Basel II and Basel III Credit, Market, Operational, and Liquidity Risks with Asset Liability Management

It is often said that the Basel Committee Standards, formally called Capital Accords, constitute the bible for banking regulators (Central Banks) everywhere. In addition to the Accords, the Basel Committee has also framed 29 principles for effective banking supervision known as the Core Principles for Effective Banking Supervision. These standards encompassed by the Capital Accord and the Core Principles have become the source of banking regulation in every country in the world. As is widely known, these standards have evolved from Basel I to Basel II and III, reflecting the evolution of the financial industry (from Basel I to II) and the lessons from the financial crisis of 2008 (from Basel II to III). The most noticeable financial regulation paradigm changes captured and fostered by the Basel standards' evolution are risk management and capital allocation. These most important changes in the international standards, and, therefore, in virtually every country´s financial regulatory framework, relate to the manner in which risks are managed and capital is calculated. By the general definition, as stated in Core Principle 15, Risk Management is the process to be used to "identify, measure, evaluate, monitor, report and control or mitigate all material risks on a timely basis and to assess the adequacy of their capital and liquidity in relation to their risk profile." This process has been presented as the IMMM process: Identify, Measure, Monitor, and Mitigate each risk. In practice, the way to manage risks, and, hence, comply with the new Basel regulations, is to introduce or enhance the IMMM process for each material risk the financial institution faces.

Along with the aforementioned international standards, there are tools that facilitate the implementation or enhancement of the IMMM processes. Briefly, these are (i) Formal Policies; (ii) Key Risk Indicators; (iii) Capital Models; and (iv) MIS/Reports.

This case study looks at the practical tools—quantitative models, Monte Carlo risk simulations, credit models, and business statistics—utilized to model and quantify regulatory and economic capital, measure and monitor key risk indicators, and report all the obtained data in a clear and intuitive manner. It relates to the modeling and analysis of asset liability management, credit risk, market risk, operational risk, and liquidity risk for banks or financial institutions, allowing these firms to properly identify, assess, quantify, value, diversify, hedge, and generate periodic regulatory reports for supervisory authorities and Central Banks on their credit, market, and operational risk areas, as well as for internal risk audits, risk controls, and risk management purposes.

In banking finance and financial services firms, *economic capital* is defined as the amount of risk capital, assessed on a realistic basis based on actual historical data, the bank or firm requires to cover the risks as a going concern, such as market risk, credit risk, liquidity risk, and operational risk. It is the amount of money that is needed to ensure survival in a worst-case scenario. Financial services regulators such as Central Banks, Bank of International Settlements, and other regulatory commissions should then require banks to hold an amount of risk capital equal at least to its economic capital times some holding multiple. Typically, economic capital is calculated by determining the amount of capital that the firm needs to ensure that its realistic balance sheet stays solvent over a certain time period with a prespecified probability (e.g., usually defined as 99.00%). Therefore, economic capital is often calculated with *Value at Risk* (VaR) type models.

Capital modeling in banks surged as a necessity for the larger international financial institutions, which discovered that the regulatory approaches taken by regulators were too basic and mainly not risk based. For example, credit risk capital requirements under Basel I were just a percentage (8% times another multiplier) of the volume of operations. This measure, which was very easy to calculate, was not risk sensitive, other than the differentiation of broad asset types. Therefore, complex banks found these capital requirements to be very inefficient in terms of capital planning, pricing, and leveraging limits and targets. With the evolution of the use of statistical models and available data—especially in market risk measurement—regulators started accepting internal capital models developed by the big international financial institutions. Accordingly, in 1996, an amendment was introduced to the Basel Accord (still Basel I) that allowed certain qualifying banks to calculate and hold capital in line with their internal models. To differentiate these measures of capital, banks started calling these internal calculations "economic capital," because it had a very close relationship with the real economics of the business, whereas "regulatory capital" was the requirement mandated by regulators. As the business evolved, and regulations became more ample, complex financial institutions started relying more on their economic capital models for the measurement and management of risks, while simultaneously having to hold regulatory capital. In most cases, the differences between these two kinds of capital for the same risk were very significant. This fact was one of the main motivators of Basel II, prompted mainly by a request from the more complex banks that the International Standards and, hence, banking regulations allow them to use their economic capital models to allocate regulatory capital. In other words, one of the outright motivations for the Basel II reforms was to close the practical gap between economic and regulatory capital.

As Basel II started to be implemented in most countries, the new regulatory paradigm established that banks—not just complex international financial institutions—must have IMMM processes for all material risks, and calculate and allocate economic capital for each and every one of these risks. For any given bank, these risks are defined by regulations as identified in the above-mentioned Core Principles: credit, market, operational, liquidity, interest rate, strategic, reputational, securitization, and so on. In this light, banks of any size, in virtually every country, need to identify, measure, monitor, and mitigate all these risks, and calculate, evaluate, and allocate economic capital for each. This case discusses a set of simple approaches with straightforward tools that allow banks of any size and complexity to generate information for the management (the IMMM process) of these risks, and for the calculation of economic capital based on available balance sheet and regulatory information.

In light of these International Standards, which are now formal regulations in virtually every country in the world, we utilize a spectrum of basic and more complex approaches to generate an economic capital model calculated on the formally defined risk drivers in each case and providing for risk sensitive capital results for each relevant risk. Additionally, for each risk, through a set of basic information, a set of key risk indicators is generated and combined with the capital model results to produce relevant risk reports. Since regulations still require many instances of regulatory capital, such calculation is still provided along with Basel Standards as another useful output of the designed tools. Finally, The Basel Committee differentiates credit, market, and operational risks from the rest, defining these three as the most relevant in any given financial institution. According to the Three Pillar design of Basel II, these are known as Pillar I risks. Under Basel II and III, economic and regulatory capital can be unified for Pillar I risks. In other words, for these three risks (credit, market and operational), economic capital models are given by the Basel Accord as a way to generate some standardization of methodologies and comparison among banks and countries.

For credit risk, the traditional approach for Basel I regulatory capital (still available as a basic choice in Basel III) is to calculate 8% of outstanding loan volume, multiplied by a factor depending on the type of asset treated (100% for uncollateralized loans, 50% for mortgages, 20% for interbank, etc.). This approach, however, does not differentiate by risk within each category. In order to create a more risk-sensitive approach, Basel II incorporated the main logic of portfolio models, where capital is the amount required to cover unexpected losses. Unexpected losses, in turn, are calculated as the residual given by the difference between the mean and the confidence interval of a loss distribution function.

Project Economic Analysis Tool on Modeling Banking Risk

Figure 1 illustrates the PEAT utility's ALM-CMOL module for Credit Risk—Economic Regulatory Capital (ERC) Global Settings tab. This current analysis is performed on credit issues such as loans, credit lines, and debt at the commercial, retail, or personal levels. To get started with the utility, existing files can be opened or saved, or a default sample model can be retrieved from the menu. The number of categories of loans and credit types can be set as well as the loan or credit category names, a *Loss Given Default* (LGD) value in percent, and the Basel credit type (*residential mortgages*, *revolving credit*, *other miscellaneous credit*, or *wholesale corporate and sovereign debt*). Each credit type has its required Basel III model that is public knowledge, and the software uses the prescribed models per Basel regulations. Further, historical data can be manually entered by the user into the utility or via existing databases and data files. Such data files may be large and, hence, stored either in a single file or multiple data files where each file's contents can be mapped to the list of required variables (e.g., credit issue date, customer information, product type or segment, Central Bank ratings, amount of the debt or loan, interest payment, principal payment, last payment date, and other ancillary information the bank or financial services firm has access to) for the analysis, and the successfully mapped connections are displayed. Additional information such as the required VaR percentiles, average life of a commercial loan, and historical data period on which to run the data files to obtain the *Probability of Default* (PD) are entered. Next, the *Exposure at Default* (EAD) analysis periodicity is selected as is the date type and the Central Bank ratings. Different Central Banks in different nations tend to have similar credit ratings but the software allows for flexibility in choosing the relevant rating scheme (i.e., Level 1 may indicate on-time payment of an existing loan whereas Level 3 may indicate a late payment of over 90 days and, therefore, constitutes a default). All these inputs and settings can be saved either as stand-alone settings and data or including the results. Users would enter a unique name and notes and save the current settings (previously saved models and settings can be retrieved, edited, or deleted, a new model can be created, or an existing model can be duplicated). The saved models are listed and can be rearranged according to the user's preference.

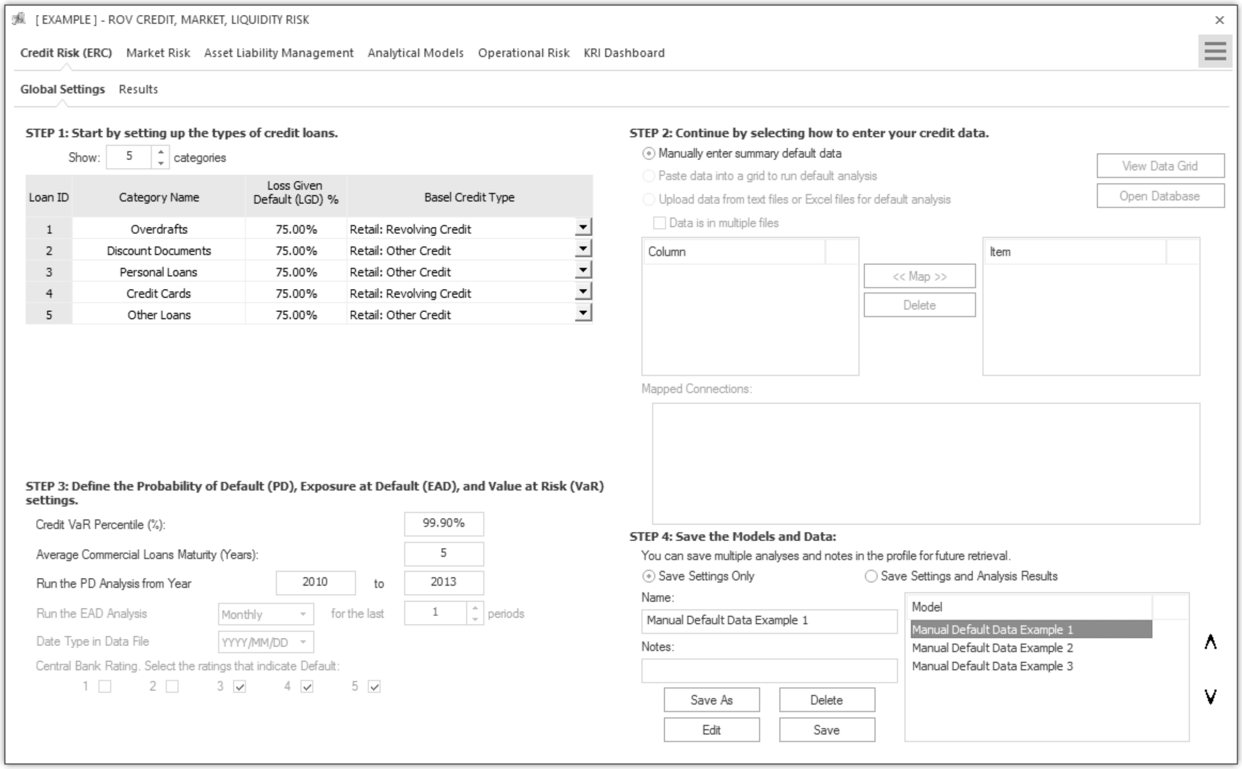
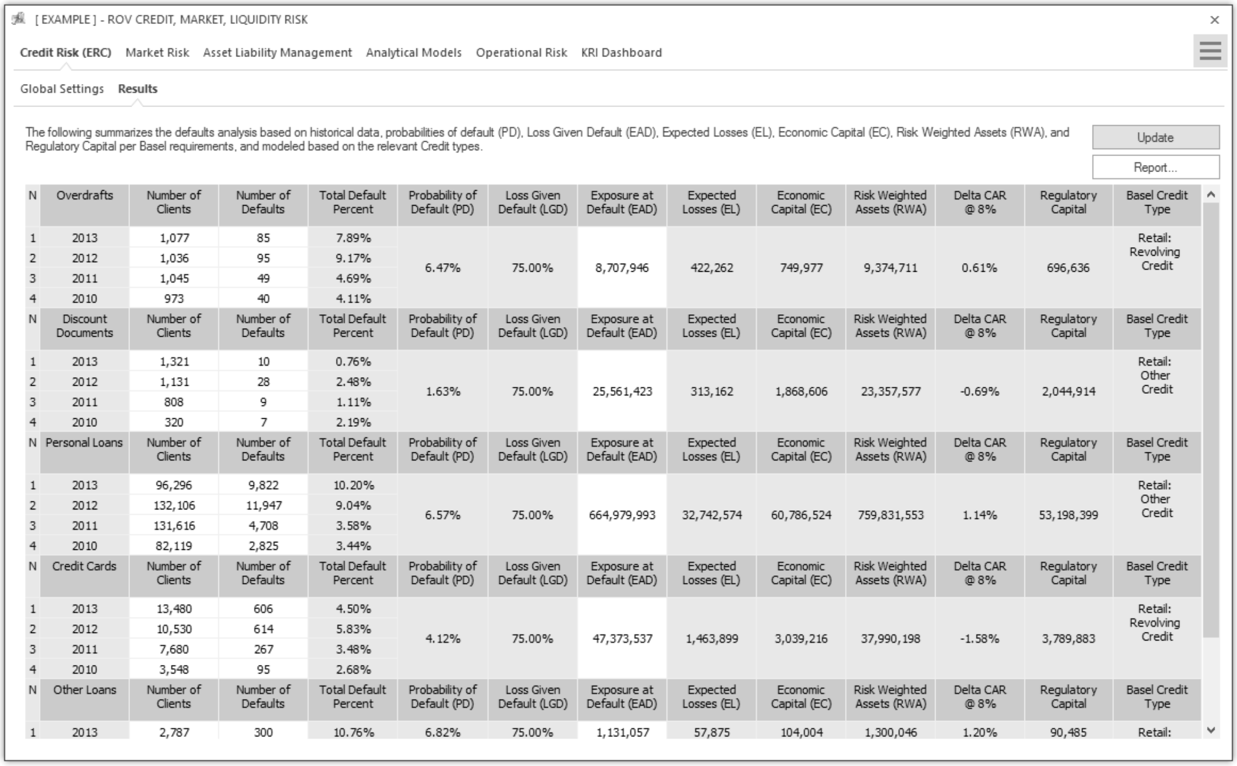


FIGURE 1 Credit risk settings.

Credit Economic and Regulatory Capital

Figure 2 illustrates the PEAT utility's ALM-CMOL module for Credit Risk—Economic Regulatory Capital's Results tab. The results are shown in the grid if data files were loaded and preprocessed and results were computed and presented here (the loading of data files was discussed in connection with Figure 1). However, if data are to be manually entered (as previously presented in Figure 1), then the grey areas in the data grid are available for manual user input, such as the number of clients for a specific credit or debt category, the number of defaults for said categories historically by period, and the exposure at default values (total amount of debt issued within the total period). One can manually input the number of clients and number of credit and loan defaults within specific annual time-period bands. The utility computes the percentage of defaults (number of credit or loan defaults divided by number of clients within the specified time periods), and the average percentage of default is the proxy used for the PD. If users have specific PD rates to use, they can simply enter any number of clients and number of defaults as long as the ratio is what the user wants as the PD input (e.g., a 1% PD means users can enter 100 clients and 1 as the number of defaults). The LGD can be user inputted in the global settings as a percentage (LGD is defined as the percentage of losses of loans and debt that cannot be recovered when they are in default). The EAD is the total loans amount within these time bands. These PD, LGD, and EAD values can also be computed using structural models as is discussed later. *Expected Losses* (EL) is the product of *PD × LGD × EAD*. *Economic Capital* (EC) is based on Basel II and Basel III requirements and is a matter of public record. *Risk Weighted Average* (RWA) is a regulatory requirement per Basel II and Basel III such as *12.5 × EC*. The change in *Capital Adequacy Requirement* (□CAR @ 8%) is simply the ratio of the EC to EAD less the 8% holding requirement. In other words, the *Regulatory Capital* (RC) is 8% of EAD.

The results obtained by the model allow for the construction of key risk indicators, comparing basic regulatory capital requirements with these economic capital requirements. Additionally, when coupled with the internal or external rating models (or credit scores) a profile of expected and unexpected losses for each product or asset type can be constructed. This is also the basis for the application of RAROC indicators, and the effective allocation of economic capital, in line with the international standards and local regulatory requirements.



N	Overdrafts	Number of Clients	Number of Defaults	Total Default Percent	Probability of Default (PD)	Loss Given Default (LGD)	Exposure at Default (EAD)	Expected Losses (EL)	Economic Capital (EC)	Risk Weighted Assets (RWA)	Delta CAR @ 8%	Regulatory Capital	Basel Credit Type
1	2013	1,077	85	7.89%	6.47%	75.00%	8,707,946	422,262	749,977	9,374,711	0.61%	696,636	Retail: Revolving Credit
2	2012	1,036	95	9.17%									
3	2011	1,045	49	4.69%									
4	2010	973	40	4.11%									
N	Discount Documents	Number of Clients	Number of Defaults	Total Default Percent	Probability of Default (PD)	Loss Given Default (LGD)	Exposure at Default (EAD)	Expected Losses (EL)	Economic Capital (EC)	Risk Weighted Assets (RWA)	Delta CAR @ 8%	Regulatory Capital	Basel Credit Type
1	2013	1,321	10	0.76%	1.63%	75.00%	25,561,423	313,162	1,868,606	23,357,577	-0.69%	2,044,914	Retail: Other Credit
2	2012	1,131	28	2.48%									
3	2011	808	9	1.11%									
4	2010	320	7	2.19%									
N	Personal Loans	Number of Clients	Number of Defaults	Total Default Percent	Probability of Default (PD)	Loss Given Default (LGD)	Exposure at Default (EAD)	Expected Losses (EL)	Economic Capital (EC)	Risk Weighted Assets (RWA)	Delta CAR @ 8%	Regulatory Capital	Basel Credit Type
1	2013	96,296	9,822	10.20%	6.57%	75.00%	664,979,993	32,742,574	60,786,524	759,831,553	1.14%	53,198,399	Retail: Other Credit
2	2012	132,106	11,947	9.04%									
3	2011	131,616	4,708	3.58%									
4	2010	82,119	2,825	3.44%									
N	Credit Cards	Number of Clients	Number of Defaults	Total Default Percent	Probability of Default (PD)	Loss Given Default (LGD)	Exposure at Default (EAD)	Expected Losses (EL)	Economic Capital (EC)	Risk Weighted Assets (RWA)	Delta CAR @ 8%	Regulatory Capital	Basel Credit Type
1	2013	13,480	606	4.50%	4.12%	75.00%	47,373,537	1,463,899	3,039,216	37,990,198	-1.58%	3,789,883	Retail: Revolving Credit
2	2012	10,530	614	5.83%									
3	2011	7,680	267	3.48%									
4	2010	3,548	95	2.68%									
N	Other Loans	Number of Clients	Number of Defaults	Total Default Percent	Probability of Default (PD)	Loss Given Default (LGD)	Exposure at Default (EAD)	Expected Losses (EL)	Economic Capital (EC)	Risk Weighted Assets (RWA)	Delta CAR @ 8%	Regulatory Capital	Basel Credit Type
1	2013	2,787	300	10.76%	6.82%	75.00%	1,131,057	57,875	104,004	1,300,046	1.20%	90,485	Retail:

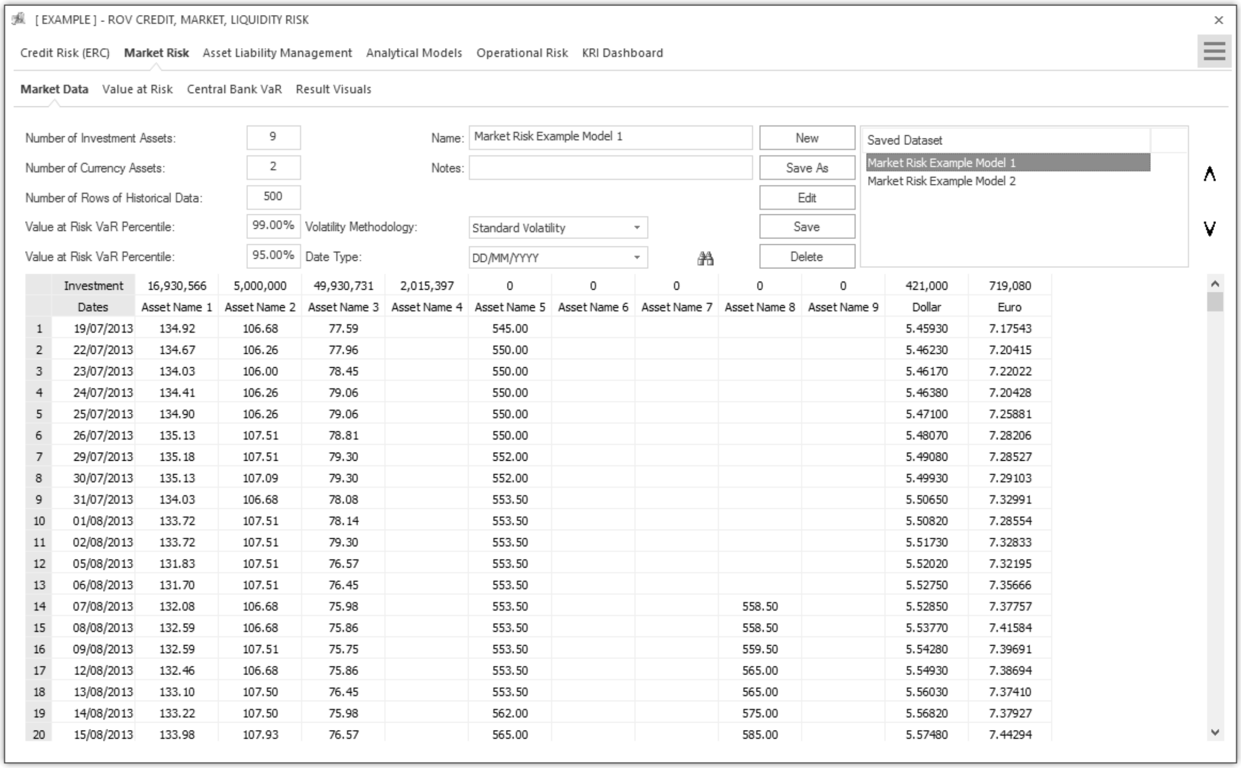
FIGURE 2 Economic Regulatory Capital (ERC).

Market Risk

For market risk, as a Pillar I risk, the requirements are similar to those for economic regulatory capital. The particularities of market risk make it, possibly, the one that is easier to model and calculate, and the one that has had more tool development so far. This is explained by the fact that the main input for market risk measurement and modeling is market prices of assets or, more practically, their volatilities. Therefore, there is great public availability of data, as opposed to the other Pillar I risks that do not have daily prices publically available. As an example, there is no public pricing of a particular group of retail loans issued by a private bank. Yet, both modeling tools for market and credit risk are based on the same approach: utilizing past stylized data to project future behavior under certain assumptions and within a confidence interval. Logically then, market risk has a great bundle of information available and the potential to better test and calibrate models. As presented, market risk models take on a Value at Risk (VAR) approach.

Figure 3 illustrates the PEAT utility's ALM-CMOL module for Market Risk where Market Data is entered. Users start by entering the global settings, such as the number of investment assets and currency assets the bank has in its portfolio, that require further analysis; the total number of historical data that will be used for analysis; and various VaR percentiles to run (e.g., 99.00% and

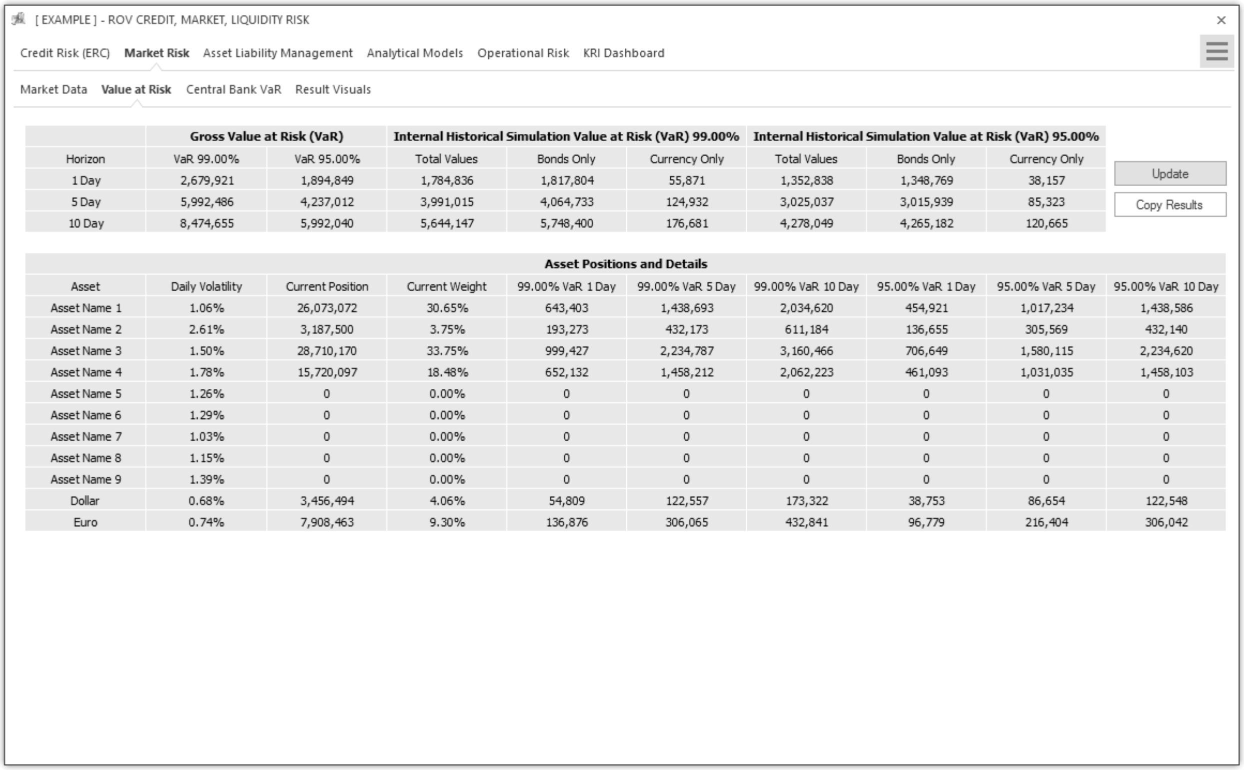
95.00%). In addition, the volatility method of choice (industry standard volatility or Risk Metrics volatility methods) and the date type (mm/dd/yyyy or dd/mm/yyyy) are entered. The amount invested (balance) of each asset and currency is entered and the historical data can be entered, copy and pasted from another data source, or uploaded to the data grid, and the settings as well as the historical data entered can be saved for future retrieval and further analysis in subsequent subtabs.



	Investment	16,930,566	5,000,000	49,930,731	2,015,397	0	0	0	0	0	421,000	719,080
	Dates	Asset Name 1	Asset Name 2	Asset Name 3	Asset Name 4	Asset Name 5	Asset Name 6	Asset Name 7	Asset Name 8	Asset Name 9	Dollar	Euro
1	19/07/2013	134.92	106.68	77.59		545.00					5.45930	7.17543
2	22/07/2013	134.67	106.26	77.96		550.00					5.46230	7.20415
3	23/07/2013	134.03	106.00	78.45		550.00					5.46170	7.22022
4	24/07/2013	134.41	106.26	79.06		550.00					5.46380	7.20428
5	25/07/2013	134.90	106.26	79.06		550.00					5.47100	7.25881
6	26/07/2013	135.13	107.51	78.81		550.00					5.48070	7.28206
7	29/07/2013	135.18	107.51	79.30		552.00					5.49080	7.28527
8	30/07/2013	135.13	107.09	79.30		552.00					5.49930	7.29103
9	31/07/2013	134.03	106.68	78.08		553.50					5.50650	7.32991
10	01/08/2013	133.72	107.51	78.14		553.50					5.50820	7.28554
11	02/08/2013	133.72	107.51	79.30		553.50					5.51730	7.32833
12	05/08/2013	131.83	107.51	76.57		553.50					5.52020	7.32195
13	06/08/2013	131.70	107.51	76.45		553.50					5.52750	7.35666
14	07/08/2013	132.08	106.68	75.98		553.50			558.50		5.52850	7.37757
15	08/08/2013	132.59	106.68	75.86		553.50			558.50		5.53770	7.41584
16	09/08/2013	132.59	107.51	75.75		553.50			559.50		5.54280	7.39691
17	12/08/2013	132.46	106.68	75.86		553.50			565.00		5.54930	7.38694
18	13/08/2013	133.10	107.50	76.45		553.50			565.00		5.56030	7.37410
19	14/08/2013	133.22	107.50	75.98		562.00			575.00		5.56820	7.37927
20	15/08/2013	133.98	107.93	76.57		565.00			585.00		5.57480	7.44294

FIGURE 3 Market risk data.

Figure 4 illustrates the computed results for the Market VaR. Based on the data entered in the interface shown as Figure 3, the results are computed and presented in two separate grids: the VaR results and asset positions and details. The computations can be triggered to be rerun or Updated, and the results can be exported to an Excel report template if required. The results computed in the first grid are based on user input market data. For instance, the VaR calculations are simply the *Asset Position × Daily Volatility × Inverse Standard Normal Distribution of VaR Percentile × Square Root of the Horizon in Days*. Therefore, the Gross VaR is simply the summation of all VaR values for all assets and foreign exchange–denominated assets. In comparison, the Internal Historical Simulation VaR uses the same calculation based on historically simulated time-series of asset values. The historically simulated time-series of asset values is obtained by the *Asset's Investment × Asset Price*$_{t\text{-}1}$ *× Period-Specific Relative Returns – Asset's Current Position*. The Asset's Current Position is simply the *Investment × Asset Price*$_t$. From this simulated time series of asset flows, the (1 – *X%*) percentile asset value is the *VaR X%*. Typically, *X%* is 99.00% or 95.00% and can be changed as required by the user based on the regional or country-specific regulatory agency's statutes.



	Gross Value at Risk (VaR)		Internal Historical Simulation Value at Risk (VaR) 99.00%			Internal Historical Simulation Value at Risk (VaR) 95.00%		
Horizon	VaR 99.00%	VaR 95.00%	Total Values	Bonds Only	Currency Only	Total Values	Bonds Only	Currency Only
1 Day	2,679,921	1,894,849	1,784,836	1,817,804	55,871	1,352,838	1,348,769	38,157
5 Day	5,992,486	4,237,012	3,991,015	4,064,733	124,932	3,025,037	3,015,939	85,323
10 Day	8,474,655	5,992,040	5,644,147	5,748,400	176,681	4,278,049	4,265,182	120,665

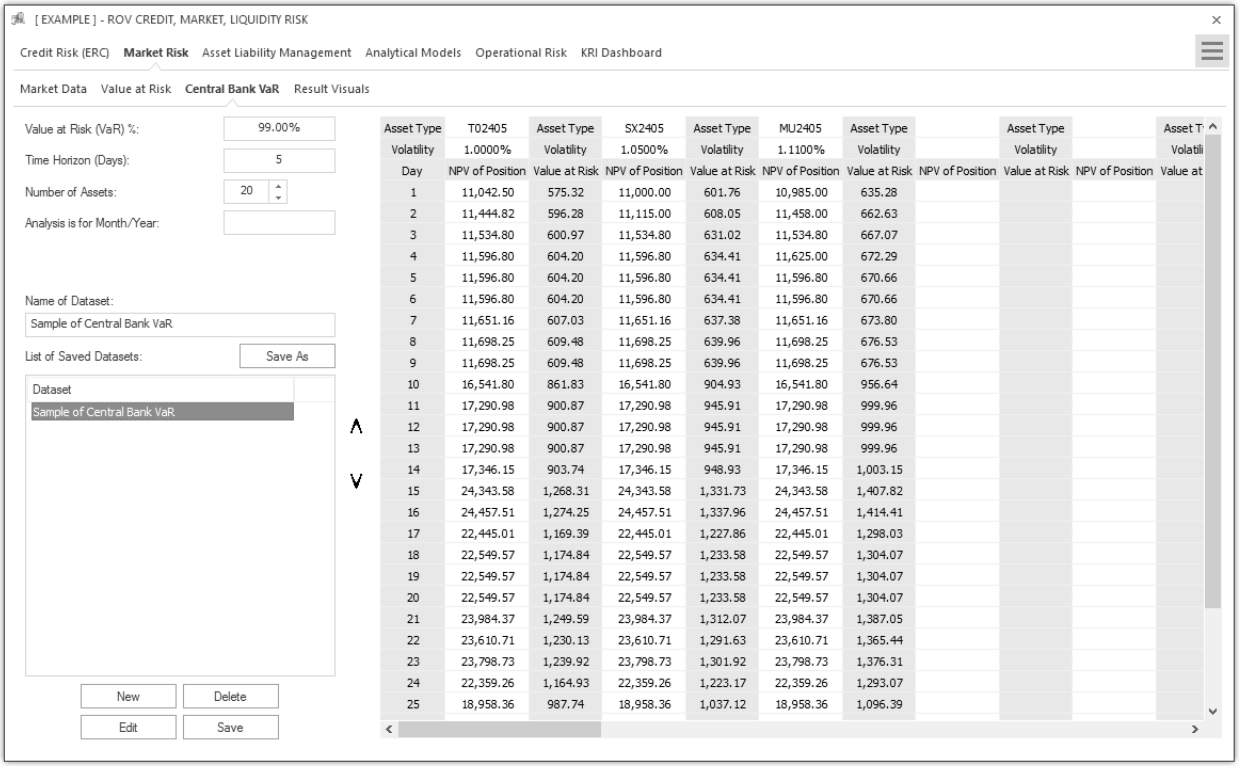
Asset Positions and Details									
Asset	Daily Volatility	Current Position	Current Weight	99.00% VaR 1 Day	99.00% VaR 5 Day	99.00% VaR 10 Day	95.00% VaR 1 Day	95.00% VaR 5 Day	95.00% VaR 10 Day
Asset Name 1	1.06%	26,073,072	30.65%	643,403	1,438,693	2,034,620	454,921	1,017,234	1,438,586
Asset Name 2	2.61%	3,187,500	3.75%	193,273	432,173	611,184	136,655	305,569	432,140
Asset Name 3	1.50%	28,710,170	33.75%	999,427	2,234,787	3,160,466	706,649	1,580,115	2,234,620
Asset Name 4	1.78%	15,720,097	18.48%	652,132	1,458,212	2,062,223	461,093	1,031,035	1,458,103
Asset Name 5	1.26%	0	0.00%	0	0	0	0	0	0
Asset Name 6	1.29%	0	0.00%	0	0	0	0	0	0
Asset Name 7	1.03%	0	0.00%	0	0	0	0	0	0
Asset Name 8	1.15%	0	0.00%	0	0	0	0	0	0
Asset Name 9	1.39%	0	0.00%	0	0	0	0	0	0
Dollar	0.68%	3,456,494	4.06%	54,809	122,557	173,322	38,753	86,654	122,548
Euro	0.74%	7,908,463	9.30%	136,876	306,065	432,841	96,779	216,404	306,042

FIGURE 4 Market Value at Risk.

Many countries issue regulations for market risk measurement and capital allocation, whereby some standardized models are suggested or even imposed, in line with the Basel Standards. We analyze such an example in Figure 5, where the regulatory model can be obtained by utilizing the parameters given by the regulator (i.e., volatilities and holding periods for given common assets). The structure of the tool allows for the comparison of regulatory, internal, and stressed scenarios, giving the analysts a large array of results to better interpret risk measurement, capital allocation, and future projections.

Central Bank Market Risk

Figure 5 illustrates the Central Bank VaR method and results in computing VaR based on user settings (e.g., the VaR percentile, time horizon of the holding period in days, number of assets to analyze, and the period of the analysis) and the assets' historical data. The VaR computations are based on the same approach as previously described, and the inputs, settings, and results can be saved for future retrieval.



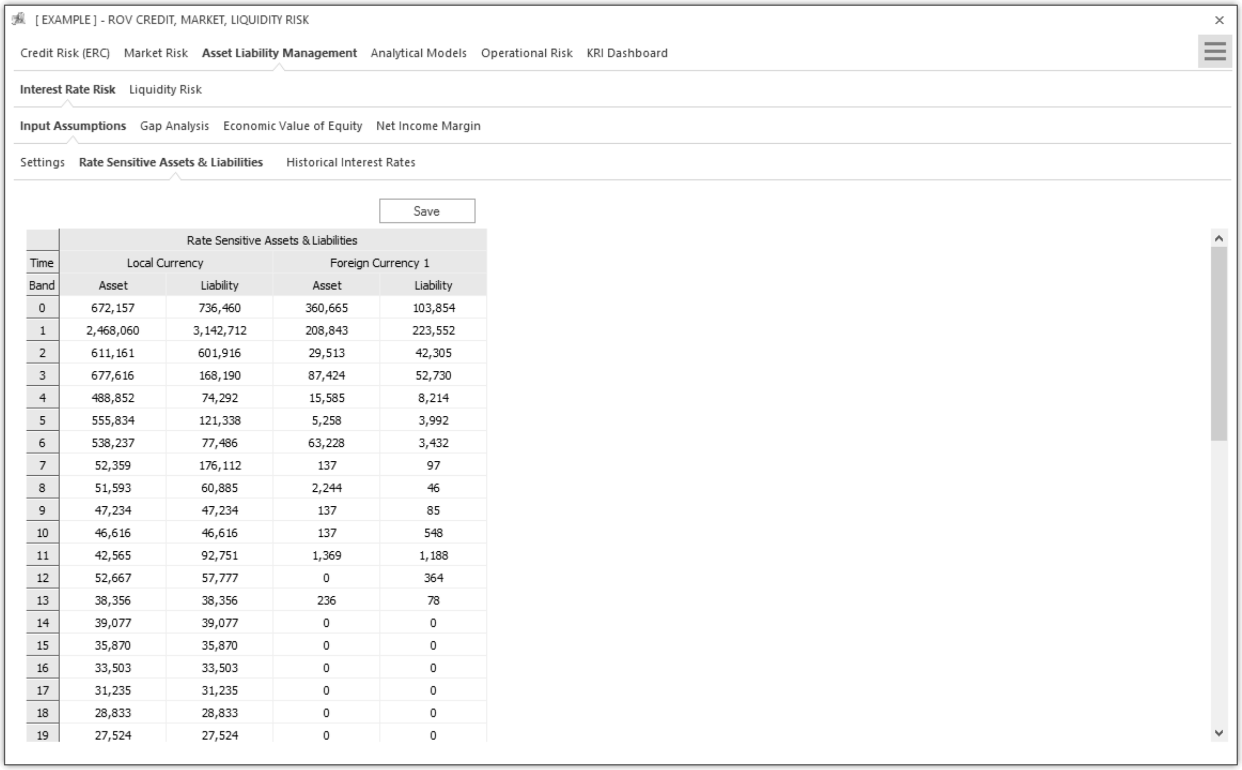
Asset Type	T02405	Asset Type	SX2405	Asset Type	MU2405	Asset Type
Volatility	1.0000%	Volatility	1.0500%	Volatility	1.1100%	Volatility
Day	NPV of Position	Value at Risk	NPV of Position	Value at Risk	NPV of Position	Value at Risk
1	11,042.50	575.32	11,000.00	601.76	10,985.00	635.28
2	11,444.82	596.28	11,115.00	608.05	11,458.00	662.63
3	11,534.80	600.97	11,534.80	631.02	11,534.80	667.07
4	11,596.80	604.20	11,596.80	634.41	11,625.00	672.29
5	11,596.80	604.20	11,596.80	634.41	11,596.80	670.66
6	11,596.80	604.20	11,596.80	634.41	11,596.80	670.66
7	11,651.16	607.03	11,651.16	637.38	11,651.16	673.80
8	11,698.25	609.48	11,698.25	639.96	11,698.25	676.53
9	11,698.25	609.48	11,698.25	639.96	11,698.25	676.53
10	16,541.80	861.83	16,541.80	904.93	16,541.80	956.64
11	17,290.98	900.87	17,290.98	945.91	17,290.98	999.96
12	17,290.98	900.87	17,290.98	945.91	17,290.98	999.96
13	17,290.98	900.87	17,290.98	945.91	17,290.98	999.96
14	17,346.15	903.74	17,346.15	948.93	17,346.15	1,003.15
15	24,343.58	1,268.31	24,343.58	1,331.73	24,343.58	1,407.82
16	24,457.51	1,274.25	24,457.51	1,337.96	24,457.51	1,414.41
17	22,445.01	1,169.39	22,445.01	1,227.86	22,445.01	1,298.03
18	22,549.57	1,174.84	22,549.57	1,233.58	22,549.57	1,304.07
19	22,549.57	1,174.84	22,549.57	1,233.58	22,549.57	1,304.07
20	22,549.57	1,174.84	22,549.57	1,233.58	22,549.57	1,304.07
21	23,984.37	1,249.59	23,984.37	1,312.07	23,984.37	1,387.05
22	23,610.71	1,230.13	23,610.71	1,291.63	23,610.71	1,365.44
23	23,798.73	1,239.92	23,798.73	1,301.92	23,798.73	1,376.31
24	22,359.26	1,164.93	22,359.26	1,223.17	22,359.26	1,293.07
25	18,958.36	987.74	18,958.36	1,037.12	18,958.36	1,096.39

FIGURE 5 Market Central Bank VaR.

Asset Liability Management

As with any other Basel-defined risk, KRIs are constructed based on the inputs and results of the modeling tool, and can be duly monitored and reported, in line with the IMMM process. Liquidity and interest rate risk are usually managed together in a function called ALM, short for Asset and Liability Management. These two risks are closely intertwined, since liquidity risk monitors the availability of liquid funds to confront disbursement requirements (usually in three time horizons: immediate and intraday, short-term structure, and long-term structure), while interest rate risk measures the impact of the difference in maturities, or duration, for assets and liabilities.

Figure 6 illustrates the PEAT utility's ALM-CMOL module for Asset Liability Management—Interest Rate Risk's Input Assumptions and general Settings tab. This segment represents the analysis of Asset Liability Management (ALM) computations. ALM is the practice of managing risks that arise due to mismatches between the maturities of assets and liabilities. The ALM process is a mix between risk management and strategic planning for a bank or financial institution. It is about offering solutions to mitigate or hedge the risks arising from the interaction of assets and liabilities as well as the success in the process of maximizing assets to meet complex liabilities such that it will help increase profitability. The current tab starts by obtaining, as general inputs, the bank's regulatory capital obtained earlier from the credit risk models. In addition, the number of trading days in the calendar year of the analysis (e.g., typically between 250 and 253 days), the local currency's name (e.g., U.S. Dollar or Argentinian Peso), the current period when the analysis is performed and results reported to the regulatory agencies (e.g., January 2015), the number of VaR percentiles to run (e.g., 99.00%), number of scenarios to run and their respective basis point sensitivities (e.g., 100, 200, and 300 basis points, where every 100 basis points represent 1%), and number of foreign currencies in the bank's investment portfolio. As usual, the inputs, settings, and results can be saved for future retrieval. Figure 6 further illustrates the PEAT utility's ALM-CMOL module for Asset Liability Management. The tab is specifically for Interest Rate Sensitive Assets and Liabilities data where historical impacts of interest-rate sensitive assets and liabilities, as well as foreign currency–denominated assets and liabilities are entered, copy and pasted, or uploaded from a database. Historical Interest Rate data is uploaded where the rows of periodic historical interest rates of local and foreign currencies can be entered, copy and pasted, or uploaded from a database.



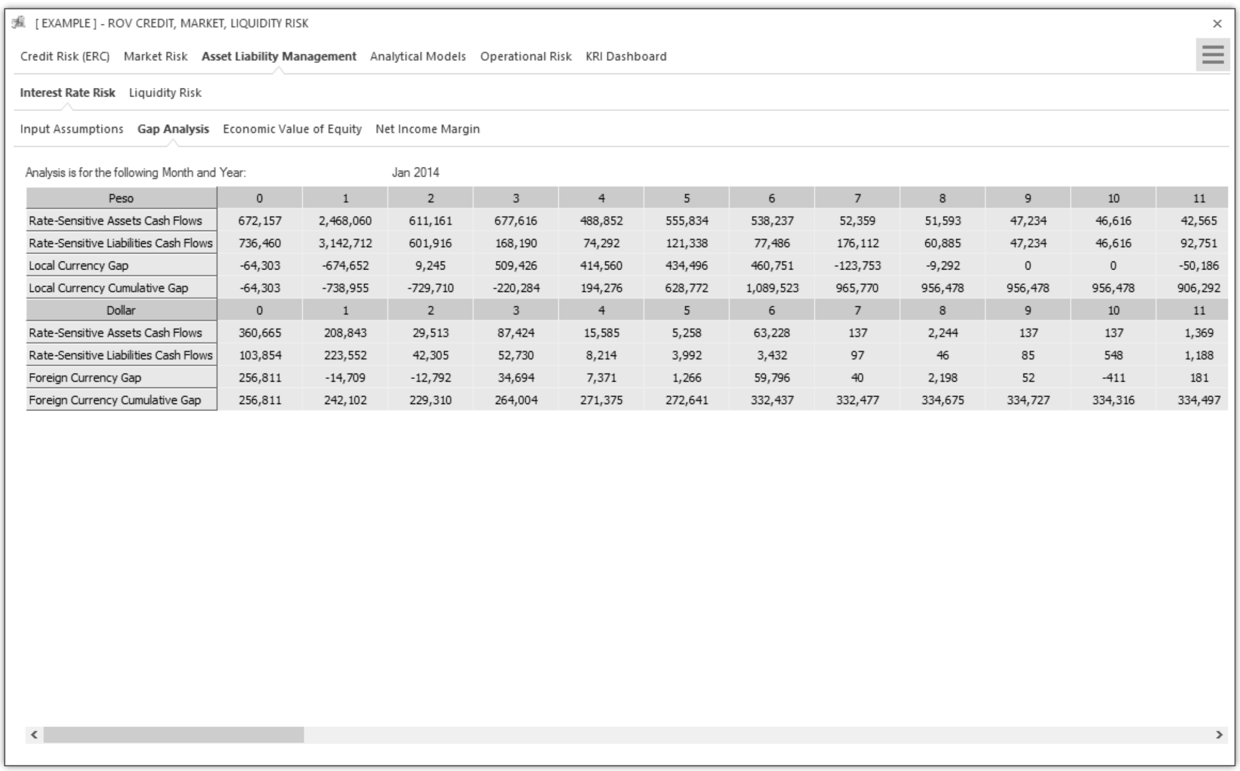
	Rate Sensitive Assets & Liabilities			
Time	Local Currency		Foreign Currency 1	
Band	Asset	Liability	Asset	Liability
0	672,157	736,460	360,665	103,854
1	2,468,060	3,142,712	208,843	223,552
2	611,161	601,916	29,513	42,305
3	677,616	168,190	87,424	52,730
4	488,852	74,292	15,585	8,214
5	555,834	121,338	5,258	3,992
6	538,237	77,486	63,228	3,432
7	52,359	176,112	137	97
8	51,593	60,885	2,244	46
9	47,234	47,234	137	85
10	46,616	46,616	137	548
11	42,565	92,751	1,369	1,188
12	52,667	57,777	0	364
13	38,356	38,356	236	78
14	39,077	39,077	0	0
15	35,870	35,870	0	0
16	33,503	33,503	0	0
17	31,235	31,235	0	0
18	28,833	28,833	0	0
19	27,524	27,524	0	0

FIGURE 6 Asset Liability Management—Interest Rate Risk (asset and liability data).

ALM: Net Interest Margin and Economic Value of Equity

The most straightforward way to present ALM structures for liquidity and interest-rate risk management is through the utilization of Gap charts. A Gap chart is simply the listing of all assets and liabilities as affected by interest rate movements or liquidity movements, respectively, ordered on time-defined buckets (i.e., days, weeks, months, or years). Typically, for interest rate risk there are two main management approaches: a shorter-term structure analysis based on a more accounting-side perspective, usually referred to as the NIM (Net Interest Margin) approach, and a longer-term structure analysis based on a more economic-side perspective, usually referred to as the EVE (Economic Value of Equity) approach. The NIM approach rests on the logic that the natural mismatch between assets and liabilities has an impact on earnings, through the net interest margin, and such impact can be measured through given deltas (variations) in the referential market interest rate. In this case, measured through the GAP chart, as applied to balance sheet items of the asset and liability sides respectively. So, on the one hand, a natural NIM approach would deliver a balance sheet impact on earnings, based on the structure and maturity of assets and liabilities, when subjected to a 100 basis point increase in the referential market interest rate risk. Since the Gap analysis defines which side of the balance sheet (assets or liabilities) has preponderance for each time bucket, analysts can define which sign would apply to earnings should interest rates go up or down. Therefore, the combination of these two tools allows for the establishment of different business and stress scenarios and, hence, the determination of targets and limits on the structure and duration of assets and liabilities. The EVE approach, on the other hand, is a long-term evaluation tool, by which analysts can determine the impact on capital (or equity, defined as assets minus liabilities) of referential market interest rate valuations, as it affects the net present value and duration of the described balance sheet items. By this approach, the system can calculate the deltas in durations and in net present value of assets, liabilities, and equity, as measured in the Gap charts. Therefore, such variations allow for the construction of scenarios for the different impacts on equity value and duration of changes in the referential market interest rate. These results are then fed into different KRIs for monitoring, defining, and calibrating targets and limits, in line with the IMMM risk management structure.

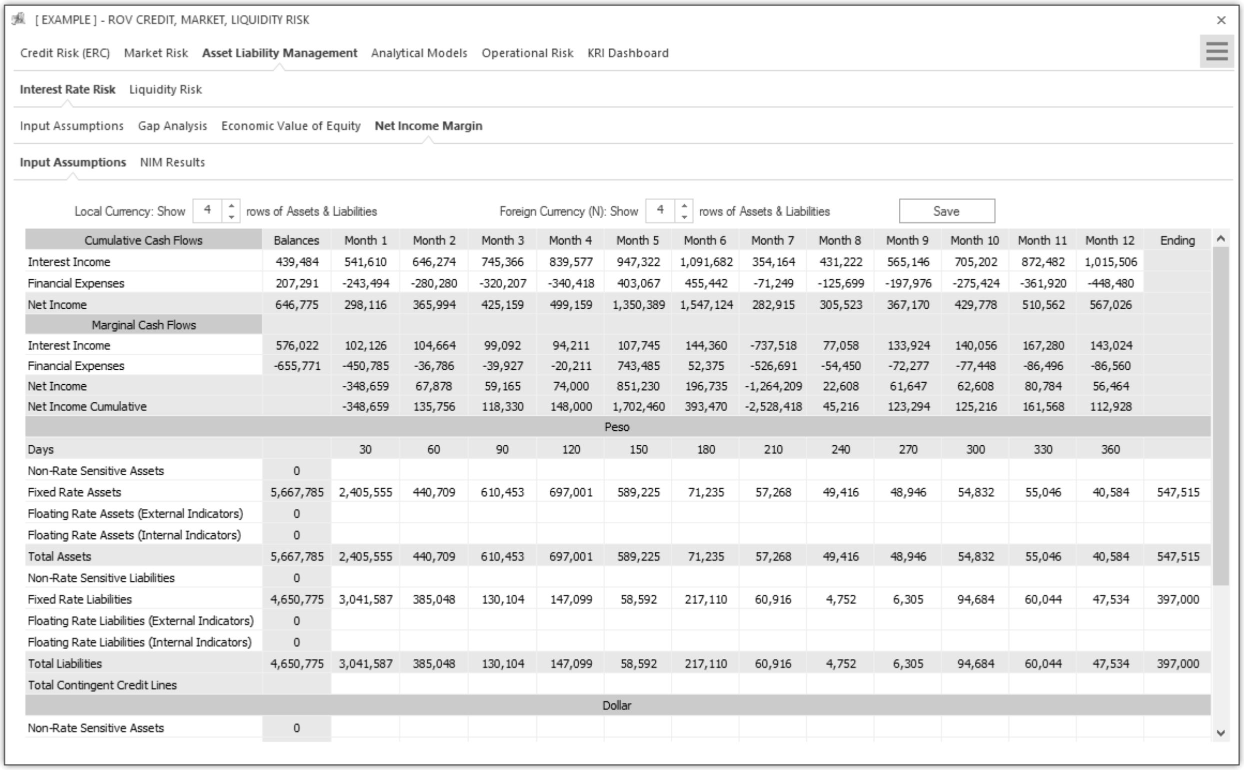
Figure 7 illustrates the Gap Analysis results of Interest Rate Risk. The results are shown in different grids for each local currency and foreign currency. Gap Analysis is, of course, one of the most common ways of measuring liquidity position and represents the foundation for scenario analysis and stress-testing, which will be executed in subsequent tabs. The Gap Analysis results are from user inputs in the input assumptions tab. The results are presented for the user again for validation and in a more user-friendly tabular format. The Economic Value of Equity results are based on interest-rate risk computations in previous tabs. The impact on regulatory capital as denoted by VaR levels on local and foreign currencies are computed, as are the duration gaps and basis point scenarios affecting the cash flows of local and foreign currencies.



Peso	0	1	2	3	4	5	6	7	8	9	10	11
Rate-Sensitive Assets Cash Flows	672,157	2,468,060	611,161	677,616	488,852	555,834	538,237	52,359	51,593	47,234	46,616	42,565
Rate-Sensitive Liabilities Cash Flows	736,460	3,142,712	601,916	168,190	74,292	121,338	77,486	176,112	60,885	47,234	46,616	92,751
Local Currency Gap	-64,303	-674,652	9,245	509,426	414,560	434,496	460,751	-123,753	-9,292	0	0	-50,186
Local Currency Cumulative Gap	-64,303	-738,955	-729,710	-220,284	194,276	628,772	1,089,523	965,770	956,478	956,478	956,478	906,292
Dollar	0	1	2	3	4	5	6	7	8	9	10	11
Rate-Sensitive Assets Cash Flows	360,665	208,843	29,513	87,424	15,585	5,258	63,228	137	2,244	137	137	1,369
Rate-Sensitive Liabilities Cash Flows	103,854	223,552	42,305	52,730	8,214	3,992	3,432	97	46	85	548	1,188
Foreign Currency Gap	256,811	-14,709	-12,792	34,694	7,371	1,266	59,796	40	2,198	52	-411	181
Foreign Currency Cumulative Gap	256,811	242,102	229,310	264,004	271,375	272,641	332,437	332,477	334,675	334,727	334,316	334,497

FIGURE 7 Asset Liability Management—Interest Rate Risk: Gap Analysis.

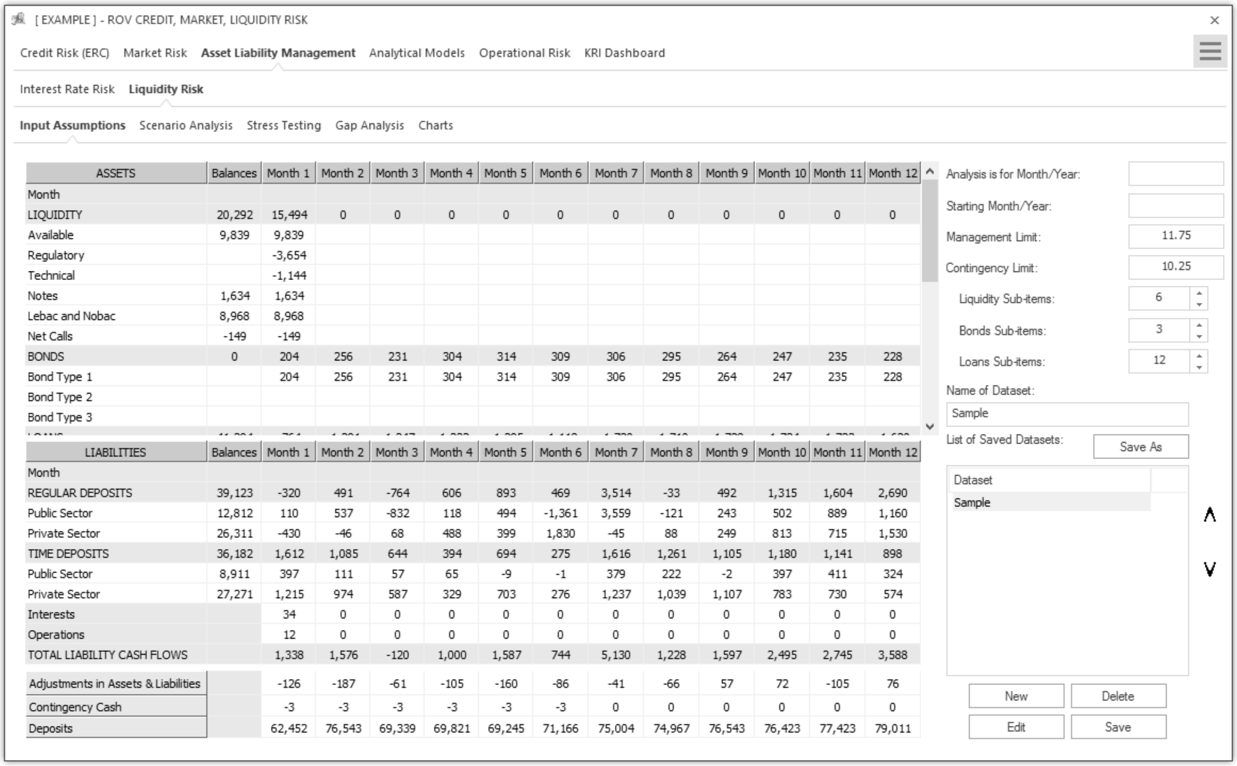
Figure 8 illustrates the *Net Income Margin* (NIM) Input Assumptions requirements based on interest-rate risk analysis. The highlighted cells in the data grid represent user input requirements for computing the NIM model. The Economic Value of Equity and Gap Analysis calculations described above are for longer-term interest-rate risk analysis, whereas the NIM approach is for shorter-term (typically 12 months) analysis of liquidity and interest-rate risk effects on assets and liabilities.



Cumulative Cash Flows	Balances	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12	Ending
Interest Income	439,484	541,610	646,274	745,366	839,577	947,322	1,091,682	354,164	431,222	565,146	705,202	872,482	1,015,506	
Financial Expenses	207,291	-243,494	-280,280	-320,207	-340,418	403,067	455,442	-71,249	-125,699	-197,976	-275,424	-361,920	-448,480	
Net Income	646,775	298,116	365,994	425,159	499,159	1,350,389	1,547,124	282,915	305,523	367,170	429,778	510,562	567,026	
Marginal Cash Flows														
Interest Income	576,022	102,126	104,664	99,092	94,211	107,745	144,360	-737,518	77,058	133,924	140,056	167,280	143,024	
Financial Expenses	-655,771	-450,785	-36,786	-39,927	-20,211	743,485	52,375	-526,691	-54,450	-72,277	-77,448	-86,496	-86,560	
Net Income		-348,659	67,878	59,165	74,000	851,230	196,735	-1,264,209	22,608	61,647	62,608	80,784	56,464	
Net Income Cumulative		-348,659	135,756	118,330	148,000	1,702,460	393,470	-2,528,418	45,216	123,294	125,216	161,568	112,928	
Peso														
Days		30	60	90	120	150	180	210	240	270	300	330	360	
Non-Rate Sensitive Assets	0													
Fixed Rate Assets	5,667,785	2,405,555	440,709	610,453	697,001	589,225	71,235	57,268	49,416	48,946	54,832	55,046	40,584	547,515
Floating Rate Assets (External Indicators)	0													
Floating Rate Assets (Internal Indicators)	0													
Total Assets	5,667,785	2,405,555	440,709	610,453	697,001	589,225	71,235	57,268	49,416	48,946	54,832	55,046	40,584	547,515
Non-Rate Sensitive Liabilities	0													
Fixed Rate Liabilities	4,650,775	3,041,587	385,048	130,104	147,099	58,592	217,110	60,916	4,752	6,305	94,684	60,044	47,534	397,000
Floating Rate Liabilities (External Indicators)	0													
Floating Rate Liabilities (Internal Indicators)	0													
Total Liabilities	4,650,775	3,041,587	385,048	130,104	147,099	58,592	217,110	60,916	4,752	6,305	94,684	60,044	47,534	397,000
Total Contingent Credit Lines														
Dollar														
Non-Rate Sensitive Assets	0													

FIGURE 8 Net Income Margin (NIM): Input Assumptions and model.

Figure 9 illustrates the PEAT utility's ALM-CMOL module for Asset Liability Management—Liquidity Risk Input Assumptions tab on the historical monthly balances of interest-rate sensitive assets and liabilities. The typical time horizon is monthly for one year (12 months) where the various assets such as liquid assets (e.g., cash), bonds, and loans are listed, as well as other asset receivables. On the liabilities side, regular short-term deposits and timed deposits are listed, separated by private versus public sectors, as well as other payable liabilities (e.g., interest payments and operations). Adjustments can also be made to account for rounding issues and accounting issues that may affect the asset and liability levels (e.g., contingency cash levels, overnight deposits, etc.). The data grid can be set up with some basic inputs as well as the number of subsegments or rows for each category. As usual, the inputs, settings, and results can be saved for future retrieval.



ASSETS	Balances	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Month													
LIQUIDITY	20,292	15,494	0	0	0	0	0	0	0	0	0	0	0
Available	9,839	9,839											
Regulatory		-3,654											
Technical		-1,144											
Notes	1,634	1,634											
Lebac and Nobac	8,968	8,968											
Net Calls	-149	-149											
BONDS	0	204	256	231	304	314	309	306	295	264	247	235	228
Bond Type 1		204	256	231	304	314	309	306	295	264	247	235	228
Bond Type 2													
Bond Type 3													

LIABILITIES	Balances	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Month													
REGULAR DEPOSITS	39,123	-320	491	-764	606	893	469	3,514	-33	492	1,315	1,604	2,690
Public Sector	12,812	110	537	-832	118	494	-1,361	3,559	-121	243	502	889	1,160
Private Sector	26,311	-430	-46	68	488	399	1,830	-45	88	249	813	715	1,530
TIME DEPOSITS	36,182	1,612	1,085	644	394	694	275	1,616	1,261	1,105	1,180	1,141	898
Public Sector	8,911	397	111	57	65	-9	-1	379	222	-2	397	411	324
Private Sector	27,271	1,215	974	587	329	703	276	1,237	1,039	1,107	783	730	574
Interests		34	0	0	0	0	0	0	0	0	0	0	0
Operations		12	0	0	0	0	0	0	0	0	0	0	0
TOTAL LIABILITY CASH FLOWS		1,338	1,576	-120	1,000	1,587	744	5,130	1,228	1,597	2,495	2,745	3,588
Adjustments in Assets & Liabilities		-126	-187	-61	-105	-160	-86	-41	-66	57	72	-105	76
Contingency Cash		-3	-3	-3	-3	-3	-3	0	0	0	0	0	0
Deposits		62,452	76,543	69,339	69,821	69,245	71,166	75,004	74,967	76,543	76,423	77,423	79,011

FIGURE 9 Asset Liability Management—Liquidity Risk model and assumptions.

Scenario Analysis and Stress Testing

The Liquidity Risk's Scenario Analysis and Stress Testing settings can be set up to test interest-rate sensitive assets and liabilities. The scenarios to test can be entered as data or percentage changes. Multiple scenarios can be saved for future retrieval and analysis in subsequent tabs as each saved model constitutes a stand-alone scenario to test. Scenario analysis typically tests both fluctuations in assets and liabilities and their impacts on the portfolio's ALM balance, whereas stress testing typically tests the fluctuations on liabilities (e.g., runs on banks, economic downturns where deposits are stressed to the lower limit) where the stressed limits can be entered as values or percentage change from the base case. Multiple stress tests can be saved for future retrieval and analysis in subsequent tabs as each saved model constitutes a stand-alone stress test.

Figure 10 illustrates the Liquidity Risk's Gap Analysis results. The data grid shows the results based on all the previously saved scenarios and stress test conditions. The *Gap* is, of course, calculated as the *difference between Monthly Assets and Liabilities, accounting for any Contingency Credit Lines*. The gaps for the multitude of Scenarios and Stress Tests are reruns of the same calculation based on various user inputs on values or percentage changes as described previously in the Scenario Analysis and Stress Testing sections.

[EXAMPLE] - ROV CREDIT, MARKET, LIQUIDITY RISK

Credit Risk (ERC) Market Risk **Asset Liability Management** Analytical Models Operational Risk KRI Dashboard

Interest Rate Risk **Liquidity Risk**

Input Assumptions Scenario Analysis Stress Testing **Gap Analysis** Charts

Analysis is for the following Month and Year:

GAP ANALYSIS RESULTS	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6	Month 7	Month 8	Month 9	Month 10	Month 11	Month 12
Individual Gap Analysis												
Current Effective Gap	15,785	199	-1,347	-288	442	-538	3,458	-487	-19	858	934	1,952
Sample Percentage	22,520	-1,295	881	-185	-1,890	3,067	-317	5,796	657	-2,833	1,879	4,549
Sample Values	22,519	-1,297	882	-184	-1,893	3,063	-318	5,792	657	-2,834	1,882	4,547
Sample Percentage	574	-6,073	-4,554	-2,266	-1,673	-2,522	-2,215	-2,207	-2,097	-2,107	-2,271	-2,086
Sample Values	573	-6,072	-4,554	-2,266	-1,674	-2,523	-2,215	-2,206	-2,097	-2,107	-2,271	-2,086
Cumulative Gap Analysis												
Current Effective Gap	15,782	15,978	14,628	14,337	14,776	14,235	17,693	17,206	17,187	18,045	18,979	20,931
Sample Percentage	22,517	21,219	22,097	21,909	20,016	23,080	22,763	28,558	29,215	26,382	28,261	32,810
Sample Values	22,516	21,216	22,095	21,908	20,012	23,072	22,754	28,546	29,203	26,369	28,251	32,798
Sample Percentage	571	-5,505	-10,062	-12,332	-14,008	-16,533	-18,749	-20,955	-23,052	-25,159	-27,430	-29,516
Sample Values	570	-5,505	-10,062	-12,331	-14,008	-16,534	-18,749	-20,955	-23,052	-25,159	-27,430	-29,516
Liquidity Indicators Analysis												
Current Effective Gap	25.28	20.88	21.11	20.55	21.36	20.03	23.61	22.98	22.48	23.64	24.54	26.51
Sample Percentage	36.06	27.73	31.88	31.40	28.93	32.46	30.37	38.12	38.19	34.54	36.52	41.55
Sample Values	36.06	27.73	31.88	31.39	28.92	32.45	30.36	38.10	38.18	34.53	36.51	41.53
Sample Percentage	0.92	-7.18	-14.50	-17.64	-20.21	-23.21	-24.97	-27.93	-30.09	-32.90	-35.41	-37.33
Sample Values	0.92	-7.18	-14.50	-17.64	-20.21	-23.21	-24.97	-27.93	-30.09	-32.90	-35.41	-37.33
Management Limit	11.75	11.75	11.75	11.75	11.75	11.75	11.75	11.75	11.75	11.75	11.75	11.75
Contingency Limit	10.25	10.25	10.25	10.25	10.25	10.25	10.25	10.25	10.25	10.25	10.25	10.25

FIGURE 10 Asset Liability Management—Liquidity Risk: Gap Analysis.

Credit and Market Risk Analytical Models

Figure 11 illustrates the Analytical Models tab with input assumptions and results. This analytical models segment is divided into Structural, Time-Series, Portfolio, and Analytics models. The current figure shows the Structural models tab where the computed models pertain to credit risk–related model analysis categories such as PD, EAD, LGD, and Volatility calculations. Under each category, specific models can be selected to run. Selected models are briefly described and users can select the number of model repetitions to run and the decimal precision levels of the results. The data grid in the Computations tab shows the area in which users would enter the relevant inputs into the selected model and the results would be computed. As usual, selected models, inputs, and settings can be saved for future retrieval and analysis.

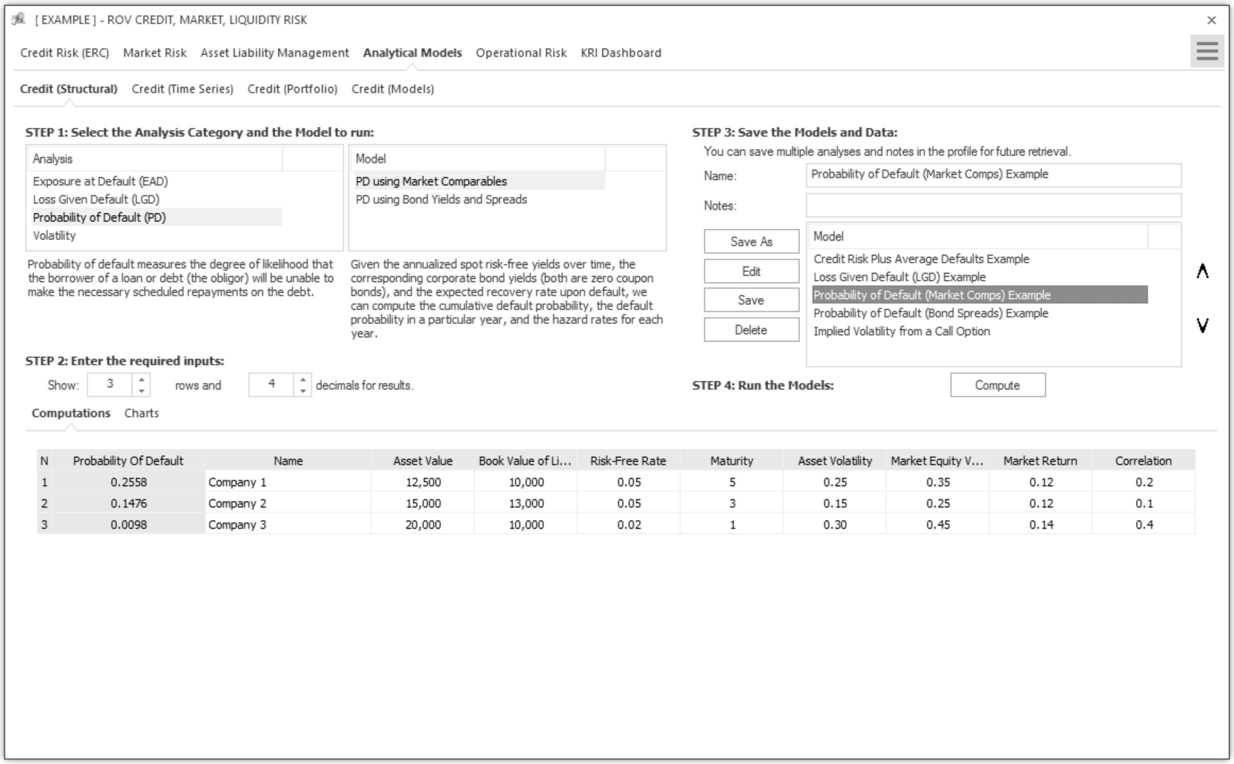


FIGURE 11 Structural credit risk models.

Figure 11 illustrates the Structural Analytical Models tab with visual chart results. The results computed are displayed as various visual charts such as bar charts, control charts, Pareto charts, and time-series charts. Figure 12 illustrates the Time-Series Analytical Models tab with input assumptions and results. The analysis category and model type is first chosen where a short description explains what the selected model does, and users can then select the number of models to replicate as well as decimal precision settings. Input data and assumptions are entered in the data grid provided (additional inputs can also be entered if required), and the results are computed and shown. As usual, selected models, inputs, and settings can be saved for future retrieval and analysis. Figure 13 illustrates the Portfolio Analytical Models tab with input assumptions and results. The analysis category and model type is first chosen where a short description explains what the selected model does, and users can then select the number of models to replicate as well as decimal precision settings. Input data and assumptions are entered in the data grid provided (additional inputs such as a correlation matrix can also be entered if required), and the results are computed and shown.

Additional models are available in the Credit Models tab with input assumptions and results. The analysis category and model type are first chosen and input data and assumptions are entered in the required inputs area (if required, users can Load Example inputs and use these as a basis for building their models), and the results are computed and shown. Scenario tables and charts can be created by entering the From, To, and Step Size parameters, where the computed scenarios will be returned as a data grid and visual chart. As usual, selected models, inputs, and settings can be saved for future retrieval and analysis.

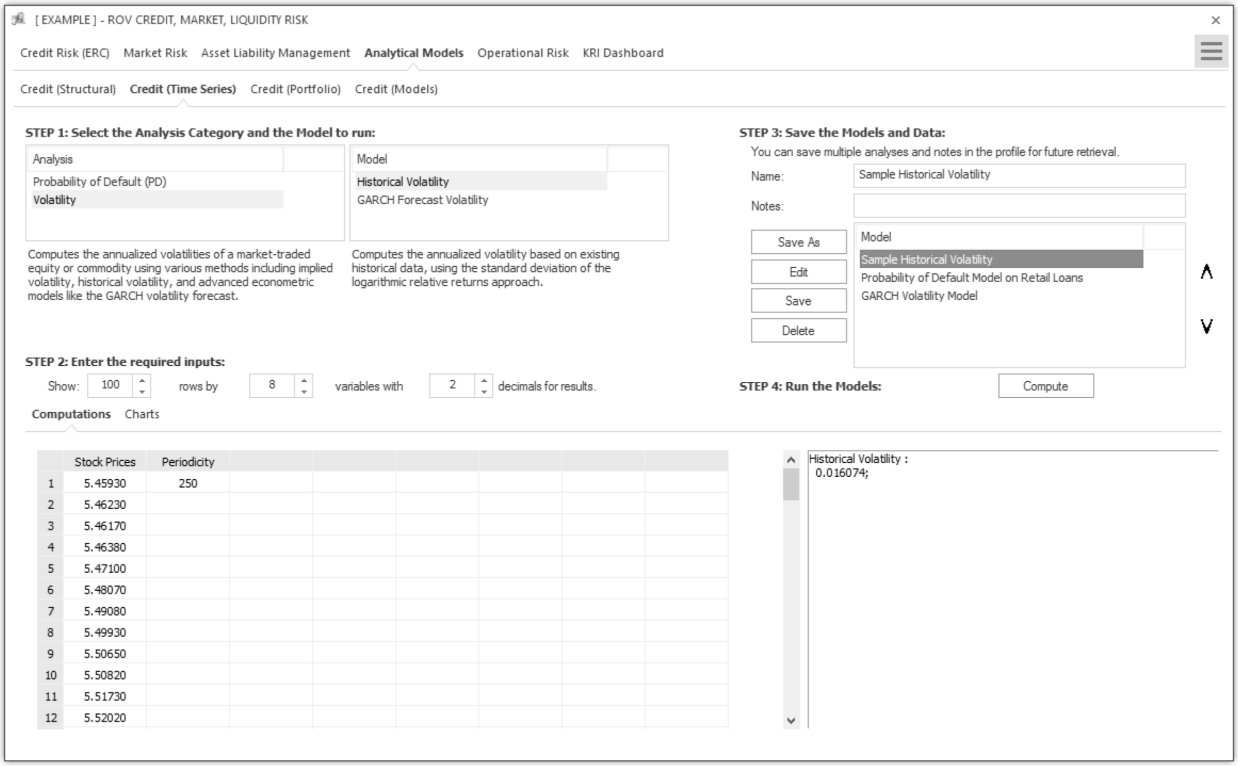


FIGURE 12 Time-series credit- and market-based models.

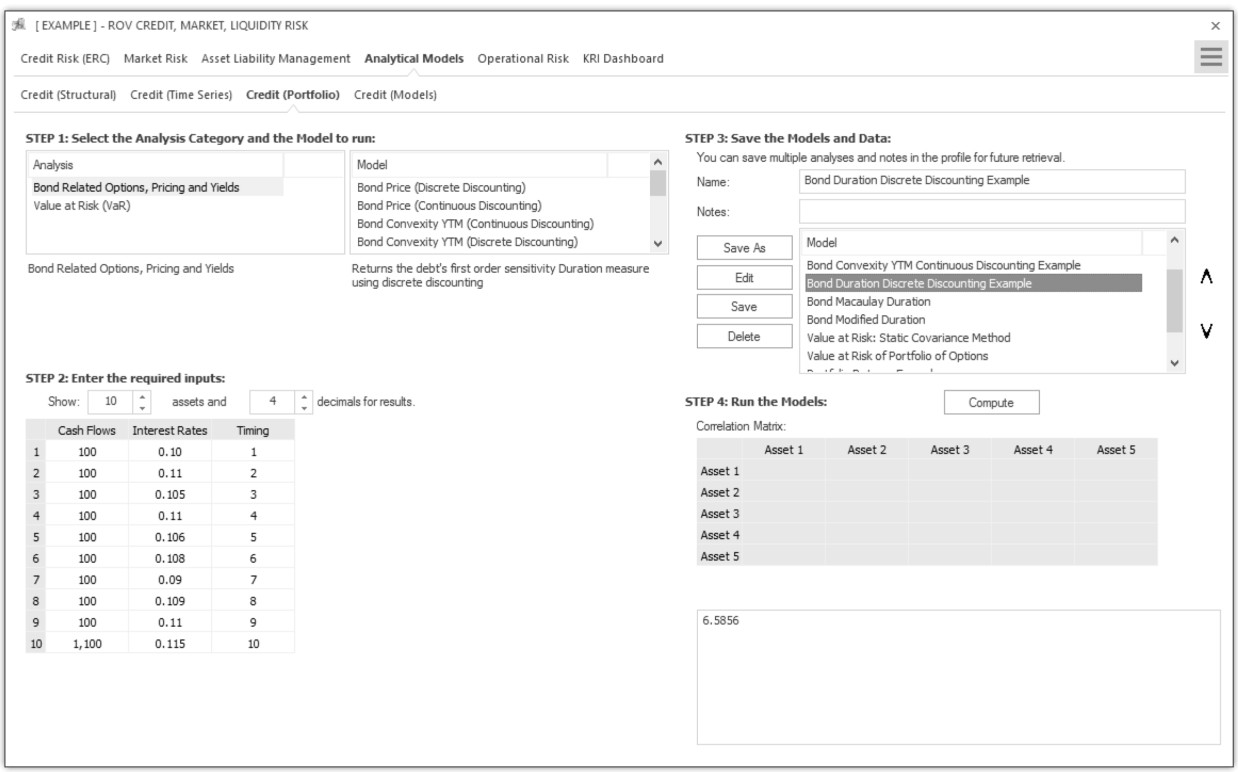


FIGURE 13 Credit portfolio models.

Operational Risk

The case of operational risk is undoubtedly the most difficult to measure and model. The opposite of market risk, by its definition, operational risk data is not only scarce, but biased, unstable, and unchecked in the sense that the most relevant operational risk events do not come identified in the balance sheet of any financial institution. Since the modeling approach is still the VAR logic type, whereby the model utilizes past empirical data to project expected results, modeling operational risk is a very challenging task. As stated, market risk offers daily, public audited information to be modeled. Conversely, operational risk events are, in most cases, not public, not identified in the general ledger, and, in many instances, not identified at all. But the utmost difficulty comes from the proper definition of operational risk. Even if we managed to go about the impossible task of identifying each and every operational risk event of the past five years, we would still have very incomplete information. The definition of operational risk entails events generated by failure in people, processes, systems, and external events. With market risk, assets prices can either go up or down, or stay unchanged. With operational risk, an unknown event that has never occurred before can take place in the study window and materially affect operations even without it being a tail event. So the logic of utilizing similar approaches for such different information availability and behavior requires very careful definitions and assumptions. With this logic in mind, the Basel Committee has defined that in order to model operational risk properly, banks need to have four sources of operational risk data: internal losses, external losses, business environment and internal control factors, and stressed scenarios. These are known as the four elements of operational risk, and the Basel Committee recommends that they are taken into account when modeling. For smaller banks, and smaller countries, this recommendation poses a definitive challenge, because many times these elements are not developed enough, or not present at all. In this light, most banks have resorted to just using internal data to model operational risk. This approach comes with some shortcomings and more assumptions, and should be taken as an initial step that considers the later development of the other elements as they become available. The example shown in Figure 14 looks at the modeling of internal losses as a simplified approach usually undertaken by smaller institutions. Since operational risk information is scarce and biased, it is necessary to "complete" the loss distributions with randomly generated data. The most common approach for the task is the use of Monte Carlo simulations that allow for the inclusion of more stable data and for the fitting of the distributions into predefined density functions.

Figure 14 illustrates the Operational Risk Loss Distribution subtab. Users start at the Loss Data tab where historical loss data can be entered or pasted into the data grid. Variables include losses in the past pertaining to operational risks, segmentation by divisions and departments, business lines, dates of losses, risk categories, and so on. Users then activate the controls to select how the loss data variables are to be segmented (e.g., by risk categories and risk types and business lines), the number of simulation trials to run, and seed values to apply in the simulation if required, all by selecting the relevant variable columns. The distributional fitting routines can also be selected as required. Then the analysis can be run and distributions fitted to the data. As usual, the model settings and data can be saved for future retrieval.

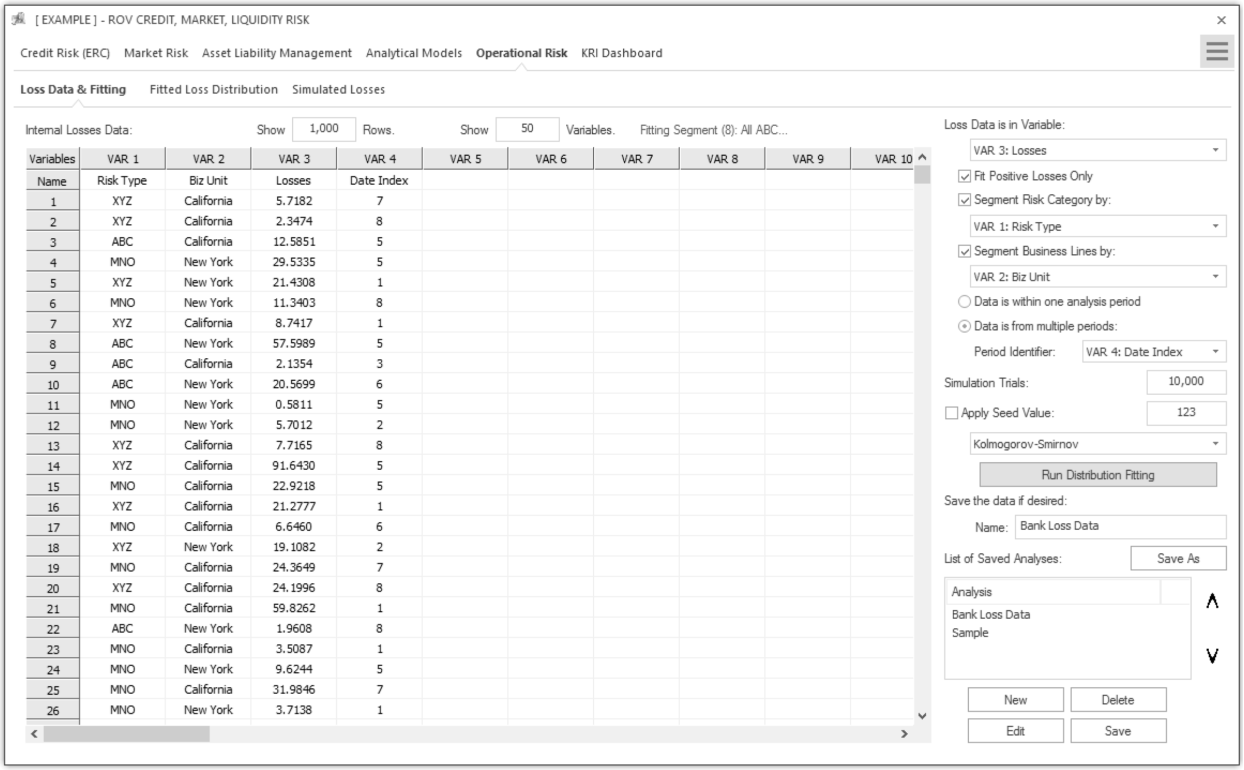


FIGURE 14 Operational Risk data.

Figure 15 illustrates the Operational Risk—Fitted Loss Distribution subtab. Users start by selecting the fitting segments for setting the various risk category and business line segments, and, based on the selected segment, the fitted distributions and their p-values are listed and ranked according to the highest p-value to the lowest p-value, indicating the best to the worst statistical fit to the various probability distributions. The empirical data and fitted theoretical distributions are shown graphically, and the statistical moments are shown for the actual data versus the theoretically fitted distribution's moments. After deciding on which distributions to use, users can then run the simulations.

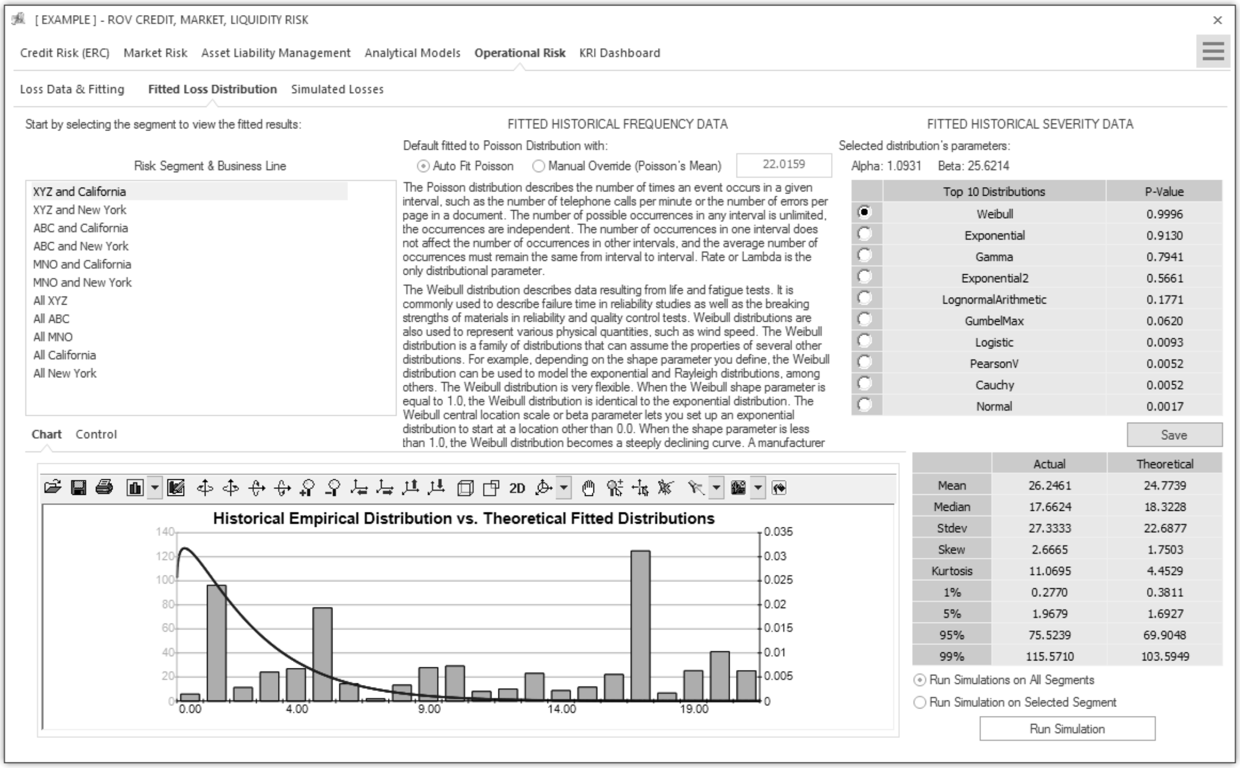
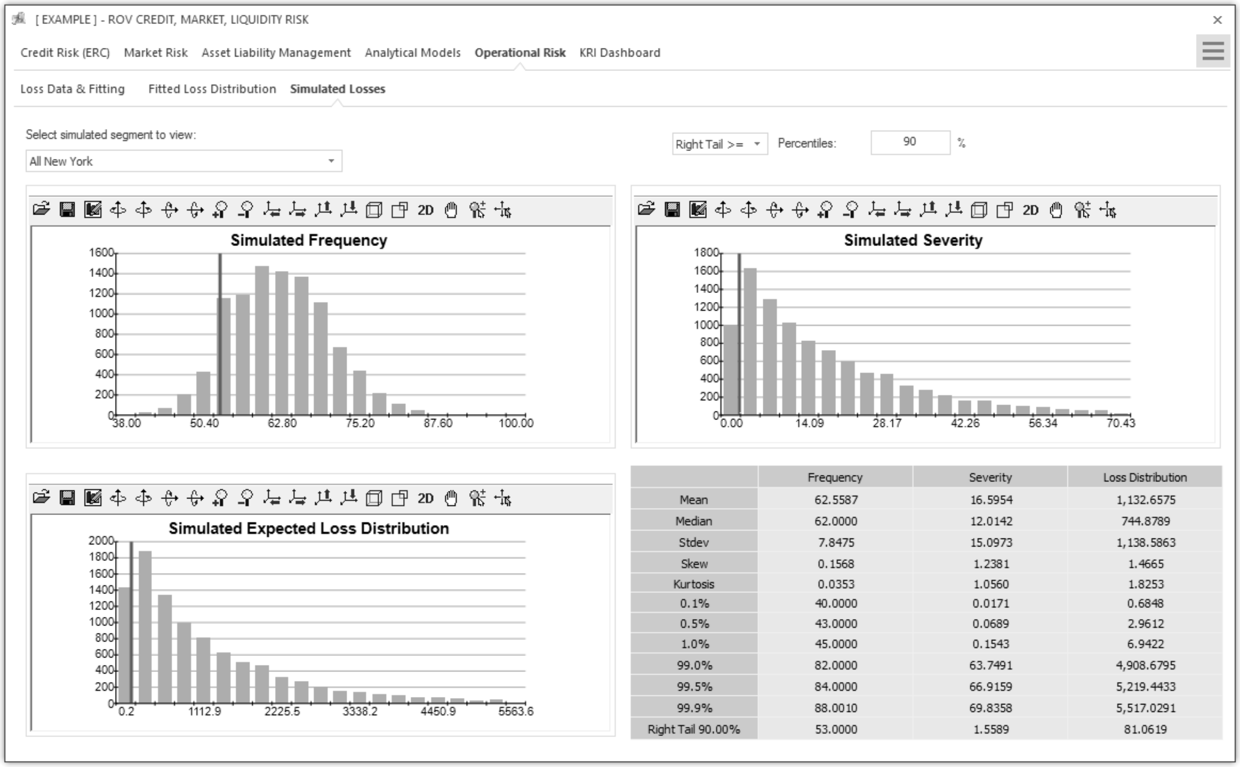


FIGURE 15 Fitted distributions on operational risk data.

Figure 16 illustrates the Operational Risk—Simulated Losses subtab where, depending on which risk segment and business line was selected, the relevant probability distribution results from the Monte Carlo risk simulations are displayed, including the simulated results on Frequency, Severity, and the multiplication between frequency and severity, termed Expected Loss Distribution, as well as the Extreme Value Distribution of Losses (this is where the extreme losses in the data set are fitted to the extreme value distributions—see the case study for details on extreme value distributions and their mathematical models). Each of the distributional charts has its own confidence and percentile inputs where users can select one-tail (right-tail or left-tail) or two-tail confidence intervals and enter the percentiles to obtain the confidence values (e.g., user can enter right-tail 99.90% percentile to receive the VaR confidence value of the worst-case losses on the left tail's 0.10%).



	Frequency	Severity	Loss Distribution
Mean	62.5587	16.5954	1,132.6575
Median	62.0000	12.0142	744.8789
Stdev	7.8475	15.0973	1,138.5863
Skew	0.1568	1.2381	1.4665
Kurtosis	0.0353	1.0560	1.8253
0.1%	40.0000	0.0171	0.6848
0.5%	43.0000	0.0689	2.9612
1.0%	45.0000	0.1543	6.9422
99.0%	82.0000	63.7491	4,908.6795
99.5%	84.0000	66.9159	5,219.4433
99.9%	88.0010	69.8358	5,517.0291
Right Tail 90.00%	53.0000	1.5589	81.0619

FIGURE 16 Monte Carlo risk simulated operational losses.

These simple modeling tools allow smaller banks to have a first approach at more advanced operational risk management techniques. The use of internal models allows for a better calibration of regulatory capital that knowingly overestimated for operational risk. The use of different scenarios providing various results can allow smaller banks to have a much more efficient capital allocation for operational risk that, being a Pillar I risk, tends to be quite expensive in terms of capital, and quite dangerous at the same time if capital was severely underestimated. Together with the traditional operational risk management tools, such as self-assessment and KRIs, these basic models allow for a proper IMMM risk management structure, aligned with the latest international standards.