Fire sales, indirect contagion and systemic stress testing

Rama Cont and Eric Schaanning

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Disclaimer

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Based on:
Rama Cont and Eric Schaanning (2016)
Fire sales, indirect contagion and systemic stress testing,
Norges Bank Working Paper,
http://ssrn.com/abstract=2541114.

1. Endogenous risk and price-mediated contagion
2. Systemic stress testing with endogenous effects
3. Systemic stress testing
4. Comparison to “leverage targeting" models
5. Granularity
6. Conclusion

Risk amplification and bank stress tests

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- Bank stress tests have become an essential component of bank supervision (EU-wide EBA stress tests, Dodd-Frank tests (DFAST, CCAR)).
- *Static balance sheet assumption*: Stress tests assume 'passive' behaviour by banks.
- BCBS 2015: "Stress tests conducted by bank supervisors still lack a genuine macro-prudential component": "*endogenous reactions* to initial stress, loss amplification mechanisms and *feedback effects*" are missing.

Bank stress tests

- How do financial institutions react when faced with stress?
  $\rightarrow$ Market stress can lead financial institutions to unwind positions (constrained by capital, liquidity, leverage...):
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- We build on previous theoretical work on the modeling of feedback effects and endogenous risk (Shleifer 2010, Kyle & Xiong 2005, Cont & Wagalath 2013,..) and recent empirical studies (Greenwood et al 2013, Eisenbach & Duarte 2014) to construct an **operational** framework for quantifying bank reactions and the associated endogenous effects in a system-wide stress test for financial institutions.

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3. **Feedback effects from fire sales**: loss contagion through mark-to-market losses in common asset holdings

Research on financial networks and their use in macroprudential regulation has focused on direct contagion mechanisms (1+2). Regulatory measures have focused on 1 (large exposure limits, central clearing, CVA, ring-fencing) or 2 (LCR, NSFR).

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- Can fire sales be replicated or accounted for by simpler models (e.g. by simply increasing the size of the macro shock)?
- How can indirect exposures arising from fire sales risk be quantified and monitored?
- What can regulators do to monitor and mitigate this channel of contagion?

A framework for systemic stress testing with endogenous effects

Systemic stress testing with endogenous effects

Ingredients:

1. Data: Portfolio holdings of financial institutions by asset class: N institutions, K *illiquid* asset classes, M *marketable* asset classes $\rightarrow N \times (M + K)$ portfolio matrix (network)

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5. Mark-to-market accounting: transmits market impact to all institutions $\rightarrow$ may lead to feedback if market losses large

Balance sheets: illiquid and marketable assets

Illiquid assets
Residential mortgage exposures
Commercial real estate exposure
Retail exposures: Revolving credits, SME, Other
Indirect sovereign exposures in the trading book
Defaulted exposures
Residual exposures

Marketable assets
Corporate bonds
Sovereign debt
Derivatives
Institutional client exposures: interbank, CCPs,...

Table: Stylized representation of asset classes in bank balance sheets. (Data: European Banking Authority)

- Illiquid holdings of institution i: $\Theta^i := \sum_{\kappa=1}^{K} \Theta^{i\kappa}$.
- Marketable Securities held by i: $\Pi^i := \sum_{\mu=1}^{M} \Pi^{i\mu}$.
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- Financial institutions are subject to various **one-sided** portfolio constraints: leverage ratio, capital ratio, liquidity ratio.
- Leverage ratio of i:

$$\lambda^i = \frac{Assets(i)}{C^i} = \frac{\Theta^i + \Pi^i}{C^i} \leq \lambda_{\max}$$

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- Capital ratio of i:

$$\lambda^i = \frac{RWA(i)}{C^i} = \frac{\sum w_\kappa \Theta^{i,\kappa} + \sum_\mu \Pi^{i,\mu} w_\mu}{C^i} \leq R_{\max}$$

  Basel 3 rules: $\lambda_{\max} = 33$, $R_{\max} = 12.5 = 1/0.08$
- Banks maintain a capital/liquidity buffer (slightly) above the regulatory requirements $\rightarrow$ target leverage ratio $\lambda_b^i < \lambda_{\max}$, target capital ratio $R^i < R_{\max}$.

Deleveraging

- Observation: when portfolio constraints are breached following a loss in asset values, financial institutions **deleverage** their portfolio by selling some assets in order to comply with the portfolio constraint.

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Deleveraging assumption: if following a loss L^i in asset values the leverage of bank i exceeds the constraint

$$\lambda^i = \frac{\Theta^i + \Pi^i - L^i}{C^i - L^i} > \lambda_{\max}$$

bank deleverages by selling a proportion $\Gamma^i \in [0, 1]$ of assets in order to restore a leverage ratio $\lambda_b^i \leq \lambda_{\max}$:

$$\frac{(1 - \Gamma^i)\Pi^i + \Theta^i - L^i}{C^i - L^i} = \lambda_b^i \leq \lambda_{\max} \quad \Rightarrow \Gamma^i = \frac{C^i(\lambda^i - \lambda_b^i)}{\Pi^i} \mathbf{1}_{\lambda^i > \lambda_{\max}}$$

Develeraging in response to a loss

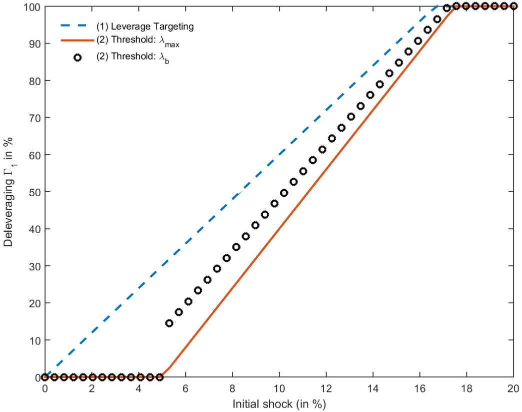
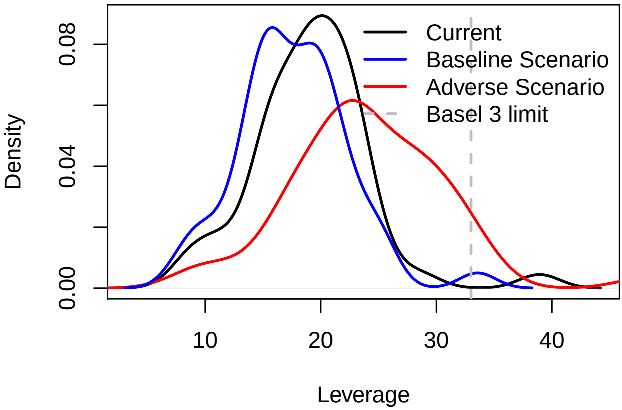


Figure: Percentage of marketable asset deleveraged in response to a shock to assets (circles) for a leverage constraint of 20. Leverage targeting (dotted blue) would lead to a linear response.

EBA 2016


Current
Baseline Scenario
Adverse Scenario
Basel 3 limit
Density
0.00
0.04
0.08
10
20
30
40
Leverage

Market impact and feedback effects

Total liquidation in asset μ at k-th round: $q^{\mu} = \sum_{j=1}^{N} \Pi_k^{j,\mu} \Gamma_{k+1}^{j}$

$$\text{Market impact :} \quad \frac{\Delta S^{\mu}}{S^{\mu}} = -\Psi_{\mu}(q^{\mu}),$$

Impact/ inverse demand function: $\Psi_{\mu} > 0, \Psi_{\mu}' > 0, \Psi_{\mu}(0) = 0$.

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Price move at k-th iteration of fire sales:

$$S_{k+1}^{\mu} = S_k^{\mu} \left(1 - \Psi_{\mu} \left(\sum_{j=1}^{N} \Pi_k^{j,\mu} \Gamma_{k+1}^{j} \right) \right),$$

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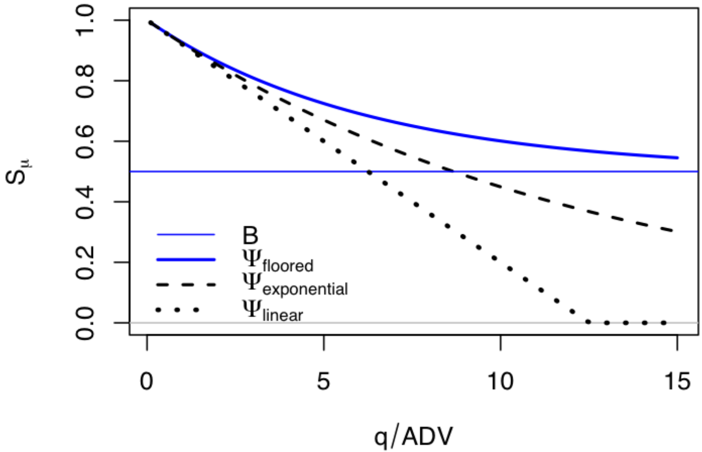
$$\Pi_{k+1}^{i,\mu} = \underbrace{\left(1 - \Gamma_{k+1}^i\right)}_{\text{Non-liquidated assets}} \overbrace{\Pi_k^{i,\mu}}^{\text{Previous value}} \underbrace{\left(1 - \Psi_\mu\left(\sum_{j=1}^N \Pi_k^{j,\mu} \Gamma_{k+1}^j\right)\right)}_{\text{Price impact on remaining holdings}}$$

Market impact function



Market impact function and market depth

The impact of a total distressed liquidation volume q is modelled by a *level-dependent market impact function*

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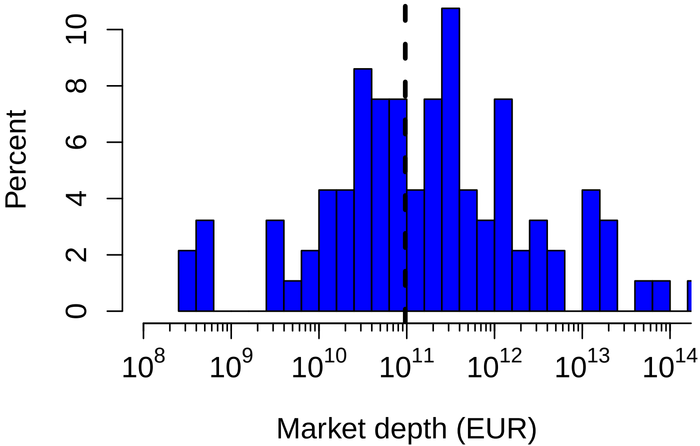
where

$$D_\mu = c\frac{ADV_\mu}{\sigma_\mu}\sqrt{\tau},$$

- $S \geq B_\mu$ where B_μ is the price-floor
- ADV: average daily volume, σ_μ: daily volatility of asset
- $c \approx 0.25$, a coefficient to make Ψ_μ consistent with empirical estimates of the linear impact model for small volumes q.
- τ is the liquidation horizon

Estimated market depth



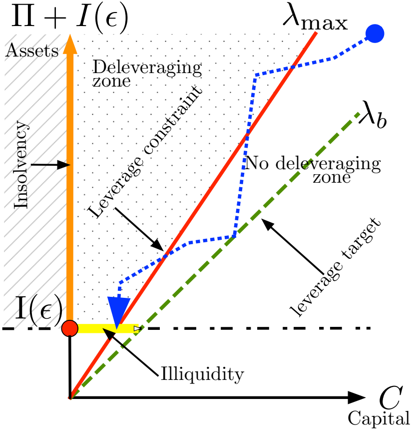


Figure: Liquidity and solvency constraints define admissible portfolios. A large loss may take the portfolio outside this set, in which case banks deleverage in order to revert back to this set.

Systemic stress testing

Stress scenarios

- A stress scenario is defined by a vector $\epsilon \in [0,1]^K$ whose components ϵ_κ are the percentage shocks to asset class κ.
- Initial/Direct loss of portfolio i: $L_i^0(\epsilon) = \epsilon.\Theta^i = \sum_\kappa \Theta^{i\kappa}\epsilon_\kappa$
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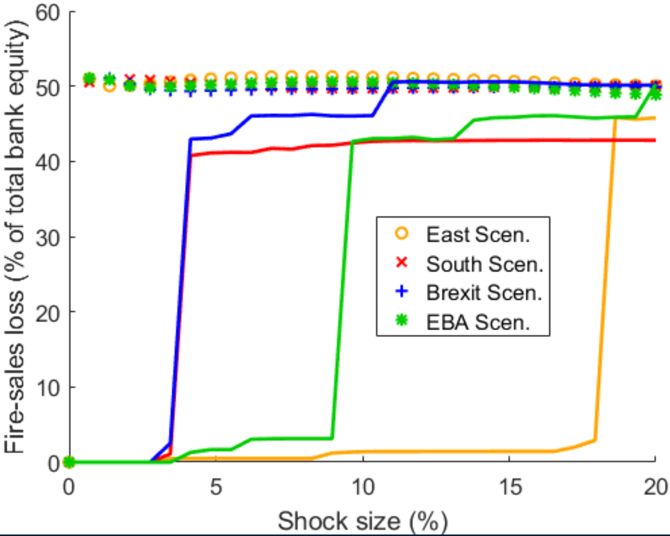
- Gradual increase of the shock size ϵ_κ from 0% to 20%.
- As an illustration we consider the following stress scenarios:
  1. Official 2016 EBA stress scenario;
  2. "Bad Brexit" scenario;
  3. Southern European scenario;
  4. Eastern European scenario.

Fire sales losses



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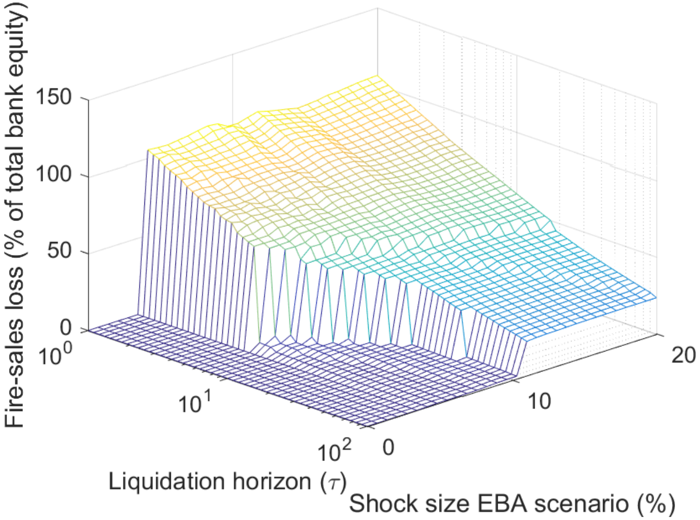
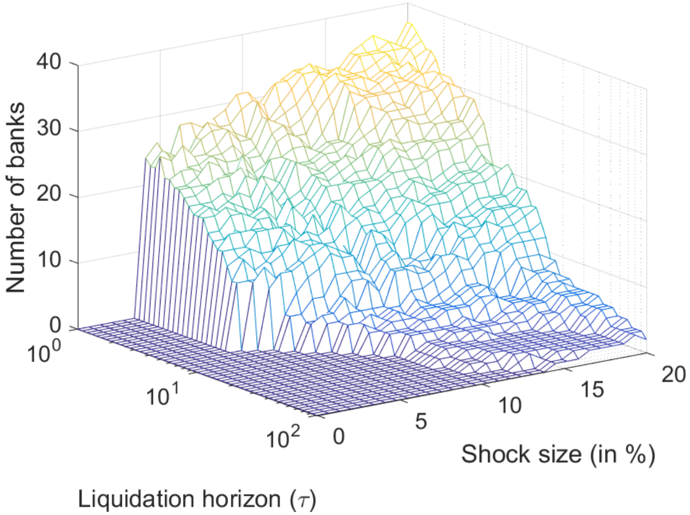


Endogenous losses modify stress test outcomes



Failures due to illiquidity and insolvency

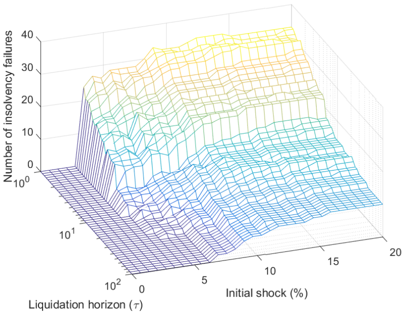


Figure: The model allows to distinguish between failures due to insolvency (negative equity - left) and failures due to illiquidity (zero liquid assets - right).

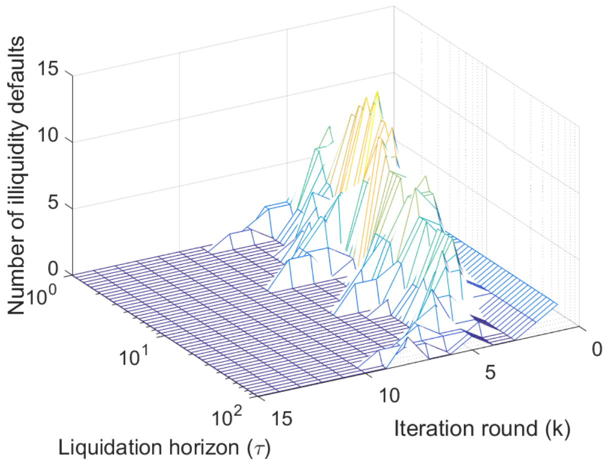


Figure: **Illiquidity** failures for an initial 6% shock in the EBA scenario.

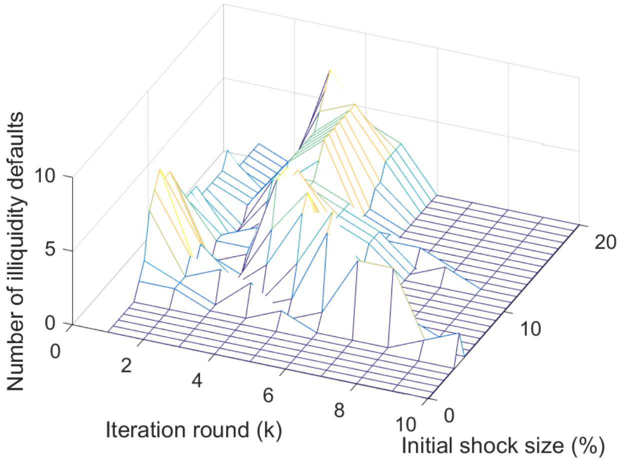
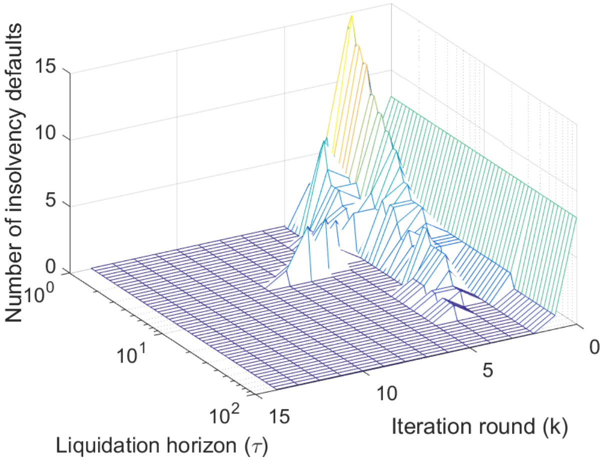


Figure: **Illiquidity** failures as a function of the iteration round and the shock size (at the estimated market depth).



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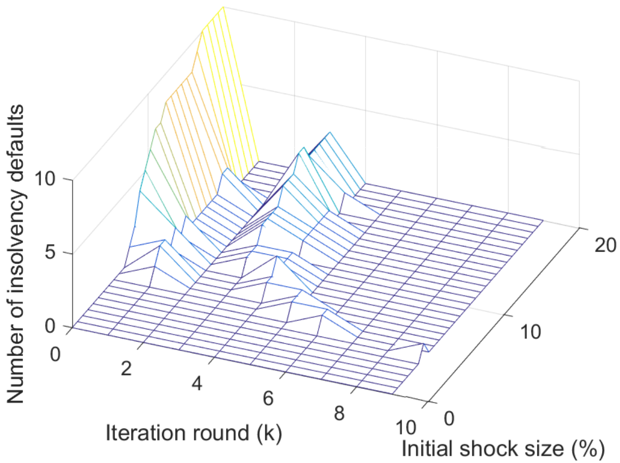

Figure: **Insolvency** failures as a function of the iteration round and the shock size (at the estimated market depth).

Comparison to “leverage targeting" models

Response functions

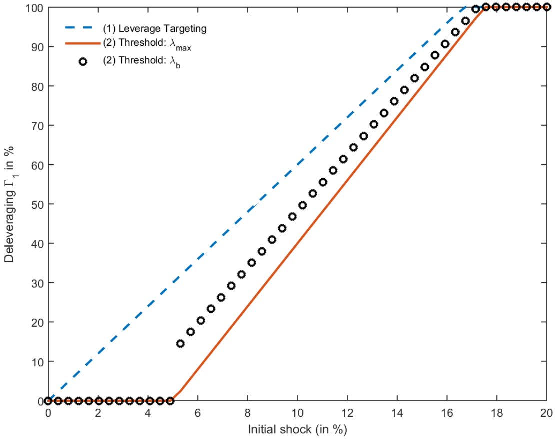

Figure: Leverage targeting response function (dashed) and two variants of the threshold model (full and circles) response functions.

Threshold model

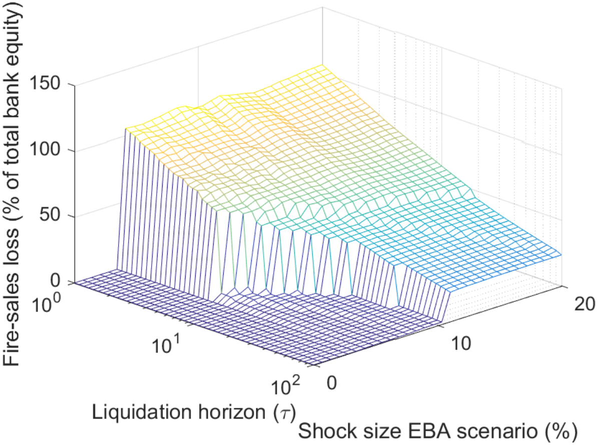

Figure: Boundary to systemic risk region clearly visible.

Leverage targeting model

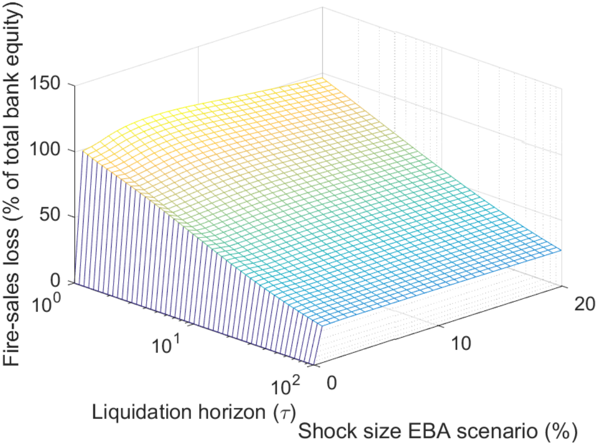

Figure: Leverage targeting model predicts large-scale contagion to occur even for very small shocks.

Sensitivity to the configuration of the stress scenario

- We will now analyse how the leverage targeting and the threshold models respond to different scenarios.
- Intuitively, we would expect that if two stress scenarios A and B are different (meaning that different institutions are hit by the initial losses), then the distribution of fire sales losses should retain some of this heterogeneity.

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- Intuitively, we would expect that if two stress scenarios A and B are different (meaning that different institutions are hit by the initial losses), then the distribution of fire sales losses should retain some of this heterogeneity.
- For this exercise, we look first at the bank-level losses in the two models. Secondly, we will analyse the correlation between loss vectors of different scenarios:

$$\rho_{\epsilon_a,\epsilon_b}^{model} := Corr(FLoss_{model}(\epsilon_a), FLoss_{model}(\epsilon_b)), \qquad (1)$$

where $FLoss_{model}(\epsilon_a) \in \mathbb{R}^N$ is the vector of individual bank fire sales losses in scenario a using the model *model* ($\in$ threshold / leverage targeting).

Distribution of fire sales losses

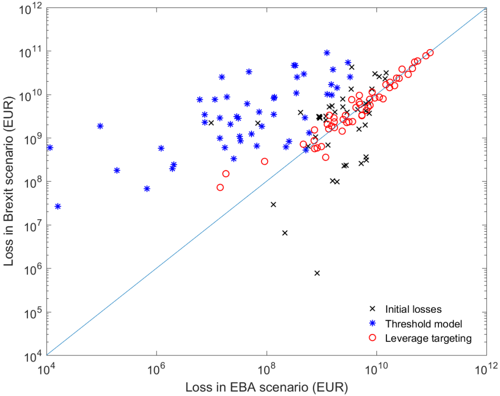

Figure: Bank-level losses under threshold vs leverage targeting dynamics: Leverage targeting implies almost identical losses despite different scenarios!

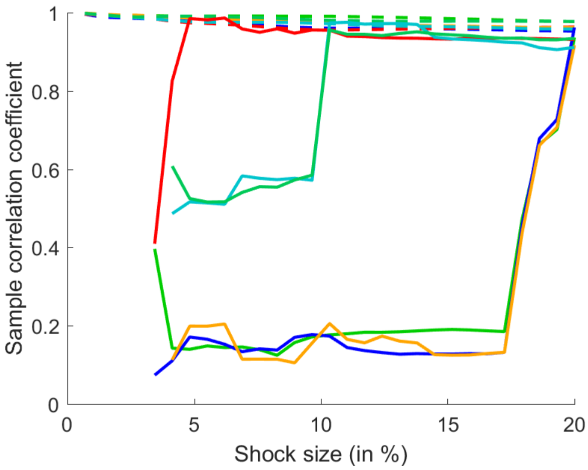

Figure: The pairwise sample correlation between the loss vectors of different pairs of scenarios as a function of the initial shock size. Solid line: threshold model, dashed line: leverage targeting.

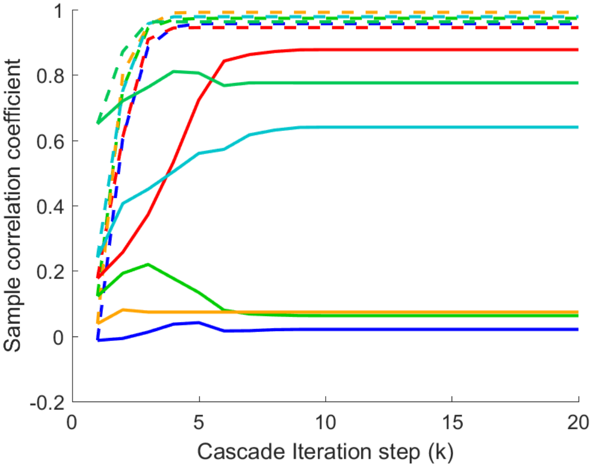

Figure: The pairwise sample correlation as a function of the iteration round. Solid line: threshold; dashed line: leverage targeting. After 5 rounds, the leverage targeting model implies that different scenarios lead to essentially colinear fire sales losses.

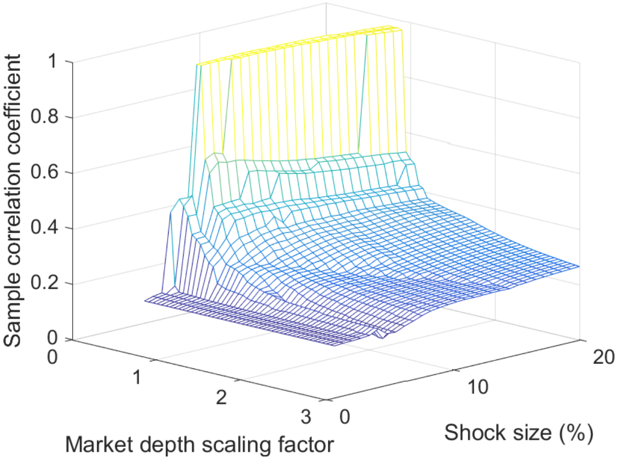

Figure: Caption: The threshold model retains this feature across all market depths. The correlation only goes up to 1 in the systemic risk region, where all banks default.

Granularity

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- Ecological fallacy: Robinson's correlation paradox of illiteracy (1950)
- Inference from the mean to individuals (average IQ in a group vs IQ of individual of the group)
- Macro risk factors in stress tests need to be mapped to portfolio risk factors
- At what level of aggregation should counterparty exposures be computed? (legal-entity level: Deutsche Bank London & Deutsche Bank Frankfurt..., or at group level "Deutsche Bank AG"?)

Granularity levels in modeling fire sales

Examples:

- Two “effectively orthogonal" portfolios: the liquidation of one asset class does not affect the price of the other asset class, e.g. Norwegian covered bonds and Japanese corporate bonds.

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- BofA bank holds on-the-run treasuries, while JPM holds off-the-run treasuries. Portfolios clearly not orthogonal!
- $\rightarrow$ smallest level of aggregation not necessarily the best/most realistic

$\rightarrow$ the choice of the “level of aggregation" will impact the “path of contagion" when simulating portfolio liquidations!

Aggregation issues in stress testing

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- Decrease of fire sales losses, because market depth of aggregated asset classes is (usually) higher
- Increase of fire sales losses, because the market depth of some asset classes is lower
- Increase of fire sales losses, because the sparsity and diameter of the matrix generating the “indirect contagion network" are reduced

From assets to asset classes

- Aggregate assets μ_1, μ_2 into asset class ν.
- Volume

$$ADV_{\nu} = ADV_{\mu_1} + ADV_{\mu_2}$$

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One can prove that even in a single bank model there *exists no (reasonable) aggregation-invariant market impact function*!

Data

- Period: Monthly end-of-month snapshots from 2006 - 2014

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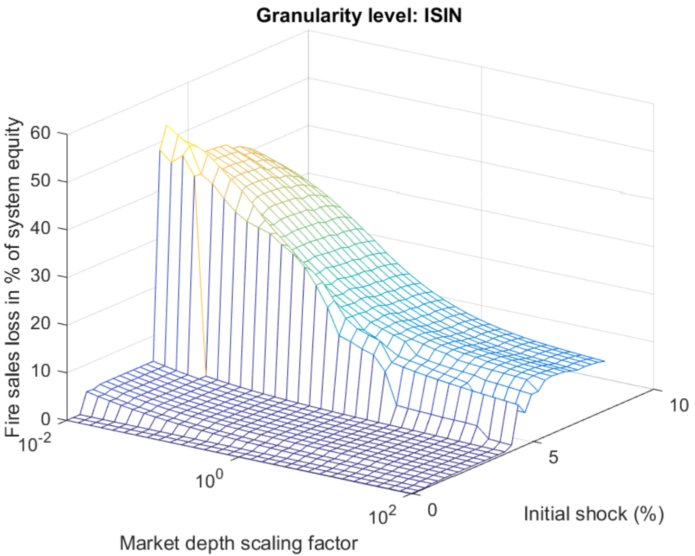
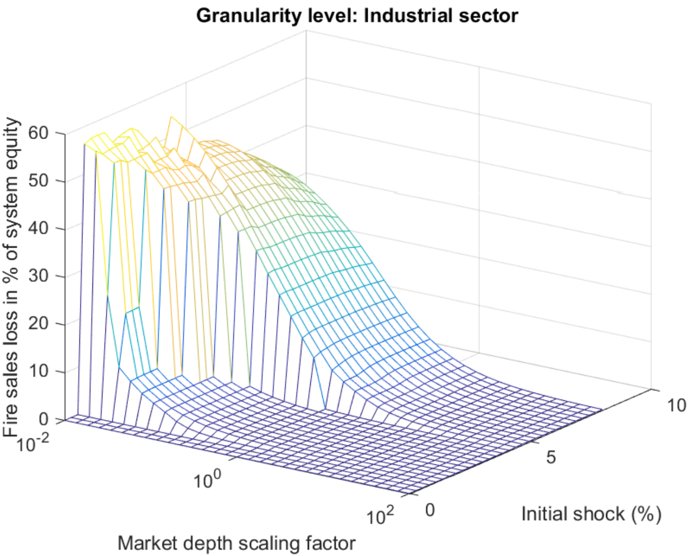
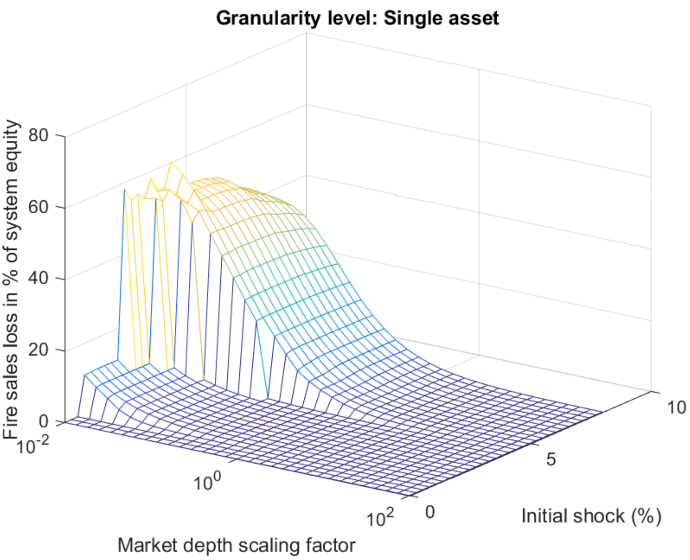
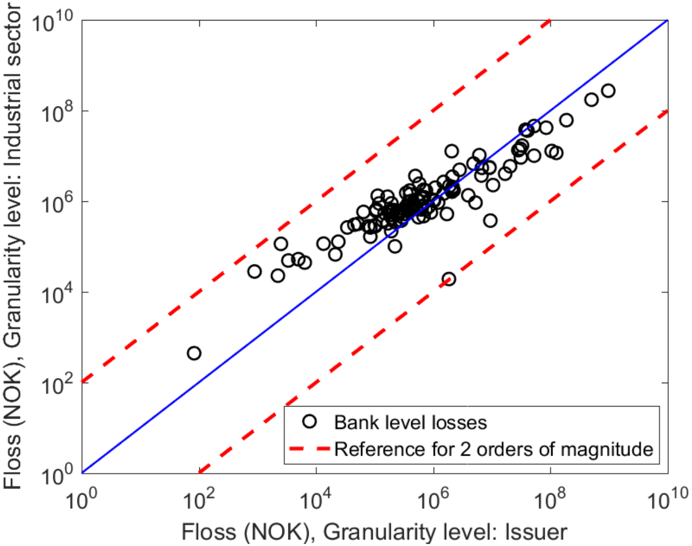
Aggregation level	Held by all	Held by banks only
ISIN	5509	2930
Issuer	1871	912
NACE	214	139
Institutional Sector	18	17
Asset class	9	9
Single asset	1	1

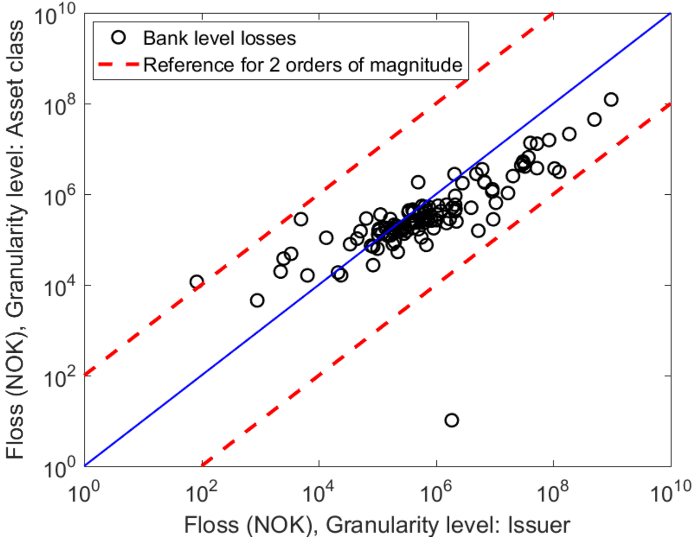
Table: Number of “asset classes" for different layers of aggregation in December 2013.

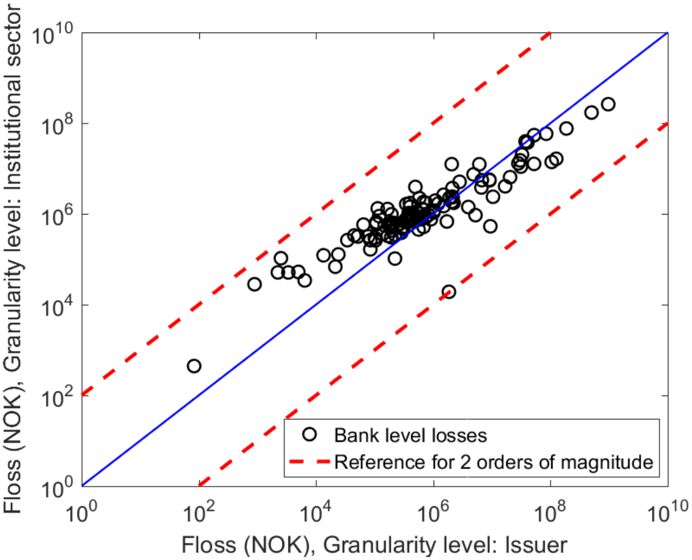

Granularity level: ISIN
Fire sales loss in % of system equity
60
50
40
30
20
10
0
10^{-2}
10^{0}
10^{2}
Market depth scaling factor
0
5
10
Initial shock (%)


Granularity level: Industrial sector
Fire sales loss in % of system equity
60
50
40
30
20
10
0
10^-2
10^0
10^2
Market depth scaling factor
0
5
10
Initial shock (%)

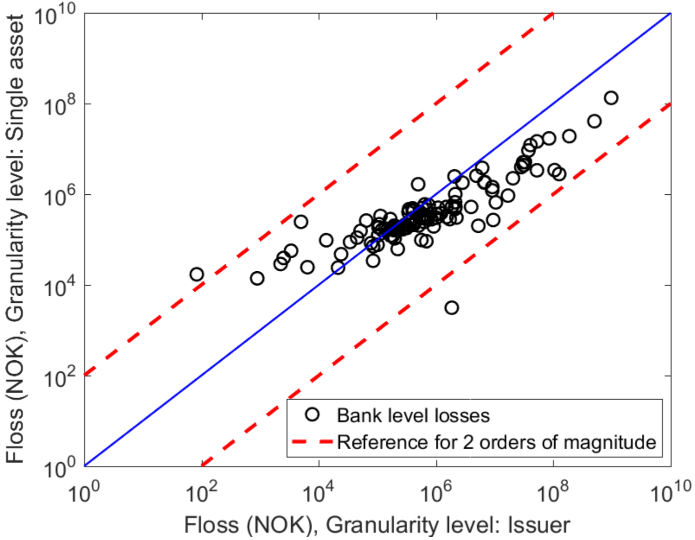

Granularity level: Single asset
Fire sales loss in % of system equity
80
60
40
20
0
10^-2
10^0
10^2
Market depth scaling factor
0
5
10
Initial shock (%)


Floss (NOK), Granularity level: Industrial sector
Floss (NOK), Granularity level: Issuer
10^0
10^2
10^4
10^6
10^8
10^{10}
Bank level losses
Reference for 2 orders of magnitude


Bank level losses
Reference for 2 orders of magnitude
Floss (NOK), Granularity level: Asset class
Floss (NOK), Granularity level: Issuer
10^0
10^2
10^4
10^6
10^8
10^{10}



Floss (NOK), Granularity level: Institutional sector
Floss (NOK), Granularity level: Issuer
10^{0}
10^{2}
10^{4}
10^{6}
10^{8}
10^{10}
Bank level losses
Reference for 2 orders of magnitude



Floss (NOK), Granularity level: Single asset
Floss (NOK), Granularity level: Issuer
Bank level losses
Reference for 2 orders of magnitude


Granularity level: Issuer vs industrial sector
Slope of regression line
1.2
1
0.8
0.6
0.4
0.2
0
10^{-2}
10^{0}
10^{2}
Market depth scaling factor
0
5
10
Initial shock (%)

Summary

Quantitative model for deleveraging in a network of institutions with common asset holdings subject to *one-sided* portfolio constraints:

- **Tipping point:** Existence of critical macro shock level beyond which fire sales are triggered and significant contagion occurs. In EU banks: threshold large – but not extreme.

Summary

Quantitative model for deleveraging in a network of institutions with common asset holdings subject to *one-sided* portfolio constraints:

- **Tipping point:** Existence of critical macro shock level beyond which fire sales are triggered and significant contagion occurs. In EU banks: threshold large – but not extreme.
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Quantitative model for deleveraging in a network of institutions with common asset holdings subject to *one-sided* portfolio constraints:

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- **Fire sales losses:** Even with optimistic estimates of market depth, fire sales losses can amount to over 20% of system bank equity. This is significant enough to *change the outcome* of stress tests.
- **Illiquidity and insolvency:** Our model allows to distinguish between failures due to insolvency and defaults due to illiquidity. Ignoring failures due to illiquidity may lead to a severe underestimation of the extent of contagion.

Summary

- **Multiple rounds:** Many bank failures (both through liquidity and solvency) occur at higher order rounds. Simulating just a single round of deleveraging may underestimate the extent of contagion.

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Summary

- **Multiple rounds:** Many bank failures (both through liquidity and solvency) occur at higher order rounds. Simulating just a single round of deleveraging may underestimate the extent of contagion.
- **Leverage targeting:** Models of portfolio deleveraging based on “leverage targeting" lead to counterintuitive results when used for modeling distressed liquidations: the fire sales loss becomes insensitive to the magnitude and composition of the initial shock.
- **Granularity:** Changing the level of asset class aggregation changes the estimated fire sales losses. The higher the level of aggregation of asset classes, the more one seems likely to underestimate the loss of the portfolios that are hit the hardest. There exists no market impact function that is aggregation invariant.

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