Stress Testing, Financial Networks and Behavioral responses

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[1] The presentation largely draws on Vansteenberghe (2017, Forthcoming). The views expressed here do not necessarily reflect those of the ACPR or the Banque de France.

Outline

- Definitions
- Integrating banks with the rest of the financial system : bank-insurance interconnections
- New Tools for modelling contagion in bank stress tests
- Application to EBA Stress tests
- Extending to liquidity shocks

I-Definitions: three rounds of contagion and feedback loop

In the following, we define 3 rounds for our model stress test and contagion as in the ACPR's Mercure (2015) model and Battiston et al. (2016).

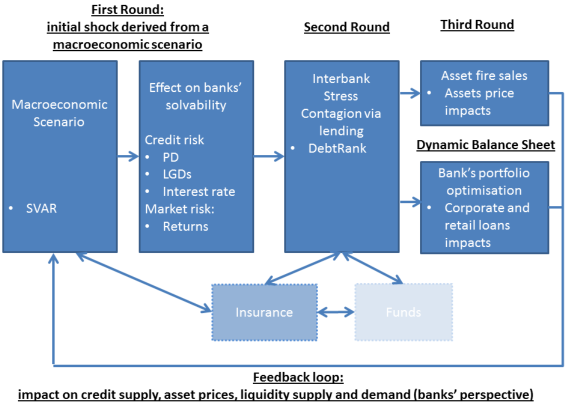


Figure : Stress Test blocks used at the ACPR

II- Bank-insurance interconnections
The Bancassurance network for France

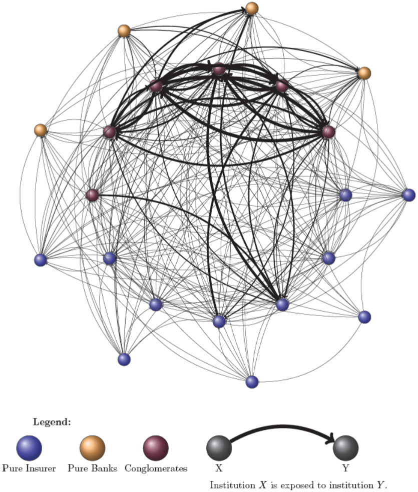


Figure : Network of French Financial Institutions for all-instrument exposures (Hauton & Heam, 2016)

Systemic Importance versus Fragility for France

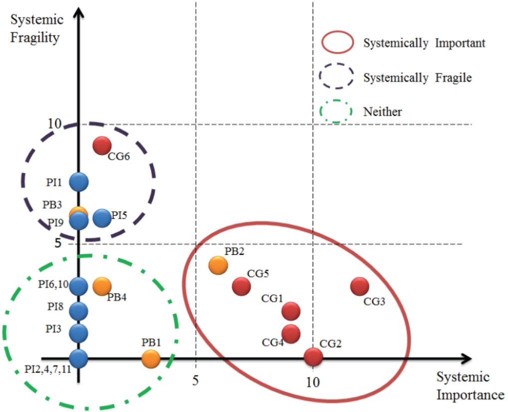


Figure : Systemic Importance and Systemic Fragility (Hauton & Heam, 2015)

Sovereign shock and insurance-sovereign link for France

Table 5. Sovereign exposure stress test results. Equity recovery is the average over the non-defaulted institutions of the ratio of equity after shock and equity before shock. Debt recovery is the average over the defaulted institutions of the ratio of debt value after shock and before shock. "." indicates that the value cannot be computed.

Country	DE	ES	FR	UK	FR	IE	IT	PT	US
No. of Defaults									
Insurance Component	0	0	6	0	0	0	1	0	0
Banking Component	0	0	1	0	0	0	0	0	0
Conglomerate	0	0	1	0	0	0	0	0	0
Equity Recovery (%)									
Insurance Component	93	75	.	100	94	93	61	83	99
Banking Component	91	96	71	99	99	99	86	97	86
Conglomerate	92	96	66	99	99	99	87	97	86
Debt Recovery (%)									
Insurance Component	.	.	90	.	.	.	98	.	.
Banking Component	.	.	97	.	.	.	.	.	.
Conglomerate	.	.	98	.	.	.	.	.	.

Figure : Impact of a Sovereign shock in France (Hauton & Heam, 2015)

III- New Tools

3.1. Second Round: DebtRank

We rely on a simple model as in Battiston et al. (2016), with a leverage matrix (exposure of bank i to bank j, divided bank i's own funds).

- E_i the tier 1 capital of bank i, if $E_i \leq \gamma$ bank i default
- p_i the Total Liabilities of bank i
- $p_{i,j}$ payment due from bank i to bank j
- L the leverage matrix

$$L_{i,j} = \begin{cases} \frac{p_{j,i}}{E_i}, & \text{if } \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

- S_i shock on some asset value (e.g. on external assets)
- $h_i(t) \in [0,1]$ is the distress status of a bank, bank is healthy if $h_i(t) = 0$ and bankrupt if $h_i(t) = 1$, distressed in-between

Contrast with the Eisenberg and Noe (2001) framework

In contrast to the Eisenberg and Noe procedure, the model allows more flexibility, introducing an indicator of bank health. In the initial state, if the core equity of the bank is $> \gamma$, then the bank is deemed healthy:

$$h_i(t) = \begin{cases} 0, & \text{if } E_i(t) \geq \gamma \\ 1, & \text{otherwise} \end{cases}$$

We first shock the external assets of bank i that needs to be compensated by a corresponding reduction in equity. At date $t+1$ a shock $S_i(t+1)$ impacts the external assets of bank i. The state of an unhealthy bank i will be measured by the relative change in own funds (in absolute value):

$$h_i(t) = \max\left[0, \min\left(1, \frac{E_i(t) - E_i(t+1)}{E_i(t)}\right)\right]$$

Distance to default and transmission

Even if no bank of the network defaults, the shock on its external assets will reduce its *distance to default* and consistently with the approach of Merton (1974) the bank will be less likely to repay its obligations in case of further distress, therefore implying that the market value of i's obligations will decrease as well.

That loss in the obligation value will be described for bank i by a function f of the state of the other banks (indexed by j):

$$h_i(t) = \max\left[0, \min\left(1, \sum_j L_{i,j} f\left[h_j(t-1)\right]\right)\right]$$

Assumptions on the transmission function

As indicated in Battiston et al. (2016),

> *Mark-to-market and in particular Credit Valuation Adjustment (CVA) is recognized as a major mechanism of financial distress propagation. During the 2007/8 financial crisis, it accounted for two thirds of all losses on the financial system.*

- For the DebtRank method, Battiston et al. (2016) defined $f[h_i(t)] = h_i(t)$.
- f would depend on the financial instrument and the pricing model used.
- f should be non-decreasing in the value of the assets of the issuer, as then the issuer will be more prone to pay dividends or interest rates to investors/creditors.

Assumptions on the transmission function

One novelty in this work is, in the spirit of the CoVaR approach, to use the Probability of Default correlation between banks i, j to calibrate f, it should in practice be calibrated instrument by instrument:

$$f_i[h_j(t)] = |cov(\Delta \mathrm{PD}_i, \Delta \mathrm{PD}_j)| h_j(t)$$

We also have to note that the historically observed correlation of Probability of Default changes significantly in times of stress.

3.2. Third round: Fire Sales

Several approaches are possible to model fire sale impacts:

1. Fixed percentage impact
If we focus on liquid assets (like US Mutual Funds), Coval and Stafford (2007) estimate the fire sale impact at a 5% discount to fair value (regardless of the amount sold).

2. Linear impact
- Greenwood et al. (2015) take a linear 10^{-13} discount, for any type of assets (a EUR 10bn selloff triggers a 10bp price decrease).
- Based on the model with agent interactions and macroeconomic feedback, Becard and Gauthier (2017), the sensitivity between the price impact and the ratio $\frac{\text{Total Asset Sold}}{\text{Total Asset}} \simeq 5$ (a 1% reduction in banks' assets leads to a 5% price fall).

3. Non-linear impact

Following Cont and Schanning (2016), we can define a market impact function which depends on the market depth of each asset class. They extrapolate to big volume of assets sold q and S the market price and express the relative price change of each asset class μ as $\frac{\Delta S^{\mu}}{S^{\mu}} = -\Psi_{\mu}(q)$, where q is normalised by average transactions :

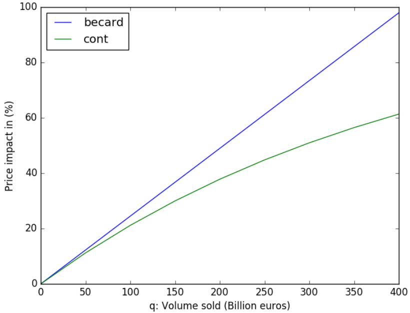
$$\Psi_{\mu}(q,S) = \left(1 - \frac{B_{\mu}}{S}\right)\left(1 - \exp(-\frac{q}{\delta_{\mu}})\right)$$

As detailed in the paper:

> *An adequate choice for Ψ_{μ} should be increasing, concave, satisfy $\Psi_{\mu}(0,S) = 0$, and lead to non-negative prices.*

Difference between the Cont and linear approach

Using the Cont and Schanning (2016) method on French market data (CAC 40 data), and based on the total assets of French G-SIB in December 2015, we differ slighlty from a simple linear price impact model:



In an extreme case, where all French G-SIB want to recover a CET1 ratio at the pre-EBA 2016 stress test exercice, deleveraging would have an estimated 19% impact on asset prices.

3.3. Dynamic balance sheet - RWA adjustments

We model deleveraging effects in a stylized dynamic balance sheet behavior of the bank, that will fire sale some of its assets in order to target a certain CET 1 ratio. A bank changes its asset portfolio with respect to their risk type. At this stage, interbank exposures are assumed to remain unchanged.

In a stress event, the CET 1 is in the first round negatively impacted while the Risk Weighed Assets increase. This means that the CET1 ratio is unambiguously decreasing.

$$\text{CET1 ratio} = \frac{\text{CET1 capital}}{\text{RWA}}$$

Data and models for RWA adjustment (1/2)

Following Greenwood et al. (2015), on may assume that all banks want to recover (at least partially) the CET1 ratio to the level before the stress event. In practice, most banks increase their CET1 ratio γ by retained earnings, which takes time. In a stressed period, they would then sell assets. The target ratio can also be set at 8%.

We model a dynamic balance sheet behavior of banks that will sell in distress some of their assets, taking into account:

- the discount imposed by the market (proxied by the Expected Loss),
- the multiplicative effect (weight) that depends on the risk category of the assets.

For the 4 G-SIB French banks, we use COREP data on credit corporate portfolio (one should also take into account the liquidity premium that varies across asset classes).

Data and models for RWA adjustment(2/2)

- We take the COREP corporate credit exposures and RWA per risk bucket: (AAA, AA, A, BBB, BB, B and CCC, CC, C). We assume that the overall portfolio of the bank is broken down in the same proportion, we also adjust the weighting to respect the overall the CET1 ratio.
- For each bucket we have the Probability of Default (PD) and the Loss Given Default (LGD). We can compute the Expected Loss ($EL = PD \times LGD$) and assume that the market is integrating this depreciation directly in the price.
- We use FINREP data on the total assets of the banks to distinguish between three categories of assets: securities (that can be sold in distress), cash (with no RWA impact), loans (which can be repriced by the market participants, but not easily sold in distress), and others (tax assets, tangible and intangible fixed assets).

Asset level to be sold to reach the γ targeted

If we call γ_{target} the CET1 ratio target that the bank wishes to reach:

$$\frac{\text{CET1 capital}_{2018} - \text{Asset sold} \times \text{EL}}{\text{RWA}_{2018} - \text{Asset sold} \times \text{RWA multiplicator}} = \gamma_{\text{target}}$$

The level of assets that the bank needs to sell to reach the target CET1 ratio is not trivial, as for each asset category i, the expected loss and the RWA multiplicative effects are not the same. Solving for j, one can get the optimal amount of asset j to be sold, starting with the riskier assets first and moving up to less risky assets.

IV- Application to EBA Stress Test 2016: modeling the second and third round

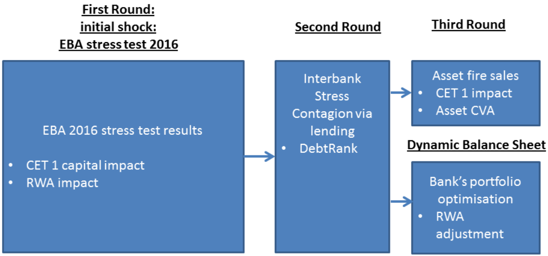
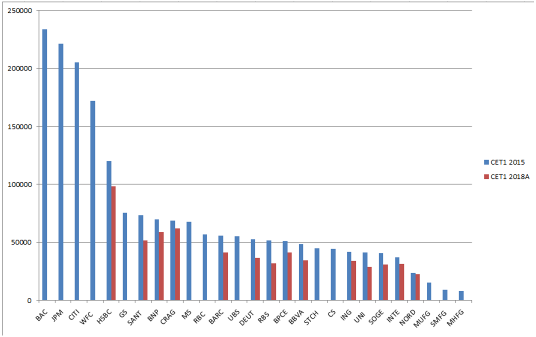


Figure : Framework to extend the 2016 bottom up stress test

EBA Stress Test 2016 data

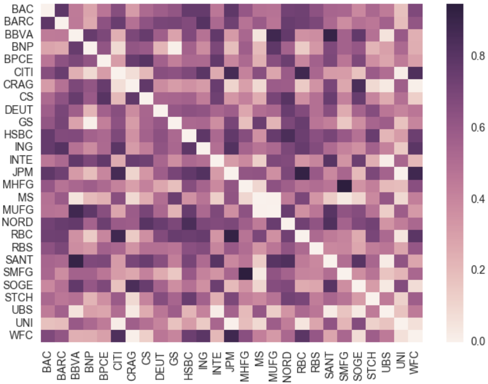
We start with data on a set of the 27 largest G-SIB banks. We use data from the EBA stress test 2016 published results and SNL database. Values are expressed in Million euros:



We use the Δ CET1 of the EBA 2016 stress test as an input to our contagion model.

Probability of Default correlation

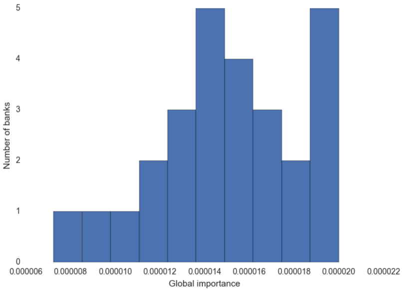
In order to illustrate our approach, we use for proxy of the interbank exposure matrix, the correlation matrix of changes in Probability of Default of the banks estimated with Bloomberg data from 2006-04-23 to 2017-01-31. We neutralize the auto-correlation before applying the DebtRank model.



Second Step Interbank contagion à la DebtRank: 27 scenarios of failure

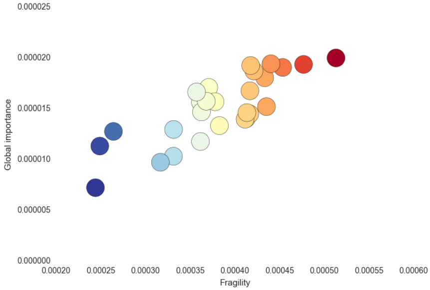
First, we perform 27 scenarios where we impose that each bank fails after another. We present a histogram of how bank impact the network (its global importance), decomposed in 10 buckets: The systemic importance of a bank $\in [0,1]$, the system is deemed more vulnerable the closer it is to 1:

$$H(t_{\text{end}}) = \frac{\sum_{i=1}^{N} E_i(t_{\text{initial}}) h_i(t_{\text{end}})}{\sum_{j=1}^{N} E_j(t_{\text{initial}})}$$



Second Step Interbank contagion à la DebtRank: Systemic importance and fragility

From the 27 scenarios, we can measure how much a bank is impacted, it is a measure of its systemic fragility, and how much the bank is impacting the others, it is a measure of its systemic importance. If we do a scatter plot of importance as a function of fragility:



Third Step: asset fire sale

For the Third step, we use the fire sale model.
In the scenario of a stress test, we assume that all non-EU banks face the average shock (in terms of CET1) that the EU banks are facing (otherwise the network is absorbing the shock).
The change in the average CET1 capital for the 27 banks are as follow:

	Stress Test 2016 Adverse	Second Round	Third Round	1000 loops
Average	-21.95%	-0.003%	-1.45%	-1.85%

We focus on the 4 French G-SIBs : we compute the average CET1 ratio after the EBA shock (1st round), the interbank contagion (2nd round), the fire sale (3rd round), and the ratio after 1000 loops of 2nd and 3rd round:

	2015 ratio	Ratio 1st round	Ratio 2nd round	Ratio 3rd round	Ratio after 1 000 loops
4 French G-SIBs	12.739%	9.541%	9.540%	9.436%	9.333%

Results of first, second, third steps, and dynamic balance sheet

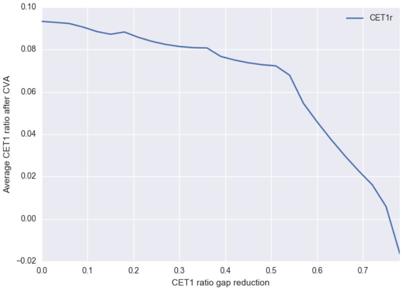
If French G-SIB banks, in our model, wanted to close 25% of the gap between their CET 1 ratio before and after the stress, it would be counterproductive as the market reaction would depress the CET 1 ratio below the ratio after the stress.

	Total Assets 2018	Assets sold	CET1 capital 2018	CET1 after sale	CET1 after CVA	RWA 2018	RWA after sale
Bn EUR	5 500	157	195	190	154	2100	1900

	CET1 ratio 2015	CET1 ratio after 1 000 loops	CET1 ratio after sale	CET1 ratio after CVA
Average	12.7%	9.3%	10.2%	8.3%

CET1 ratio gap closure: negative externality

According to our model, closing the CET1 ratio gap would be overall counter productive for the banking sector



So far we assumed that markets for balance sheet asset were perfectly liquid which can be far from reality in a period of stress.

Impacts of first, second, third and RWA adjustements

We can compare the order of magnitude of the impact on the CET1 ratio for the French G-SIB of the first step (EBA stress test 2016), the second step (interbank contagion), third step (fire sale), and RWA adjustment (coupled with market repricing):

First step
−24.9%
Second step
−0.002%
Third step
−1.07%
RWA adjustment (closing 25% of the gap)
−18%
RWA adjustment (target the BCBS 8% ratio)
−5%

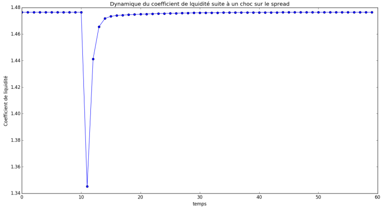
After the 2016 EBA stress test, only one French bank was below the 8% CET1 ratio.

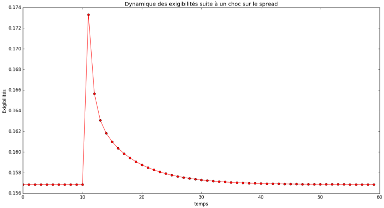
V- Extending to liquidity spillovers

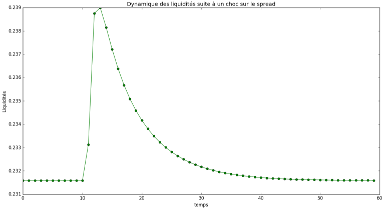
- Data definitions: liquidity reporting
- Sample: French banks, non consolidated, 2001Q1-2015Q1 period
- Assessing the link between macro-economic and financial shocks and CDS Spreads, liquidity inflows and outflows, as well as capital ratio
- Overall conclusion : evidence of liquidity hoarding after a shock
- Need to be integrated in the overall framework

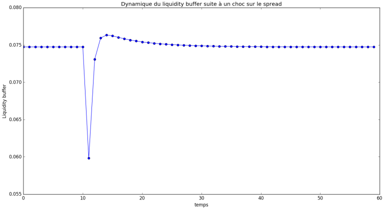
Including liquidity spillovers - Risk of liquidity hoarding

We get the following Impulse response functions following a shock on EURIBOR-TBILL Spread









Conclusion and further research

- On the basis of our results on French GSIBs, the market impact of fire sales appears to have potentially a much more material effect on CET1 ratio than direct exposures
- But relies on several parametric assumptions, which require sensitivity analysis (timing, horizon, size of market)
- Liquidity spillover channel need to be further investigated beyond capital spillovers

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Annex 1: Non-linear impact on asset prices

Following Cont and Schanning (2016), we can define a market impact function which depends on the market depth of each asset class. They extrapolate to big volume of assets sold q and S the market price and express the relative price change of each asset class μ as $\frac{\Delta S^\mu}{S^\mu} = -\Psi_\mu(q)$, where q is normalised by average transactions :

$$\Psi_\mu(q,S) = \left(1 - \frac{B_\mu}{S}\right)\left(1 - \exp(-\frac{q}{\delta_\mu})\right)$$

with:

- B_μ a floor on the price decrease, set at 50% as in the paper
- $\delta_\mu = \left(1 - \frac{B_\mu}{S_0^\mu}\right) D_\mu$
- $D_\mu = c\frac{ADV_\mu}{\sigma_\mu}\sqrt{\tau}$ the adjustment
- c a coefficient estimated at 0.5 from transaction data
- τ the liquidation horizon, set at 20 days as in the paper
- σ_μ the daily volatility of the asset
- ADV is the Average Daily traded Volume

Annex 2: Data and models for RWA adjustment(1/2)

- We take the COREP corporate credit exposures and RWA per risk bucket: (AAA, AA, A, BBB, BB, B and CCC, CC, C). We assume that the overall portfolio of the bank is broken down in the same proportion, we also adjust the weighting to respect the overall the CET1 ratio.
- For each bucket we have the Probability of Default (PD) and the Loss Given Default (LGD). We can compute the Expected Loss ($EL = PD \times LGD$) and assume that the market is integrating this depreciation directly in the price.
- When selling assets to deflate the RWA, the bank also loses some CET1 capital.
- The RWA multiplicative effect will depends on which risk category of assets are sold. We compute the RWA multiplicative effect using the BCBS formula.

Annex 2: Data and models for RWA adjustment(2/2)

We use FINREP data on the total assets of the banks to distinguish between three categories of assets: securities (that can be sold in distress), cash (with no RWA impact), loans (which can be repriced by the market participants, but not easily sold in distress), and others (tax assets, tangible and intangible fixed assets).

For our French bank sample, here are the shares:

- 50% loans
- 37% securities
- 7% cash
- 7% others

Annex 3: Asset level to be sold in RWA adustment model- section 3.3

If we call the CET1 ratio target γ_{target}:

$$\frac{\text{CET1 capital}_{2018} - \text{Asset sold} \times \text{EL}}{\text{RWA}_{2018} - \text{Asset sold} \times \text{RWA multiplicator}} = \gamma_{\text{target}}$$

The level of assets that the bank needs to sell to reach the target CET1 ratio is not trivial, as for each asset category i, the expected loss and the RWA multiplicative effects are not the same:

$$\text{Asset sold}_j = \frac{\text{CET1 c.}_{2018} - \gamma_{\text{tgt}}\text{RWA}_{2018} - \sum_{i \neq j}\left(\text{Asset sold}_i \times \text{EL}_i - \gamma_{\text{tgt}}\text{Asset sold}_i \times \text{RWA mult}_i\right)}{\text{EL} - \gamma_{\text{tgt}}\text{RWA mult}_j} \tag{1}$$

Annex 4: Second Step Interbank contagion à la DebtRank: Loss in the obligation value

- At the core of the DebtRank algorithm, there is the function f that we calibrated with historical Probability of Default correlation to describe the loss in an obligation value.
- We do not distinguish here between equity and loan exposures for the inter-bank market.
- We could add the hypothesis that in case of a default, the equity would lose close to 100% of its face value, while a loan would lose 40% of its face value.
- The function f could then be augmented with those differences in Loss Given Default and exposure types (equity or loans) as a transmission mechanism.
- At this stage we lack LGD data on banks and calibrating this function would need further study.

Annex 5: Robustness check

We perform a robustness check of our results (that RWA adjustment in a period of stress are counterproductive) with modifications on the price impact in the market:

- with a linear price impact à la Becard and Gauthier (2017),
- with the assumption that assets are sold linearly during a calendar year,
- **our conclusions are unchanged**.

Annex 6: future research based on modeled impacts

With our model and data sets:

- the impact of the RWA adjustment depends on the target being set by the banks.
- In the medium run, we consider that banks want to recover their original ratio, as this would be the optimal ratio based on the regulator requirement and market discipline.
- We would need to further study how the market react if the target is set in the medium run (rather than during the period of stress).

Based on highly material effect of such a mechanism, further research is warranted on the RWA adjustment and the fire sale impact.