Portfolio Stress Testing Methodologies

White Paper

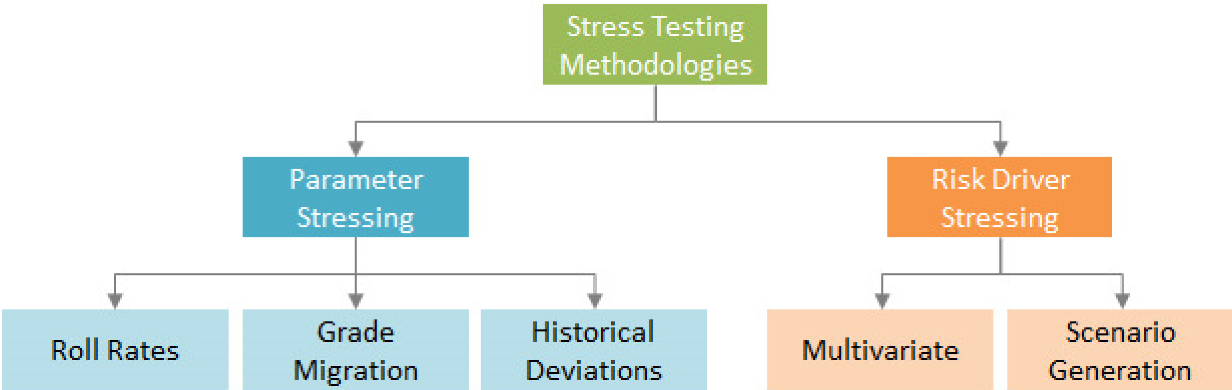
Introduction

As the world is crawling out of the global economic crisis, several efforts are underway by regulators as well as international organizations, such as the International Monetary Fund (IMF) and Bank of International Settlements, to institutionalize stress testing as an integral part of bank's functioning. The intent is to better understand system-wide risks that can trigger widespread economic and financial instability. US Fed, therefore, has mandated an annual Comprehensive Capital Adequacy Review (CCAR) exercise for all banks to submit their capital plans for multiple scenarios (Baseline and Stressed scenarios).

However, the road to implementing these methodologies is not as smooth. We often get asked about: Which stress-testing method should be used? Which system would pass muster with the regulators? What level should we stress at – loan, cluster or portfolio level? In this paper, we have attempted to highlight the different types of stress testing methodologies and their advantages / disadvantages. The objective is to share our perspectives on different methodologies and equip the reader with working knowledge of the same.

Stress Testing Methodologies

While there are multiple types of stress testing methodologies, fundamentally, there are two broad categories – 'Parameter Stressing' and 'Risk Driver Stressing'. 'Parameter Stressing' approach is intuitive and simple. In 'Parameter Stressing' approach, the default rate is directly stressed without evaluating or worrying about the fundamental default risk drivers. In 'Risk Driver Stressing' approach, the drivers of model parameters (such as Probability of Default (PD) or roll rates) are stressed and an estimate of the parameter is computed based on stressed values of risk drivers. The figure below highlights the different types of techniques available under each of these categories:



Let us now understand the individual methodologies in more details.

Roll Rates

'Roll rate' is defined as the migration rate of customer portfolio to a more severe performance bucket. For example, % of customers in 30 Days Past Due (DPD) bucket who migrate to 60-DPD delinquency bucket, with a lag of one month, is called 'Roll Rate' for 30-DPD bucket

"Higher roll rates are observed under severe economic periods or financial crisis. Roll Rates based stress testing is one of the most popular methods for stress testing in the banks."

To stress the PD using roll rate approach, current portfolio is incrementally rolled to high delinquency buckets imitating the high roll rates at downturn period. As an illustration: say 100K 30-DPD delinquent accounts have 10% roll rate at current economic environment and had 15% roll rate to 60-DPD at the downturn as shown in the table below.

Roll Rate	Baseline	Downturn	Change
0-30DPD	10%	15%	5%
30-60DPD	40%	48%	8%
60-90DPD	60%	70%	10%
90-120DPD	70%	86%	16%
90-120+DPD	90%	98%	8%

Roll rates: Baseline vs Downturn

Under the 'Roll Rate' approach, the incremental 5% accounts (5K) are rolled into 60-DPD bucket. This modifies the distribution of accounts across delinquency buckets, as shown in the table below.

Delinquency	# Accounts (Baseline '000)	# Accounts (Downturn '000)
Current	100	92
30DPD	10	15
60DPD	6	7
90DPD	4	5
120+DPD	4	5

Portfolio distribution: Baseline vs Stressed

These accounts are assigned the average PD values of 60-DPD bucket. The revised PD is now the 'stressed PD'using roll rate approach.

The advantages of roll rate approach are several:

- This is an easy to interpret methodology, since roll rates are one of the most commonly used measurement indices in credit risk domain.
- This methodology is easy to implement and does not require any elaborate computation.
- In certain banks, impairment computation is dependent upon roll rates based methodology, and hence this approach attracts immediate synergy with senior management.

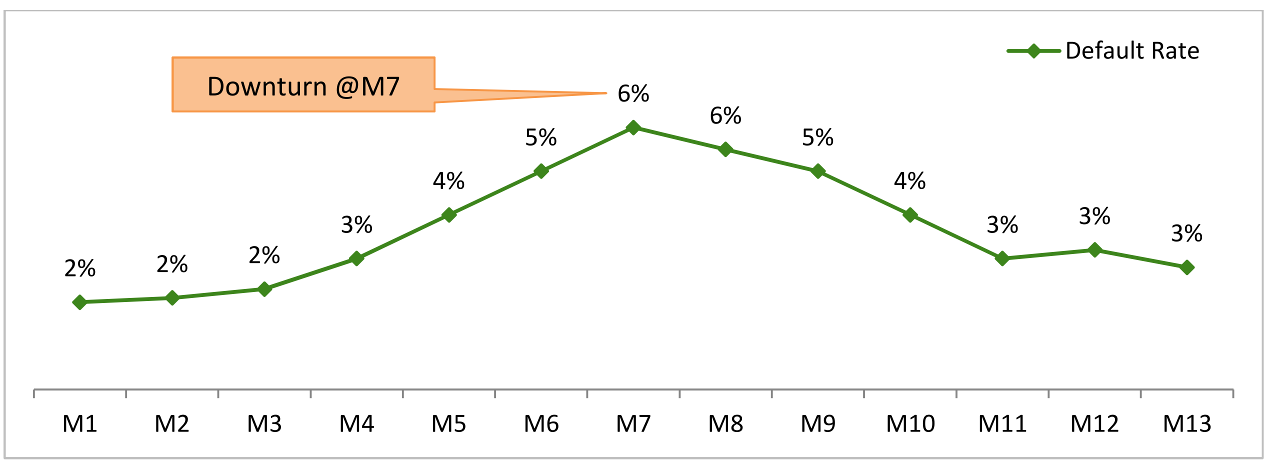
The roll rate approach has certain disadvantages too, as outlined below:

- It's an effect based approach to risk management. It does not expound on any cause-effect relationship between portfolio risk and inherent risk drivers.
- Benchmarking is possible with only past observed roll rates, any scenario that is created other than the observed roll rate is impractical in creation and rhetorical in interpretation.
- This methodology does not provide rank ordering with-in the group of accounts migrated from one DPD bucket to another.
- This methodology lacks the ability to understand customer behavior dynamics. It thus is not usable for a granular stress test.

Grade Migration

Another approach, very similar to 'Roll Rate' approach is 'Grade Migration'. Under 'Grade Migration' methodology, the losses are evaluated as customer portfolio migrates to lower risk grade buckets. It has to be noted that while in 'Roll Rate' approach, the delinquency bucket (a metric which is difficult to benchmark across portfolios in the market) is used; in 'Grade Migration' approach, the risk grades of PD are used to evaluate the impact of stress.

In this methodology, the first step is to establish the downturn period accurately. This is done by plotting the default rates across months, as shown in the chart below.



Identification of downturn

The peak default rate (located within a period of high default rates) indicates the presence of a downturn period. Once the downturn period is established, 'Migration Probability Table' is created which captures, in a matrix form, distribution of rating grades during pre-downturn and downturn period. The same is illustrated in the table below.

		Downturn PD Rating Grades							
	Rating Grades	AAA	AA	A	BBB	BB	B	CCC	CC
Pre-Downturn Rating Grades	AAA	77%	8%	5%	3%	3%	2%	1%	1%
	AA	0%	77%	8%	6.5%	3%	2%	2%	2%
	A	0%	1%	79%	8.5%	5%	3%	2%	2%
	BBB	0%	1%	1%	84%	4.3%	5%	3%	2%
	BB	0%	0%	0%	0%	83%	8.8%	5%	3%
	B	0%	0%	0%	1%	2%	79%	13%	5%
	CCC	0%	0%	0%	0%	2%	3%	79%	16%
	CC	0%	0%	0%	0%	0%	0%	3%	97%

PD Migration Table

The values referred from 'Migration Probability table' are then used to migrate the existing population across risk grades, simulating a downturn scenario. As an illustration, based on the table above, only 77% of accounts currently in AAA would stay as AAA under stressed situation – the remaining would be "migrated" to different risk grades.

The stressed PD (for moved accounts) is then assessed as mean PD of the rating grade they are moved into.

The advantages of 'Grade Migration' approach are:

- It is easy to implement and does not need any elaborate computation.
- It provides additional flexibility to utilize market benchmark risk grades distributions to simulate downturn for portfolios which have not observed a downturn.

However, this approach suffers from similar disadvantages as observed in 'Roll Rate' approach. These are as follows:

- This methodology is also an effect based approach to risk management. It does not expound on any cause-effect relationship between portfolio risk and inherent risk drivers.
- There is inherent inability to explicitly incorporate variance between PD and default rate which helps bank assess buffer capital requirements in case of an anticipated downturn.

- It does not provide rank ordering within the group of accounts migrated from one risk grade to another thus limiting banks' ability to assess intra portfolio risk contours.
- This methodology also suffers from the need to benchmark it against historical rates, which may not provide information about the intensity (Rating grades default rate) or the depth (number of accounts that migrate from lower to higher risk grades) of "next" downturn.

Historical Deviation

A more evolved approach under 'Parameter Stressing' is 'Historical Deviation' methodology. The concept behind this approach is that during historical downturn period, PD model output tends to have considerable deviation from observed default rates – This happens since PD models are usually built at a point which reflects conditions similar to the foreseeable future (and not necessarily a severe downturn). As a result, in downturn period, although PD models may retain their ability to rank order across risk grades, deviation with actual default rate can be significant. 'Historical Deviation' approach, thus, incorporates the deviation of the model PD and default rates, by computing stress buffer as observed at the point of downturn. Constructing a 'Historical Deviation' methodology based stress test is illustrated below:

The first step that is required is to create a deviation matrix (difference between observed default rate and model PD) during downturn. This is shown in the graphic below. One axis of the matrix represents the downturn rating grades. The other axis is typically populated through a profiling variable (e.g. risk driver like FICO) which adds more granularities to the deviation estimates. Then, for each cell of the matrix, the difference of scored PD at the downturn month and the default rate observed over the next 12 month is computed.

		Primary Risk Driver – FICO							
	Rating Grades	<500	<600	<650	<700	<750	<800	<850	>=850
Downturn Rating Grades	AAA	1.6%	1.0%	0.3%	1.8%	0.1%	1.0%	0.8%	0.2%
	AA	0.6%	0.1%	1.1%	0.2%	1.6%	0.0%	0.4%	2.4%
	A	2.7%	1.9%	0.9%	0.1%	2.2%	0.2%	0.3%	1.1%
	BBB	2.4%	1.1%	0.0%	2.8%	0.8%	1.2%	0.6%	0.9%
	BB	0.3%	2.2%	0.7%	1.6%	1.6%	2.2%	0.3%	2.2%
	B	0.1%	1.1%	1.2%	2.0%	1.0%	1.9%	0.4%	1.0%
	CCC	1.7%	1.3%	0.8%	0.6%	0.7%	1.4%	1.7%	1.0%
	CC	0.0%	0.1%	0.2%	1.7%	0.2%	1.8%	1.2%	1.0%

Deviation matrix (Observed Default Rate – Score PD)

Then, for each risk grade, mean and standard deviation *of the difference* is computed by using the values populated against each of the profiling variable (FICO in the graphic above) band.

Stressed PD is then assessed by adding µ+2σ (or 3σ), depending on the level of stressing required, to the model PD of the existing portfolio. This is illustrated in the table below. .

Existing Portfolio			
Rating Grades	Model PD	Population	Stressed PD
AAA	0.1%	10,000	0.1% + µAAA+2σAAA
AA	2.0%	8,000	2.0% + µAA+2σAA
A	5.0%	6,000	5.0% + µA+2σA
BBB	8.0%	2,000	8.0% + µBBB+2σBBB
BB	12.0%	1,000	12.0% + µBB+2σBB
B	15.0%	500	15.0% + µB+2σB
CCC	20.0%	400	20.% + µCCC+2σCCC
CC	25.0%	200	25.0% + µCC+2σCC

The advantages of this methodology are as follows:

- It is more granular due to incorporation of risk driver based distribution. It is thus more accurate in capturing downturn impact.
- It provides insight into impact of selected risk drivers on default rates and accuracy of PD models across risk driver bands.
- It incorporates deviation between default rate and model PD, thereby providing much needed cushion to stressed PD forecasts.

However, this methodology suffers from select disadvantages too, as mentioned below:

- It still does not capture true risk contours within the portfolio, since it depends upon one risk driver and distribution of risk scores across its deciles.
- There is no flexibility to the user in terms of simulating rare and hypothetical events, since it also depends upon observed historical downturn in the portfolio.

The above three approaches, as can be observed, do not stress the underlying drivers. The causality (of stressed output) is thus not well understood in any of the above three approaches. This weakness is addressed under the 'Risk Driver Stressing' approaches viz. Multivariate and Scenario Generation. Let us delve into these two approaches in more details.

Multivariate Stress Testing

This is one of the most popular methodologies currently being used in banks that are conducting the CCAR initiative. This methodology stresses on PD model drivers (individually or in cohorts) to assess the overall loss impact. The stressed PD is calculated by using the stressed values of the drivers (instead of current values) in the PD model equation. There are four different methods of creating stress factors across the model drivers as discussed below:

1. **User Defined Stress Factoring:** In this method, the user specifies the particular drivers for a model/segment to be stressed; as well as the stress factors to be applied upon it. For each such stressing, an estimate of PD is calculated. It has to be noted that prior to using this method, it is critical to establish "break point" of a model-driver combination. The "break point" is defined as the point at which the accuracy of the model deviates significantly from the development sample. Typically a deterioration of 20% in R^2 is used as an indicator for break point. Estimates made beyond the break point range are often unreliable and hence stress factors should always remain below the break point threshold.

   This method is intensive in nature. It needs significant effort and business expertise on the part of the user to identify relevant stress factors and infer results thereof. However, it ends up giving lot of flexibility to the user in terms of selection of drivers and the stress factors. Further, it is quite useful in helping understand intra-portfolio risk characteristics and the sensitivity towards specific risk drivers.

2. **Monte Carlo Simulations:** This method goes a step further to 'User defined Stress Factoring'. It obviates the need (for the user) of selecting a stress factor. Instead, the stress factors are generated using Monte-Carlo simulations. The simulations generate stress factors following a pre-defined statistical distribution (typically log-normal since it simulates long tailed nature of unexpected losses). For each point of the stress factor distribution, the impact on PD is assessed.

   This allows the user to have a complete view of PD changes across the distribution of stress factors in one shot. The method, however, is very time consuming given the computational intensity needed to generate the simulations and assess the impact of each stress factor generated.

3. **Downturn Stress Factoring:** In this method, the stress factor is calculated by benchmarking the risk driver values during downturn period against the current (baseline) period. The mean of the risk driver is computed for each of the two periods, across the deciles of risk driver. Stress factor is then assessed for each of the decile by dividing the mean of the driver's value as of downturn period by the mean as of the baseline period, as shown in the table below:

Driver: Payment to Balance Range	Driver Mean (Downturn) A	Driver Mean (Baseline) B	Stress Factor A/B
90-100%	94%	98%	0.96
80-90%	83%	89%	0.93
70-80%	72%	78%	0.92

Driver: Payment to Balance Range	Driver Mean (Downturn) A	Driver Mean (Baseline) B	Stress Factor A/B
60-70%	61%	69%	0.88
40-60%	51%	58%	0.88
30-40%	35%	31%	1.13
20-30%	23%	21%	1.10
0-20%	12%	3%	4.00

Driver Mean distribution: Downturn vs Baseline

These deciles-wise stress factors are then multiplied across all accounts within each decile to compute the stressed values of the driver. Subsequently, once all the desired drivers have been similarly stressed, stressed PD computation is made by using the model equations.

This method is effective in simulating a downturn scenario on existing portfolio; and deriving insights into portfolio performance if downturn were to re-occur. However, this method cannot be used if the portfolio has not witnessed any downturn.

4. **Downturn Frequency Weighted Stress Factoring:** Even though the name of this method appears to be similar to the earlier one, there is a fundamental difference between this method and the previous one. While in the 'Downturn Stress Factoring' approach, the values of a particular driver are stressed as observed during downturn period; in this method - the account distribution of each driver across variable distribution bands is aligned with the account distribution during a downturn period. This is highlighted in the table below:

Driver: Payment to Balance Range	% Accounts (Downturn) A	% Accounts (Baseline) B	Stress Factor A/B
90-100%	28%	40%	0.70
80-90%	13%	20%	0.65
70-80%	12%	10%	1.20
60-70%	11%	9%	1.21
40-60%	11%	8%	1.35
30-40%	10%	6%	1.67
20-30%	9%	4%	2.25
0-20%	6%	3%	2.00

Account Distribution: Downturn vs Baseline

Once the stress factors across the deciles have been calculated (using weights of frequency), the approach to calculate stressed PD is exactly the same described in the previous method. As can be expected, the advantages and disadvantages of this method are similar to those of 'Downturn Stress Factoring' method.

Frequency weighted, however, does provide insight into distribution of variable across accounts. In case of a normal distribution both downturn and downturn frequency weighted approaches are likely to provide similar results whereas in case of a skewed variable distribution the results of frequency weighted are likely to be different from pure downturn approach.

All the methods of 'Multivariate Stress Testing' approach are computationally intensive; they all need appropriate data quality and comprehensiveness as well as strong analytics capabilities to execute them accurately.

Scenario-Generation

This methodology too has gained lot of traction in the recent past; ever since CCAR released Fed's projections on several macro-economic indicators (e.g. GDP, Unemployment Rate, Oil Prices, Bond Yields, and Personal Consumption Index etc.) under baseline and stressed environments. This methodology is typically used to capture the impact of the movements in macro-economic indicators on default rates. At times, the methodology is utilized to generate scenarios and assess impact using internal drivers too (e.g. FICO, Charge Volume, Financial Ratios etc.); in conjunction with macro-economic indicators.

Under this methodology, the default rate, aggregated at portfolio level, is modelled against selected set of internal and macro-economic drivers using time series modelling techniques. Once a time series (and regression) equation has been established between the portfolio default rate and independent drivers (internal and macro-economic), it is used to score and compute PD score for the portfolio for a set of scenarios. Typically, these scenarios are constructed using any of the below-mentioned three ways:

1. **Historical Scenarios**: The values of independent drivers are selected as per the historical scenarios like 2008 recession or consecutive quarters of negative GDP growth.
2. **Hypothetical Scenarios**: The values of independent drivers are selected on the basis of expert judgment of the modellers.
3. **CCAR Scenarios**: CCAR provided scenarios highlighting projections under Baseline, Stressed, Severely Stressed environments. The same can be used to model the impact on the portfolio.

'Scenario Generation' approach has significant advantages:

- It captures both specific and systematic risks effectively
- It tends to have high accuracy in default rate estimates

- It captures time variant component of macroeconomic indicators and its impact of portfolio
- It provides flexibility to create hypothetical scenarios and assess required capital

However, it has certain disadvantages too as enumerated below:

- It requires high level of skill to create a robust and stable (time series) model
- The interpretation is sometimes difficult, thereby requiring significant knowledge of time series modeling
- Selection of relevant macroeconomic risk drivers is crucial for interpretability of results – e.g. unemployment rate might play a crucial role in credit card charge-offs, but housing price movements would be more critical for mortgage delinquencies.
- Although it is highly accurate, it doesn't provide any insights into portfolio risk distribution across accounts.

As one would have observed after reading through the 'Stress Testing Methodologies' section , there are several methods and approaches available to stress test the portfolio. Given the wide array of choices available, the natural question comes – which is the most appropriate methodology?

In our view, there is no 'holy grail' answer. The appropriate methodology to use is dependent on the testing requirements of the portfolio – which is driven by the type of risk one is trying to measure and manage. In our view and experience, often a combination of the above-mentioned approaches is the best way to triangulate effectively on portfolio's performance under stress.

Conclusions

Stress testing, with or without regulatory pressure; can be a source of competitive advantage to a diligent risk manager. It has the ability to empower a risk manager with deep knowledge of portfolio dynamics with respect to internal and external drivers - which can help avoid significant exposure loss.

This paper provides an overview of the methodologies available to banks wishing to conduct effective stress testing of their portfolios. As is evident from the discussion above, no single methodology exists which is capable of providing answer to all the questions that face any modeller within the paradigm of stress testing. This is not necessarily a challenge, since each test and its methodology is created with the aim of satisfying specific needs of the discerning audience.

While ‘Roll Rate’ and ‘Grade Migration’ approaches are pretty straight forward and widely used in the risk world, practitioners are advised to temper the results of these approaches by viewing outputs from more sophisticated methodologies like ‘Multivariate and Scenario Generation’ based stress testing. As the organizations mature, a hybrid approach is adopted where the portfolio losses are triangulated by leveraging different stress testing methodologies.

Further, it has been our experience; executing stress testing efficiently is not an easy job. Banks need significant tools and software support to run stress testing processes optimally. Banks which have invested in the right set of tools and solutions tend to be much faster, comprehensive and more accurate in stress testing their portfolios adequately. They are also equipped to respond to regulatory pressures satisfactorily.

We hope and wish our thoughts will help you in refining your stress testing capabilities and enable you to provide appropriate thought leadership to your business counterparts. Happy lending!!

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