Reverse Stress Testing

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Outline

1. Introduction: Motivation
2. Modeling Fire Sales
3. Reverse Stress Testing and Scenario Design
4. Empirical Application to European Banks
5. Conclusion

Automated stress scenario design

Find scenarios that are economically consistent
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Automated stress scenario design

Find scenarios that are economically consistent
and target the vulnerabilities of current portfolio holdings.

- What type of scenario could lead
  to a "worst-case" contagion in terms of fire sales?
- Which banks (or other institutions)
  may become key channels of contagion in a stress scenario?
- Is the current financial system particularly vulnerable
  to specific "classes/families" of scenarios?

The literature is burgeoning

Stress testing and policy:

(Baudino et al., 2018)

(Bookstaber et al., 2013)

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(Henry et al., 2013), (Dees et al., 2017)

(Aymanns et al., 2018) (Aikman et al., 2019)

Contagion:

(Covi et al., 2019), (Battiston et al., 2016)

(Baptista et al., 2016), (Hüser, 2015)

(Calimani et al., 2017), (Coen et al., 2019)

(Cont and Schaanning, 2016), (Cont et al., 2019), (Bardoscia et al., 2019)

(Brinkhoff et al., 2018)

Monitoring and portfolio overlaps:

(Abad et al., 2017)

(Cont and Wagalath, 2016)

(Guo et al., 2015)

(Caccioli et al., 2015)

(Cont and Schaanning, 2019)

Scenario design:

(Glasserman et al., 2015)

(Breuer and Summer, 2017)

(Breuer et al., 2009)

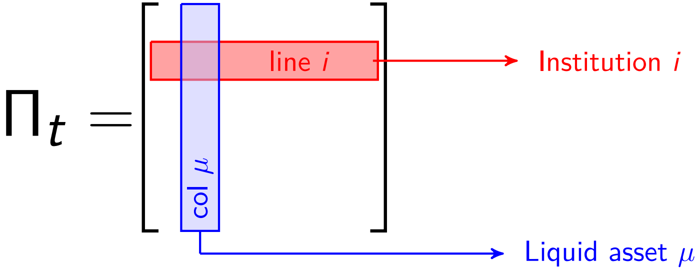
(Bassanin et al., 2019)

Vast literature - very incomplete overview!

Stylized bank portfolios from EBA 2016 stress test data

$N = 51$ institutions	$i \in [N]$
$M = 93$ liquid asset classes	$\mu \in [M]$
$K = 89$ illiquid asset classes	$k \in [K]$

$\Pi_t \equiv [\Pi_t^{i,\mu}]_{i,\mu}$: N-by-M matrix collecting liquid assets of institutions at time t



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marketable assets of institutions at time t:

- Corporate bonds
- Sovereign sovereign
- Securitized exposures

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collecting liquid assets of institutions at time t

$\Theta_t \equiv [\Theta_t^{i,k}]_{i,k}$: N-by-K matrix
illiquid assets of institutions at time t:

- Residential mortgage exposures
- Commercial real estate exposures
- Retail exposures
- Defaulted exposures
- Residual exposures
- Marketable asset holdings beyond market depth

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$C_t \equiv [C_t^i]_i$ N-vector: Tier 1 capital of institutions

Data source: European Banking Authority (EBA)

Regulatory leverage constraint

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The *leverage ratio* of i at t is

$$\frac{\text{All Assets of } i}{\text{Capital of } i} = \frac{\sum_\mu \Pi_t^{i,\mu} + \sum_k \Theta_t^{i,k}}{C_t^i}$$

and should be kept smaller than $\lambda_{\max} := 33$ (Basel III).

Stress scenario reduces the value of non-marketable assets

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- If the leverage constraint $\frac{\sum_\mu \Pi_t^{i,\mu} + \sum_k \Theta_t^{i,k}}{C_t^i} \leq \lambda_{\text{max}}$ is violated, i will liquidate a part of its liquid assets to satisfy the leverage constraint again.
- These fire sales have an **impact on the price** of the liquidated assets (hence a further loss - also for institutions that were not exposed to the initial shock, but are holding the same marketable assets)

Modeling the price impact

Following shock $\epsilon \in [0,1]^K$ at time t, institution i liquidates a portion $\Gamma_t^{i,\mu}(\epsilon) \in [0,1]$ of its liquid asset μ.

Overall, a quantity $q^\mu = \sum_i \Gamma_t^{i,\mu}(\epsilon)\Pi_t^{i,\mu}$ of asset μ is liquidated.

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This leads to the following revaluation of asset μ for institution j:

$$\Pi_t^{j,\mu} = \underbrace{\Pi_{t-1}^{j,\mu}}_{\text{Previous value}} \overbrace{\left(1 - \Gamma_t^{j,\mu}(\epsilon)\right)}^{\text{Non-liquidated assets}} \underbrace{\Psi_\mu\left(\sum_i \Pi_{t-1}^{i,\mu}\Gamma_t^{i,\mu}(\epsilon)\right)}_{\text{Price impact on remaining holdings}} ,$$

where $\Psi_\mu(q) = 1 - q/D_\mu$ is an example of a linear impact function.

Optimal liquidations under linear impact

Given a stress scenario ϵ, minimize the fire-sales loss:

$$FSL_i(\epsilon) := \min_{\Gamma^i \in [0,1]^M} \sum_{\mu=1}^{M} \frac{\Pi^{i,\mu} \Pi^{i,\mu}}{\delta_\mu} \Gamma^{i,\mu}$$

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subject to complying with the leverage constraint:

$$\frac{\sum_{\mu=1}^{M}(1-\Gamma^{i,\mu})\Pi^{i,\mu} - \frac{\Pi^{i,\mu}\Pi^{i,\mu}}{\delta_\mu}\Gamma^{i,\mu} + \sum_{\nu=1}^{K}\Theta^{i,\nu}(1-\epsilon_\nu)}{C^i - \sum_{\nu=1}^{K}\Theta^{i,\nu}\epsilon_\nu - \sum_{\mu=1}^{M}\frac{\Pi^{i,\mu}\Pi^{i,\mu}}{\delta_\mu}\Gamma^{i,\mu}} \leq \lambda_{\max}.$$

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Solution: Selling assets sequentially in decreasing order given by the ratios $\frac{\delta_{\mu_1}}{\Pi^{i,\mu_1}} > \ldots > \frac{\delta_{\mu_M}}{\Pi^{i,\mu_M}}$ until the constraint is fulfilled, or the bank runs out of marketable assets to delever.

Reverse Stress Testing and Scenario Design

Looking for the worst-case scenario

Find the stress scenario(s) $\epsilon \in [0,1]^K$, that

- generate(s) the worst total fire-sales loss,
- under the assumption that banks react optimally,

Also, the initial shock should not be “too severe” ,
and should make economic sense (historically consistent) .

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$$\max \sum_{j=1}^{N} \mathrm{Loss}_j(\Gamma^j(\epsilon))$$

$$\text{s.t. } 0 \leq \epsilon \leq 1$$

$$\sum_{i=1}^{N} \sum_{\nu=1}^{K} \Theta^{i,\nu} \epsilon_\nu \leq L_{\max}$$

$$\underline{\epsilon_\nu} \leq \epsilon_\nu \leq \overline{\epsilon_\nu}$$

$$\text{some "historical constraint"}$$

Worst-case scenarios that are historically meaningful

Let Σ_Θ be the covariance matrix of the 89 illiquid assets' returns.

It turns out that the 14 first eigenvectors of Σ_Θ account for 90% of its spectrum.

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It turns out that the 14 first eigenvectors of Σ_Θ account for 90% of its spectrum.

Let H be the 14-dimensional subspace spanned by these eigenvectors.

We require for ϵ to be at a Euclidean distance of 0.05 from H.

That is, we want $\langle u^k, \epsilon \rangle \leq 0.05$ for all eigenvectors u^k of Σ_Θ, $15 \leq k \leq K$.

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$$\langle u^k, \epsilon\rangle \leq 0.05 \quad \text{for } k_{\min} \leq k \leq K$$

We have a convex *maximization* problem over a polyhedron

$$
\begin{aligned}
\max_{0 \leq \epsilon \leq 1} \quad & \sum_{j=1}^{N} \mathrm{Loss}_j(\Gamma^j(\epsilon)) \\
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- We find a collection of local maximums by a multiple starting points gradient ascent method.

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We can prove that $\mathrm{Loss}_j(\Gamma^j(\epsilon))$ is convex in ϵ.

- We can have multiple local maximums.
- We find a collection of local maximums by a multiple starting points gradient ascent method.
- We have to take full advantage of the simplicity of the constraints set (projections are cheap)
- We critically needed an efficient method for evaluating $\mathrm{Loss}_j(\Gamma^j(\epsilon))$ and $\partial\mathrm{Loss}_j(\Gamma^j(\epsilon))/\partial\epsilon$.

Systematic algorithmic exploration of “scenario space”

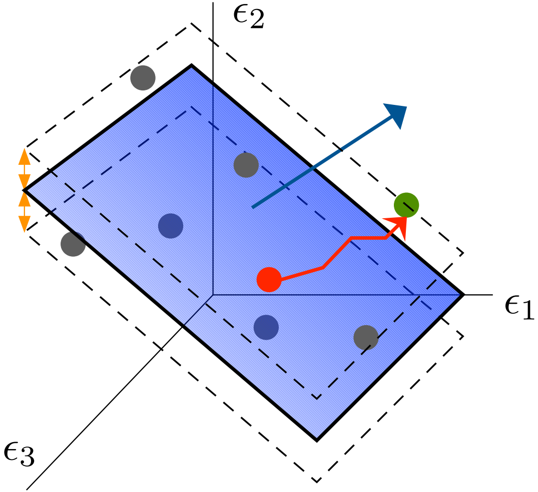


Figure: Intuitive visualization of our algorithmic approach.

Empirical Application to European Banks

Application to European Banks

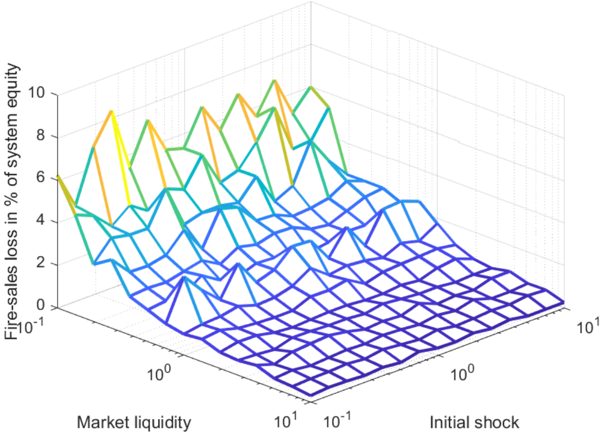
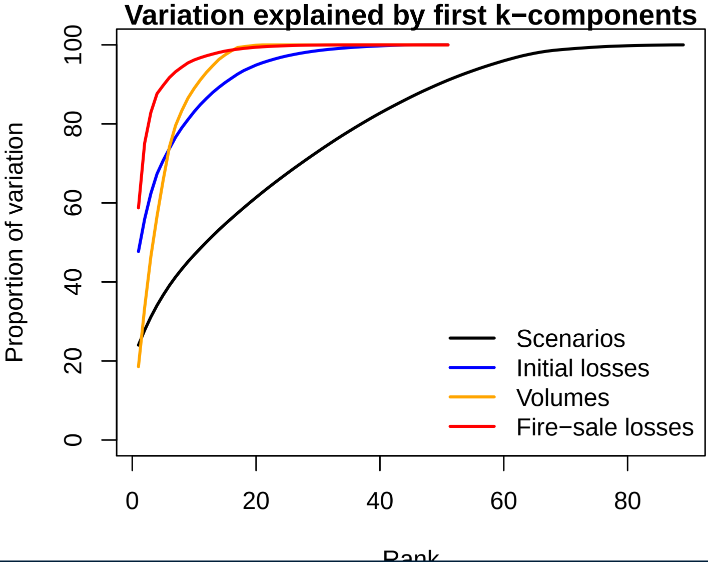


Figure: Fire-sales losses as function of price impact and initial shock size.

An Anna Karenina principle of stress test scenarios



Mean losses and sales

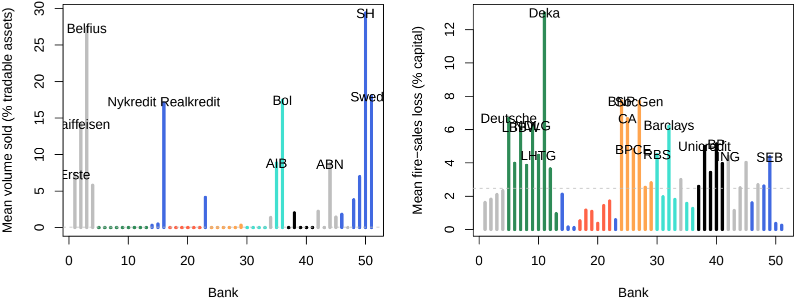


Figure: Left: Mean volume liquidated, right: mean fire-sales loss.

Clustering analysis

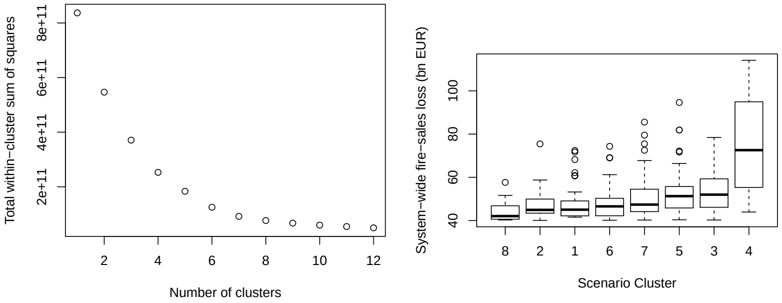
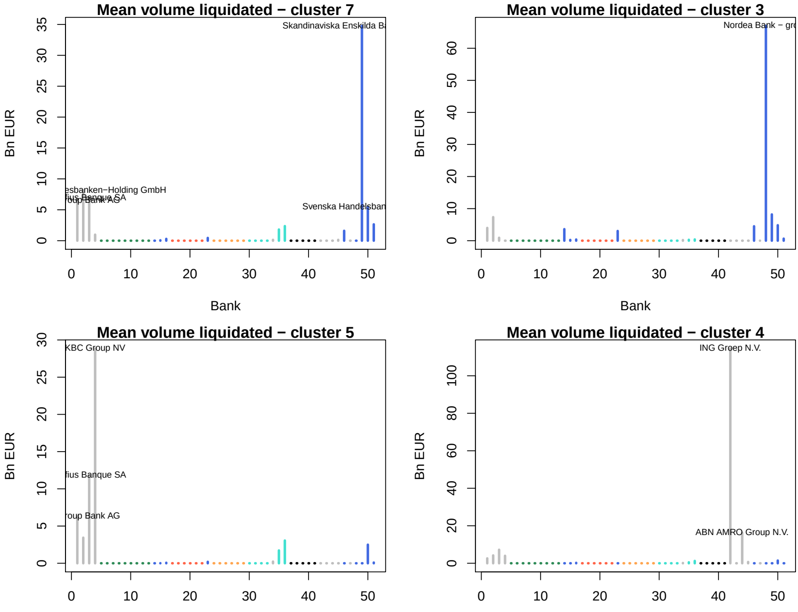
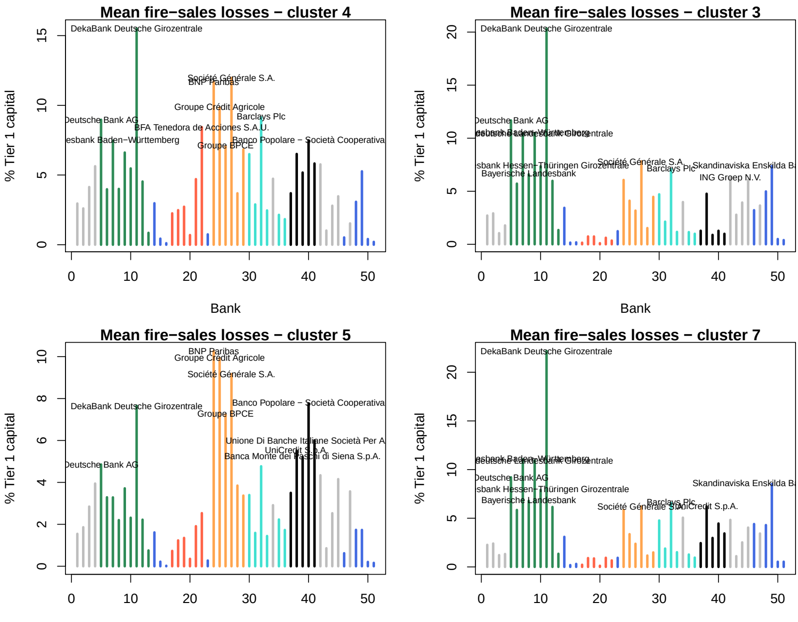


Figure: Clustering analysis unveils 8 "scenario" clusters.

Next two slides show the *volume of liquidations* and the *fire-sales losses* in the four worst scenarios respectively.


Mean volume liquidated − cluster 7
Skandinaviska Enskilda Ba
esbanken−Holding GmbH
fius Banque SA
oup Bank AG
Svenska Handelsban
Bn EUR
Bank
Mean volume liquidated − cluster 3
Nordea Bank − gro
Bn EUR
Bank
Mean volume liquidated − cluster 5
KBC Group NV
fius Banque SA
oup Bank AG
Bn EUR
Mean volume liquidated − cluster 4
ING Groep N.V.
ABN AMRO Group N.V.
Bn EUR


Mean fire−sales losses − cluster 4
% Tier 1 capital
Bank
DekaBank Deutsche Girozentrale
Société Générale S.A.
BNP Paribas
Groupe Crédit Agricole
Barclays Plc
Deutsche Bank AG
BFA Tenedora de Acciones S.A.U.
esbank Baden−Württemberg
Banco Popolare − Società Cooperativa
Groupe BPCE
Mean fire−sales losses − cluster 3
% Tier 1 capital
Bank
DekaBank Deutsche Girozentrale
Deutsche Bank AG
sbank Hessen−Thüringen Girozentrale
Bayerische Landesbank
Société Générale S.A.
Barclays Plc
ING Groep N.V.
Mean fire−sales losses − cluster 5
% Tier 1 capital
BNP Paribas
Groupe Crédit Agricole
Société Générale S.A.
DekaBank Deutsche Girozentrale
Banco Popolare − Società Cooperativa
Groupe BPCE
UniCredit S.p.A.
Banca Monte dei Paschi di Siena S.p.A.
Deutsche Bank AG
Mean fire−sales losses − cluster 7
% Tier 1 capital
DekaBank Deutsche Girozentrale
Deutsche Bank AG
sbank Hessen−Thüringen Girozentrale
Bayerische Landesbank
Barclays Plc
UniCredit S.p.A.

Scenario design - targeting vulnerabilities

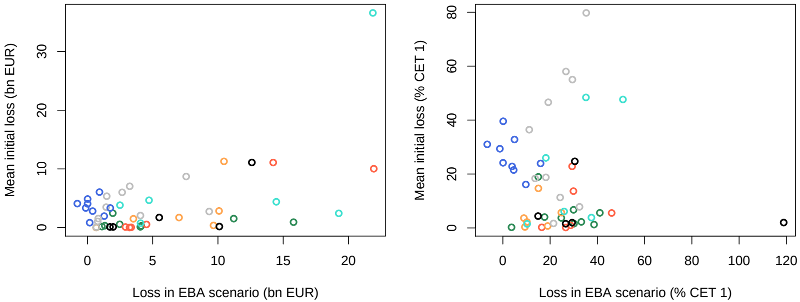


Figure: Preliminary results: Comparing the losses in the EBA scenario to the average initial loss across the worst case scenarios

Conclusion

Conclusions (preliminary)

- We introduce a computational approach to search systematically for scenarios that exploit the vulnerabilities of current portfolio holdings.
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- An Anna Karenina principle of scenario design: *All stressful scenarios stress the same set of banks, each stressful scenario is stressful in its own way.* $\rightarrow$ This suggests that regulators may wish to focus on identifying vulnerable institutions, rather than plausible scenarios.
- EBA 2016 scenario seems not to have specifically targeted the banks that were most vulnerable to drive contagion losses (according to this methodology & metric).
- Implications for micro- and macroprudential stress testing.

Thank you!

Abad, J., D'Errico, M., Killeen, N., Luz, V., Peltonen, T., Portes, R., and Urbano, T. (2017). Mapping the interconnectedness between eu banks and shadow banking entities. NBER Working Paper No. 23280.

Aikman, D., Chichkanov, P., Douglas, G., Georgiev, Y., Howat, J., and King, B. (2019). System-wide stress simulation. Bank of England Working paper 809.

Aymanns, C., Farmer, J. D., Kleinnijenhuis, A. M., and Wetzer, T. (2018). Chapter 6 - models of financial stability and their application in stress tests. In Hommes, C. and LeBaron, B., editors, Handbook of Computational Economics, volume 4 of Handbook of Computational Economics, pages 329 – 391. Elsevier.

Baptista, R., Farmer, J. D., Hinterschweiger, M., Low, K., Daniel, T., and Uluc, A. (2016). Macroprudential policy in an agent-based model of the uk housing market. Bank of England Staff Working Paper 619.

Bardoscia, M., Ferrara, G., Vause, N., and Yoganayagam, M. (2019). Simuating liquidity stress in the derivatives market. Working paper.

Bassanin, M., Ferreiro, J. O., and Rancoita, E. (2019). The MacroFin Copula: a probabilistic approach for countercyclical scenario calibration. Working paper.

Battiston, S., Caldarelli, G., D'Errico, M., and Gurciullo, S. (2016). Leveraging the network: A stress-test framework based on DebtRank. Statistics & Risk Modeling.

Baudino, P., Goetschmann, R., Henry, J., Taniguchi, K., and Zhu, W. (2018). Stress-testing banks - a comparative analysis. FSI Insights on policy implementation.

Bookstaber, R., Cetina, J., Feldberg, G., Flood, M., and Glasserman, P. (2013). Stress tests to promote financial stability: Assessing progress and looking to the future. Journal of Risk Management in Financial Institutions, 7(1):16–25.

Bookstaber, R., Paddrik, M., and Tivnan, B. (2014). An agent-based model for financial vulnerability. Office for Financial Research Working Paper.

Breuer, T., Jandacka, M., Rheinberger, K., and Summer, M. (2009). How to find plausible, severe, and useful stress scenarios. International Journal of Central Banking.

Breuer, T. and Summer, M. (2017). Systematic and systemic stress tests. Working paper.

Brinkhoff, J., Langfield, S., and Weeken, O. (2018). From the horse's mouth: surveying responses to stress by banks and insurers. ESRB Occasional Paper Series.

Caccioli, F., Farmer, J. D., Foti, N., and Rockmore, D. (2015). Overlapping portfolios, contagion, and financial stability. Journal of Economic Dynamics and Control, 51(0):50 – 63.

Calimani, S., Halaj, G., and Zochowski, D. (2017). Simulating fire-sales in banking and shadow banking system. ESRB Working Paper Series.

Coen, J., Lepore, C., and Schaanning, E. (2019). Taking regulation seriously: Fire sales under solvency and liquidty constraints. Bank of England Staff Working Paper No 793.

Cont, R., Kotlicki, A., and Valderrama, L. (2019). Liquidity at risk: Joint stress testing of solvency and liquidity. Working paper.

Cont, R. and Schaanning, E. (2016). Fire sales, indirect contragion and systemic stress testing. Norges Bank Working paper.

Cont, R. and Schaanning, E. (2019). Monitoring indirect contagion. Journal of Banking and Finance, forthcoming.

Cont, R. and Wagalath, L. (2016). Fire sales forensics: Measuring endogenous risk. Mathematical Finance, 26:835–866.

Covi, G., Gorpe, M. Z., and Kok, C. (2019). CoMap: mapping contagion in the euro area banking sector. ECB Working Paper Series No 2224.

Dees, S., Henry, J., and Martin, R. (2017). STAMP€: Stress-Test Analytics for Macroprudential Purposes in the euro area. ECB eBook.

Glasserman, P., Kang, C., and Kang, W. (2015). Stress scenario selection by empirical likelihood. Quantitative Finance, 15(1):25–41.

Guo, W., Minca, A., and Wang, L. (2015). The topology of overlapping portfolio networks. Statistics and Risk Modeling, 33(3-4):139–155.

Henry, J., Kok, C., Amzallag, A., Baudino, P., Cabral, I., Grodzicki, M., Gross, M., Halaj, G., Kolb, M., Leber, M., Pancaro, C., Sydow, M., Vouldis, A., Zimmermann, M., and Zochowski, D. (2013). A macro stress testing framework for assessing systemic risks in the banking sector. Occasional Paper Series 152, European Central Bank.

Hüser, A.-C. (2015). Too interconnected to fail: A survey of the interbank networks literature. Journal of Network Theory in Finance, 1(3):1–50.