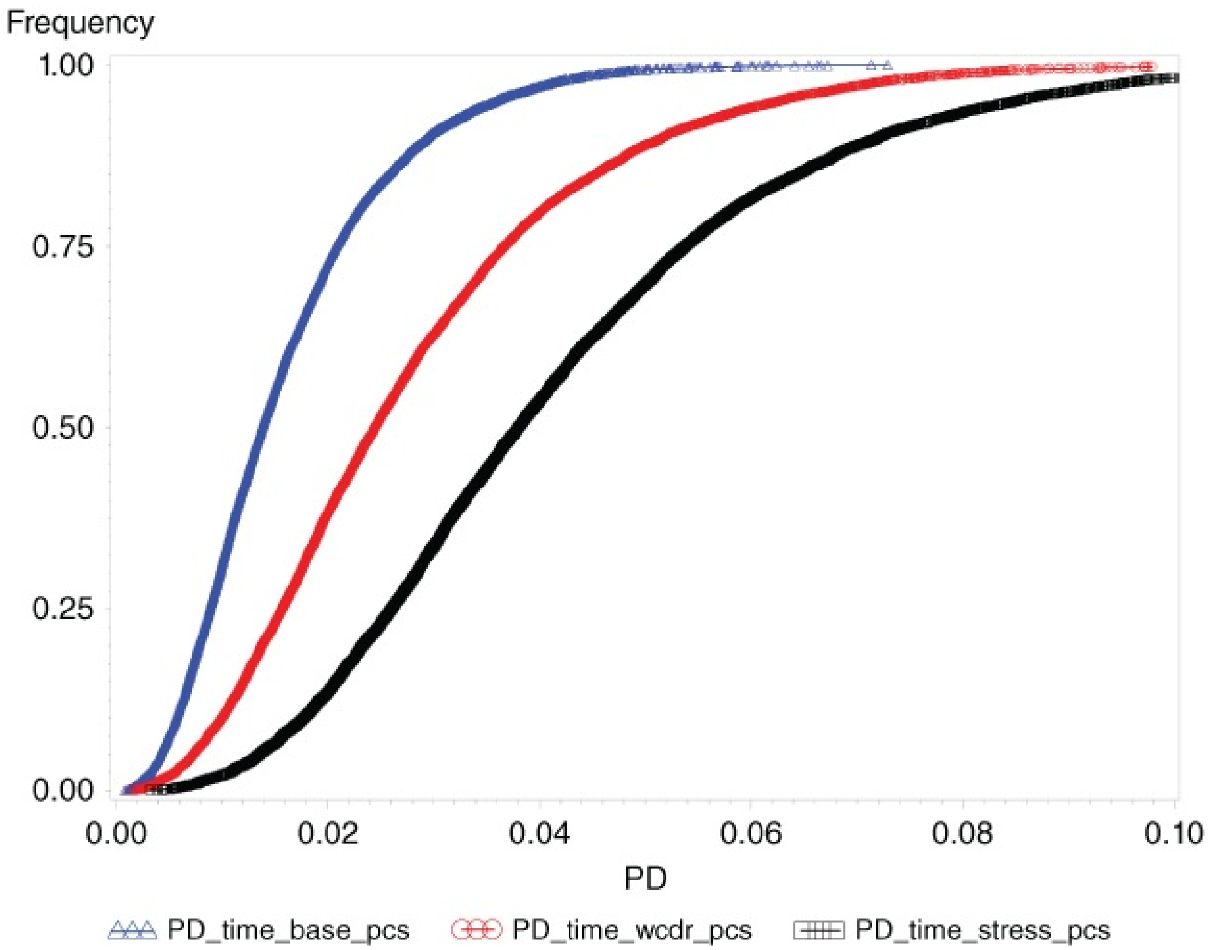

Exhibit 14.10 Cumulative Distribution Function for Baseline PDs, Basel Worst-Case Default Rates, and Stressed PDs

Stress Testing and Parameter Uncertainty

Another important aspect is the consideration of model risk. Examples in the literature include Rösch and Scheule (2007), Tarashev and Zhu (2008), and Lee, Rösch, and Scheule (2016).

Most risk models rely on the estimation of parameters β that in a linear combination $\beta' x$ with covariates characterize the risk measure PD, EAD, or LGD. A similar concept may apply to asset correlations, but we do not discuss this further due to time-series data limitations. The parameter estimates are random, and it is common to assume a multivariate (if there are two or more parameters) normal distribution, which can also be justified by maximum-likelihood theory:

$$\beta \sim N(\hat{\beta}, \Sigma)$$

with the parameter estimates being the mean and the estimated covariance matrix. The variances on the diagonal are equal to the squared standard errors that are reported in addition to the parameter estimates in SAS.

Next, we work out an example based on the probit model from our PD chapter (including the macroeconomic variable GDP growth rate) where we add the COVB in the MODEL statement to show the estimated parameter estimates and covariance matrix. We export both into the SAS data sets ParameterEstimates and covb:

```
PROC LOGISTIC DATA=data.mortgage DESCENDING;
MODEL default_time = FICO_orig_time
LTV_time GDP_time/ LINK=probit COVB;
STORE OUT=model_probit;
ODS OUTPUT ParameterEstimates=ParameterEstimates COVB=covb;
RUN;
```

The parameter estimates and estimated covariance matrix are presented in Exhibit 14.11.

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	−1.0091	0.0354	814.0574	<.0001
FICO_orig_time	1	−0.00242	0.000050	2366.9776	<.0001
LTV_time	1	0.00781	0.000158	2447.5807	<.0001
gdp_time	1	−0.0496	0.00167	883.8005	<.0001

Estimated Covariance Matrix				
Parameter	Intercept	FICO_orig_time	LTV_time	gdp_time
Intercept	0.001251	−1.58E−6	−2.08E−6	−0.00001
FICO_orig_time	−1.58E−6	2.473E−9	−443E−12	4.097E−9
LTV_time	−2.08E−6	−443E−12	2.492E−8	9.593E−8
gdp_time	−0.00001	4.097E−9	9.593E−8	2.789E−6

Exhibit 14.11 Probit Model

Note that the parameter estimates are different from those of the probit model in the previous section, as this model does not include the unemployment rate.

Basic Stress Testing of Parameter Uncertainty

We may be interested in computing the probabilities of default under consideration of the upper percentile (e.g., the 99th percentile) for all parameters. To do this, we proceed as follows:

In a first step, we compute the stressed PDs by computing the stressed parameters. We take the upper or lower percentile for the parameter distribution that produces the highest default probability in a stress test. For covariates that are positive throughout (e.g., FICO_orig_time and LTV_time), we take the upper percentile, and for covariates that are negative and positive (GDP_time), we take the lower percentile. For example, the parameters for both the FICO score and GDP growth are negative and the stressed PD will be higher if the stressed parameter for FICO score is higher (as FICO is always positive) and the stressed parameter for GDP growth is lower (as GDP growth is generally positive in economic upturns and negative during economic downturns).

```
DATA ParameterEstimates(KEEP=variable estimate estimate_stress);
SET ParameterEstimates;
estimate_stress=estimate+StdErr*PROBIT(0.99);
IF variable= 'gdp_time' THEN estimate_stress=estimate-StdErr*PROBIT(0.99);
RUN;
```

In a second step, we transpose the parameter estimates:

```
PROC TRANSPOSE DATA=ParameterEstimates OUT=ParameterEstimates2(DROP=_NAME_)
SUFFIX=_base;
VAR estimate;
ID variable;
RUN;
PROC TRANSPOSE DATA=ParameterEstimates OUT=ParameterEstimates3(DROP=_NAME_)
SUFFIX=_stress;
VAR estimate_stress;
ID variable;
RUN;
```

In a third step, we merge the resulting data set with the covariate data set for the time period 60. The match merge is by joint variable “one,” which is one for all observations. We do this as we require the base and stressed parameter estimates for all covariate observations to compute the base and stressed default probabilities:

```
DATA ParameterEstimates2;
set ParameterEstimates2;
one=1;
RUN:
DATA ParameterEstimates3;
set ParameterEstimates3;
one=1;
RUN:
DATA mortgage;
SET data.mortgage;
WHERE time=60;
one=1;
KEEP FICO_orig_time LTV_time one gdp_time;
run;
DATA mortgage_parameters;
MERGE mortgage ParameterEstimates2 ParameterEstimates3;
BY one;
RUN;
```

In a fourth step, we compute the base PDs using the base parameter estimates and covariates and the stressed PDs using the stressed parameters and covariates:

```
DATA mortgage_parameters;
SET mortgage_parameters;
PD_time_base=probnorm(
intercept_base+FICO_orig_time_base*FICO_orig_time+LTV_time_base*LTV_time
+GDP_time_base*GDP_time);
PD_time_stress=probnorm(
```

```
intercept_stress+FICO_orig_time_stress*FICO_orig_time+LTV_time_stress*LTV_t

+GDP_time_stress*GDP_time);
RUN;
```

The cumulative distribution functions for the base and stressed PDs are computed using the same methodology as in the previous section with the PLOT statement PLOT PD_time_base_pcs * PD_time_base PD_time_stress_pcs * PD_time_stress in PROC GPLOT. The resulting figure (Exhibit 14.12) shows that the stressed default probability is greater than the base default probability.

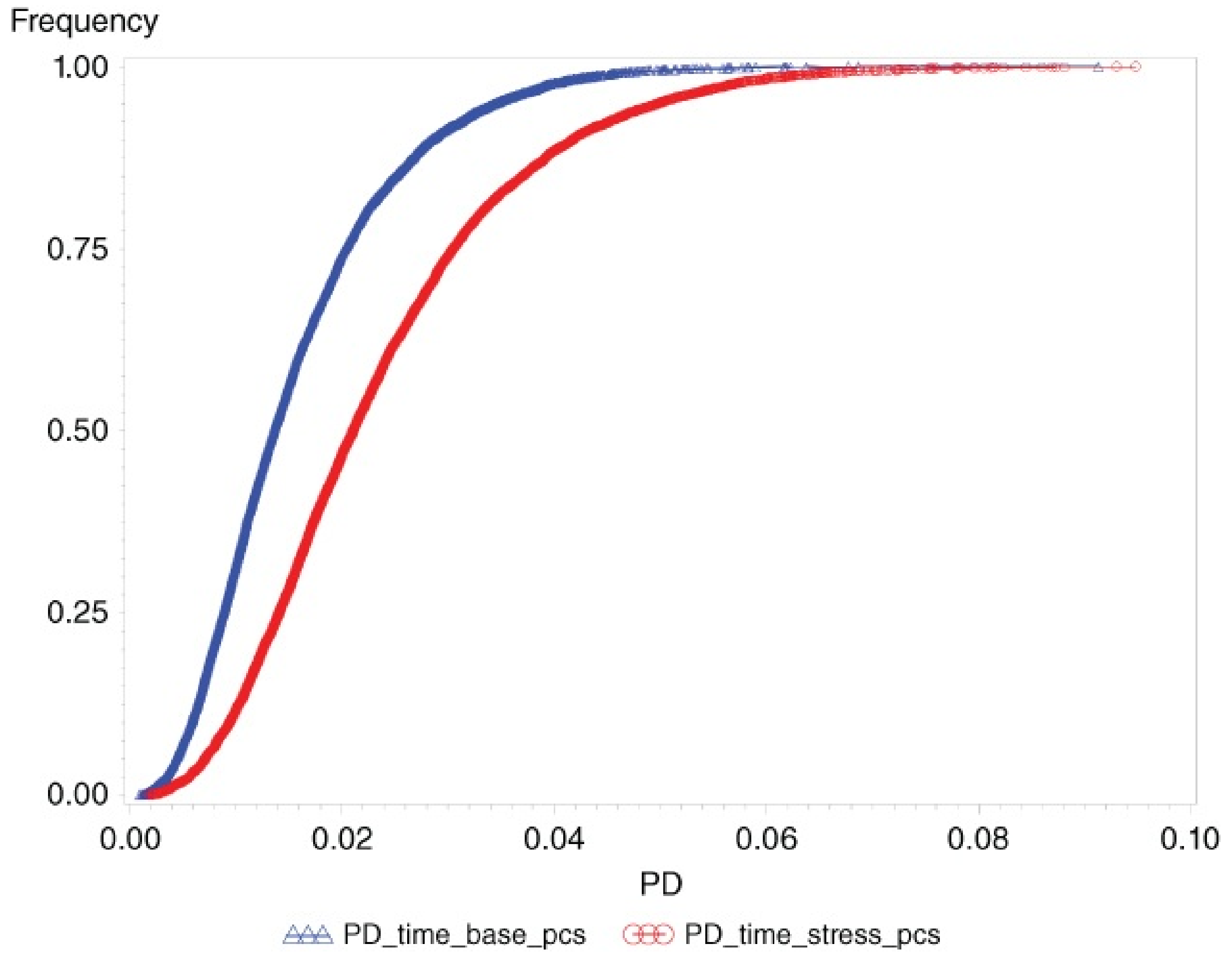

Exhibit 14.12 Cumulative Distribution Function for Baseline and Stressed PDs under Consideration of Model Risk (Basic Stress Test)

Multivariate Stress Testing of Parameter Uncertainty

In the basic stress test of the previous section, we assigned an error likelihood of 1 percent to all stressed parameters. In other words, we assume that every stressed parameter estimate is set to the 99th percentile. As we have multiple covariates and parameters, a more sophisticated stress test would be to construct joint, simultaneous (e.g., Bonferroni) confidence intervals instead of separate intervals for each parameter.

In order to compute this stressed PD, we need to consider the covariance matrix and apply Monte Carlo simulation analysis, which can be implemented in PROC IML. We have shown earlier examples in the context of the simulation of portfolio loss distributions in our default correlations and credit portfolio risk chapter.

In terms of data preprocessing, we continue with the data set from the basic stress test of model risk, which already contains the base PD and stressed PD from the basic parameter stress test. Care must be taken to ensure that the variables are in the order of the covariates specified in PROC LOGISTIC as we will import the parameter estimates, estimated covariance matrix, and covariates into PROC IML, which numbers but does not name columns and rows. In other words, the first (second, and so on) row in the parameter estimates and covariance data must match the first (second, and so on) column in the covariate data set.

```
DATA mortgage_parameters;
RETAIN FICO_orig_time LTV_time GDP_time;
SET mortgage_parameters;
RUN;
```

We now import the three SAS data sets ParameterEstimates and covb as well as the data set from the previous section mortgage_parameters that includes base and stressed PDs (basic stress test) into PROC IML. We add comments in the code as indicated by /*[...]*/. We then run 1,000 simulations with 1,000 stressed parameter values and compute a PD for every borrower and iteration.

```
PROC IML;
/*import data*/
USE ParameterEstimates;
READ ALL VAR _ALL_ INTO ParameterEstimates;
USE covb;
READ ALL VAR _ALL_ INTO cov;
USE mortgage_parameters;
READ ALL VAR _ALL_ INTO mortgage_parameters;
/*limit data sets*/
mean=ParameterEstimates[,1];
mortgage_parameters=mortgage_parameters[,1:2];
/*start simulation - multiple iterations*/
DO k=1 TO 1000;
/*draw random correlated normals*/
param_sim= RANDNORMAL(1, mean, cov);
/*compute stress PD*/
linear_predictor=param_sim[,1]+param_sim[,2]*mortgage_parameters[,1]
+param_sim[,3]*mortgage_parameters[,2];
PD_time_stress=PROBNORM(linear_predictor);
print PD_time_stress;
/*collect all PD vectors*/
IF k=1 THEN DO;
PD_time_stress2=PD_time_stress;
END;
IF k>1 THEN DO;
PD_time_stress2=PD_time_stress2||PD_time_stress;
END;
END;
/*export to Base SAS*/
CREATE PD_time_stress2 FROM PD_time_stress2;
```

```
APPEND FROM PD_time_stress2;
QUIT;
```

The result is a data set that has 1,000 columns (for every iteration one column) and I_{60} rows with I_{60} being the number of borrowers at time period 60 (here: 8,004). We can then compute the 99th percentile for every borrower by using PROC TRANSPOSE and PROC MEANS:

```
PROC TRANSPOSE DATA=PD_time_stress2 OUT=PD_time_stress3;
RUN;
PROC MEANS DATA=PD_time_stress3;
OUTPUT OUT=PD_time_stress4 P99(COL1-COL8004)=COL1-COL8004;
RUN;
```

We then transpose the resulting data set with the stressed PDs and append it to the data set mortgage_parameters:

```
PROC TRANSPOSE DATA=PD_time_stress4 OUT=PD_time_stress5;
RUN;
data PD_time_stress5;
SET PD_time_stress5;
IF _NAME_='_TYPE_' or _NAME_='_FREQ_' THEN DELETE;
RENAME COL1=PD_time_stress2;
RUN;
DATA mortgage_parameters2;
SET mortgage_parameters;
SET PD_time_stress5;
RUN;
```

We can now again plot the base PD, stressed PD (basic stress test), and stressed PD (multivariate stress test) using PROC GPLOT with PLOT statement: PLOT PD_time_base_pcs * PD_time_base PD_time_stress_pcs * PD_time_stress PD_time_stress2_pcs * PD_time_stress2. (See Exhibit 14.13.)

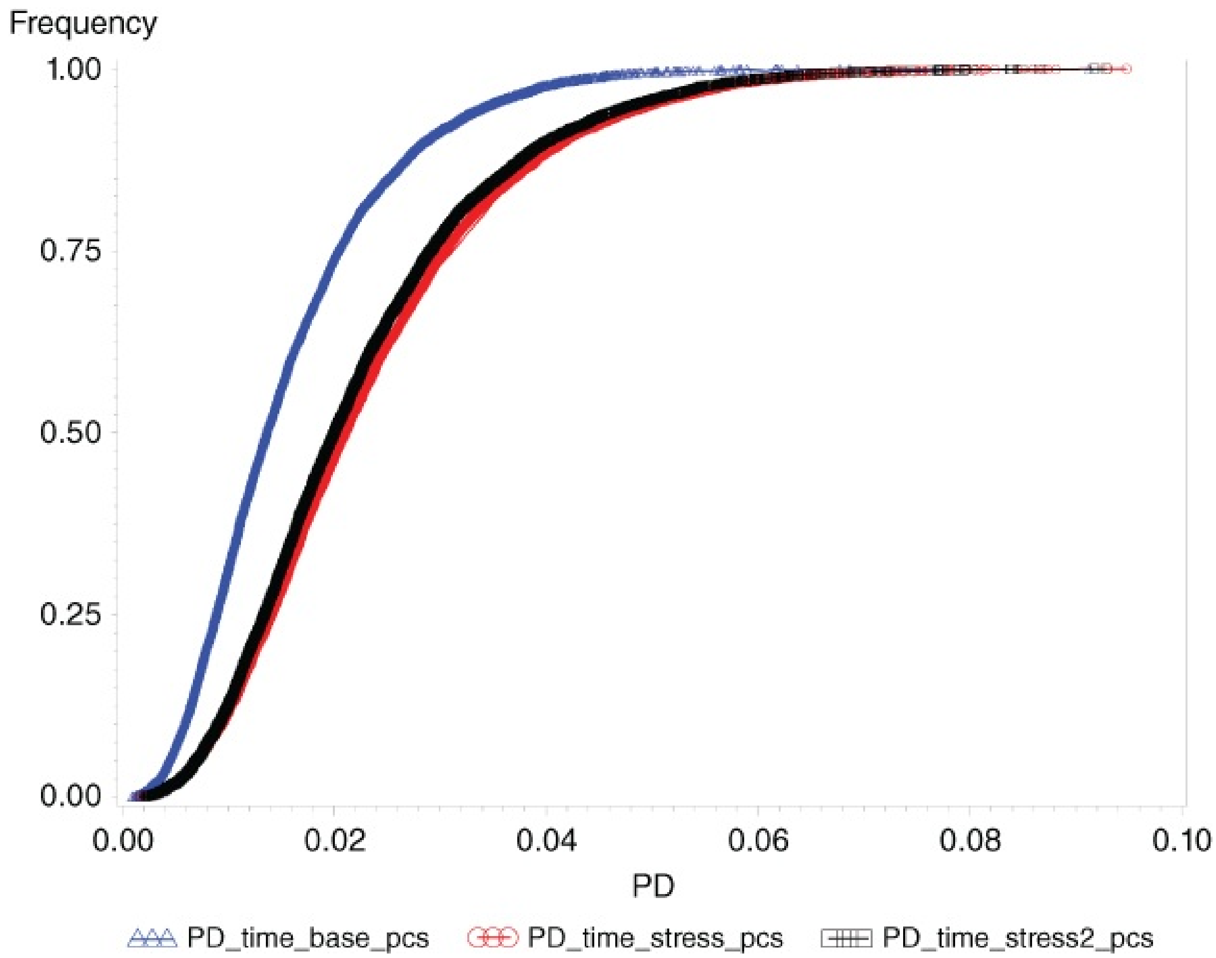

Exhibit 14.13 Cumulative Distribution Function for Baseline and Stressed PDs under Consideration of Model Risk (Basic Stress Test and Multivariate Stress Test)

```
proc sort data=mortgage_parameters2;
  by PD_time_stress2;
run;
data mortgage_parameters2;
set mortgage_parameters2 nobs=totalobs;
PD_time_stress2_pcs = _n_ / totalobs;
run;
ODS GRAPHICS ON;
AXIS1 ORDER=(0 to 0.1 BY 0.02) LABEL=('PD');
AXIS2 ORDER=(0 to 1 BY 0.25) LABEL=('Frequency');
SYMBOL1 interpol=SPLINE WIDTH=2 VALUE=TRIANGLE C=BLUE;
SYMBOL2 interpol=SPLINE WIDTH=2 VALUE=CIRCLE C=RED;
SYMBOL3 INTERPOL=SPLINE WIDTH=2 VALUE=SQUARE C=BLACK;
LEGEND1 LABEL=NONE SHAPE=SYMBOL(4,2) POSITION=(BOTTOM OUTSIDE);
PROC GPLOT DATA=mortgage_parameters2;
PLOT PD_time_base_pcs*PD_time_base PD_time_stress_pcs*PD_time_stress
PD_time_stress2_pcs*PD_time_stress2 /
OVERLAY LEGEND=legend1 HAXIS=axis1 VAXIS=axis2;
RUN;
ODS GRAPHICS OFF;
```

The multivariate stress test is less pronounced than the basic stress test, as the 99th percentile of the simulated default probabilities is only slightly higher than the base default probabilities.

As an extension, correlations between the risk model (via extended PD, LGD, and EAD models, which include random effects) and model risk may be included by applying the same methodology.

PRACTICE QUESTIONS

1. Explain the Berkowitz critique and show how stress testing and bank capital are related.
2. Estimate a logit model for PDs based on the FICO score and LTV ratio at origination. Stress the resulting PDs using the Basel worst-case default rate. Categorize the LTV ratio at origination and compute the maximum average current LTV per time for every bucket: Use this value to compute a second stressed PD. Compare and interpret the two stress definitions. Use data set mortgage.
3. Estimate a cloglog model for PDs based on the FICO score and LTV ratio at origination. Compute the expected PD, worst-case default rate, and stressed PD. Compute the loan loss provisions, regulatory capital, and minimum capital buffer assuming an EAD of $1 million and an LGD of 20 percent. Assume that Basel and stressed EAD/LGD are equal to the expected EAD/LGD. Use data set mortgage.
4. Estimate the expected and stressed LGD based on the LTV ratio using the OCC and a historical approach. Use data set lgd.
5. Estimate a stressed PD based on parameter uncertainty for a probit model based on the FICO score and LTV ratio at origination. Apply a one-sided error likelihood of 5 percent to all parameters. Use data set mortgage.
6. Parameter uncertainty is one source of model risk. Can you think of other sources of model risk?

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