In the proposed example, let us suppose that, after the default, the time necessary for the bankruptcy procedure is 24 months. Every month the credit institution has to pay a fixed amount of money equal to EUR 1,000 (EF_t) for legal fees. The Exposure at default (EAD) is EUR 100,000 and there is a positive expectation for the bank that it will be able to recover a total amount of EUR 60,000 divided into tranches: 10,000 at the end of the 21st month and 50,000 at the end of the second year. Changing variable i in the script, the code can be run under different scenarios of the rates adopted for discounting.

- Setting i=RiskFree, the risk-free interest rate is used for discounting the future cash flows. The market interest rates term structure, which we have already used in the counterparty module, section "PD via bond spread", was implemented. In this case the LGD is equal to 63.58%.

- Setting i=AdjRate, a spread of 350 bps has been added over the risk free curve. In this second scenario the LGD is equal to 66.69%.

- Running the code with a hypothetical contractual rate of 4% used for the discounting process, we obtain an LGD equal to 67.48%.

The output of the code is a tuple of two elements: the first is the estimated LGD and the second is a Numpy array with the details of the future cash flows. The Tableau automatically generated from the LGDestimation function has in the first column the year fractions (t), in the second column the discount rates (i), the third column contains the recovery cash flows (RF_t), cost flows are displayed in the fourth column (EF_t) and the discounted cash flows are reported in the last two columns. So far we have discussed the issues related to the estimation of LGD. Now let us proceed and consider the most important factors for performing predictions. With this aim, it is useful to classify the variables used for LGD forecasting into four categories:

- **Instrument-related variables**. Debt instruments can differ in several aspects that are relevant for LGD estimation. In the event of default, not all borrowers are equal. They are divided in function of the priority of repayment in a liquidation or restructuring (i.e. the seniority). Furthermore, some debt instruments are secured, giving the debt holders the right to claim specific assets connected with the instrument. For instance in a mortgage loan, in case of default, the bank has the right to seize the building and use the sale proceeds to partially recover the debt. There may also be differences between the LGD of bank loans and public bonds because the quality of the security is typically higher for bank loans than for bonds.

Debt Type	Average LGD
Bank loans	0.262
Senior secured bonds	0.428
Senior unsecured bonds	0.57
Senior subordinated bonds	0.717
Subordinated bonds	0.806

Table VIII.25 Average LGD, 1987-2009 (Source: Standard & Poor's, 2010)

In a regression model, we can capture such average differences in two alternative ways:

a) Create one variable that contains the historical average LGD of the respective debt type. For a senior secured bond, this variable would record the average LGD of a senior secured bond; for a subordinated bond, the same variable would record the average LGD of subordinated bonds, and so forth.

b) Introduce dummy variables for debt types. The senior secured bond dummy, for example, would take the value 1 for senior secured bonds, and 0 otherwise.

In the second approach, we estimate average LGD differences across debt types with our data. Any differences not explained by other variables will be reflected in the regression coefficients of the dummy variables. With the first approach, we can bring in information from other sources. This can help to increase the precision of the estimates, particularly if the size of the data set is small. When using the dummy variable approach to model differences among K debt types, we would only include dummy variables for $K-1$ debt types. The coefficients of the dummy variables then reflect how LGDs differ from the LGD of the type that is not represented in the regression. Unluckily, modeling average differences across debt types is typically not sufficient to capture the effects of seniority and security. Let us consider a firm whose outstanding debt consists only of subordinated bonds. In this case, the subordinated are the most senior bonds. We can capture such effects by ordering the claims according to their seniority and security. We can summarize the priority standing of an instrument in different ways. One of the most well-established techniques is to define it through the ratio:

$$\frac{Face\ value\ of\ debt\ with\ higher\ priority - Face\ value\ of\ debt\ with\ lower\ priority}{Total\ face\ value\ of\ debt} \quad (Eq.\ VIII.71)$$

The higher this measure, the higher is the expected LGD.

- **Firm-specific variables**. The overall losses incurred by creditors will equal the value of liabilities minus the value of the firm's assets after bankruptcy costs. We can therefore hope to increase predictive accuracy if we find variables that contain information about the post-default asset value or bankruptcy costs. Among the most considered variables in the literature are the following:

Tangibility: For several reasons, tangible assets (usually defined as property, plant and equipment) could on average lead to lower LGD. For instance, they can be used to generate revenue during restructuring, or they may tend to lose less value than intangible assets.

$$\frac{Property, Plant, Equipment}{Total\ assets} \quad (Eq.\ VIII.72)$$

Market-to-book ratio: For firms with traded equity, the market-to-book ratio, which is often referred to as Tobin's Q, is usually computed as:

$$\frac{Market\ value\ of\ equity + book\ value\ of\ liabilities}{Total\ assets} \quad (Eq.\ VIII.73)$$

where the total of assets is the book value of assets. The higher the ratio, the higher is the market valuation of the firm's assets. If the valuation continues to be relatively high after default, the LGD will be relatively low. On the other hand, firms with a high market-to-book ratio are typically growth firms, which are highly valued

because they promise high profits in the future. As such promises can dissipate quickly in the case of default, a high market-to-book ratio could also indicate high LGDs.

Leverage: It is typically measured as:

$$\frac{Total\ debt}{Total\ assets} \quad (Eq.\ VIII.74)$$

This ratio is usually expected to be positively correlated with the LGD. One possible reason for such relationship is that debt structure is typically more complex for highly leveraged firms. This can complicate bankruptcy procedures, leading to larger bankruptcy costs and a higher LGD.

- **Macroeconomic variables**. Macroeconomic conditions can be useful for predicting LGD because they can help to estimate the value of the assets in case of default. In many cases, we would use figures for the country in which the borrower is domiciled or where he generates the largest part of its income. In other cases, regional or global aggregates can be more suitable. Variables that could be considered include the following:

Capacity utilization: If capacity utilization is low, demand for the firm's assets will tend to be low because competitors do not need additional production capacities. This depresses prices and leads to a high LGD.

GDP growth: The explanation is similar to the capacity utilization. A negative economic environment is expected to go along with high LGDs.

Corporate bond spreads: Generally, the value of an asset is obtained as the present value of cash flows that can be generated with the asset. Ceteris paribus, the asset value will therefore fall with increasing discount rates. To capture variation in discount rates we can use a yield spread, for instance defined through: Corporate bonds yield or Treasury bonds yield. The higher the spread, the higher is the expected LGD.

Default rates: High default rates indicate a negative economic environment. The mechanism leading to high LGDs would therefore be similar to the ones described above. Default rates may measure the relevant valuation factors in a more specific way. High default rates imply a high supply of defaulted debt, which tends to depress prices of such debt.

- **Industry-specific variables**. It can also be a good idea to replace the suggested variables above with variables defined on the level of the industry to which the observed firm belongs. For instance:

Capacity utilization: At a given point in time, the economic environment can differ substantially between industries. Using industry capacity utilization instead of (or in addition to) economy-wide capacity utilization can help to better capture the economic environment that is relevant for the valuation of a bankrupt firm's assets.

Market-to-book ratio: If a firm does not have traded equity, we cannot compute the firm-specific market-to-book ratio. In such cases, we can use the average market-to-book ratio of traded firms in an industry.

Let us now examine an example of LGD prediction based on a database provided in the "Credit Risk Modeling" book by Löffler & Posch. In this yearly dataset, we have three explanatory variables:

a) the historical average LGD of the respective debt type, computed with data ending the year before default.