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A Macroprudential Contagion Stress Test Framework[*]

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Abstract

We develop a macroprudential contagion stress test framework to examine how a network of Norwegian banks can amplify a shock to bank capital at the macro level. The framework looks at how fire sales of common asset holdings can lead to valuation losses for banks (indirect contagion), and how recapitalisation of banks can lead to direct contagion. We perform Monte Carlo simulations to quantify contagion-driven systemic risk and to evaluate the importance of the mechanisms in our model. Using data for 22 banks from 2019 Q2 we find that losses due to contagion can reach 2 percentage points (pp) of the banking sector's Common Equity Tier 1 (CET1) ratio, but most likely losses are around one-fourth of this. The losses result almost exclusively from indirect contagion. Further, we find that losses are high in the cases where banks quickly run into funding problems. We also find that market liquidity and which assets banks' fire sale first (pecking order) are important determinants of the results. Last but not least, losses due to contagion are highly correlated with losses on covered bonds.

JEL: C63, D85, G17, G21

Keywords: financial contagion, fire sales, bail-in, systemic risk

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1 Introduction

Interconnected banks under stress can amplify shocks. This was one of the insights gained in the wake of the Global Financial Crisis (GFC). Since then, stress tests have been conducted on a regular basis in order to assess the vulnerabilities of individual banks and systemic risk. Most of the stress testing models used are microprudential in nature.[1] We propose a contagion[2] stress test that combines a macroprudential top-down stress test with a contagion model.

An extensive body of literature highlights that interconnectedness in the financial sector matters. This literature either focuses on direct links between banks (Allen and Gale, 2000; Eisenberg and Noe, 2001; Espinosa-Vega and Solé, 2011) or indirect contagion (Cont and Wagalath, 2016; Greenwood et al., 2015; Shleifer and Vishny, 1992).

Regulatory developments, especially bail-in, large exposure limits and collateral requirements have been put in place over the past few years to limit the potential for direct contagion, and simulation studies confirm the effect on systemic risk (Glasserman and Young, 2015; Hüser et al., 2017). Indirect contagion due to fire sales of common exposures appears to be the more powerful channel of contagion and has received a lot of attention in the literature (Adrian and Shin, 2010; Caccioli et al., 2014; Cont and Schaanning, 2017). If banks have substantial cross-holdings of securities, price drops on these securities can significantly increase bank losses. In other words, fire sales are a pecuniary externality that also feature in models of collateralised (over-)borrowing and justify the intervention of macroprudential policy (Bianchi and Mendoza, 2010; Dávila and Korinek, 2018).

When it comes to assessing contagion risk in stress testing in practice, there are a number of approaches (Cont et al., 2013; Dees et al., 2017; Espinosa-Vega and Solé, 2011; Hüser et al., 2017). For direct contagion, Espinosa-Vega and Solé (2011) is a common framework for International Monetary Fund (IMF) Financial Sector Assessment Programs (FSAPs). In this framework,

[1]See Cont and Wagalath (2016); Duarte and Eisenbach (2013); Greenwood et al. (2015). These frameworks focus on individual banks rather than the macroeconomic implications of fire sale externalities.

[2]By contagion we mean that negative shocks to the solvency or liquidity of one bank has a negative impact on the whole banking system. Direct contagion arises due to exposures of one bank to another bank and indirect contagion arises due to common asset holdings.

the shock is the default of a bank and the measure of contagion is how many additional banks would fail as a consequence of the initial bank failure. Indirect contagion is to the best of our knowledge not currently used in stress tests even though there are available frameworks (Cont and Schaanning, 2017). What most of the previously mentioned frameworks lack is a focus on the system-wide implications. More recently Budnik et al. (2019) proposed a model that is similar to the one we develop in this paper in the sense that it combines a macroeconomic model with a detailed modelling of the banking sector (including bank heterogeneity and direct contagion).

We propose a contagion stress testing framework that can be used, and has already been used by Norges Bank in the Financial Stability Report 2019 (FSR 2019),[3] to assess financial stability risks due to contagion. The framework enhances the yearly cyclical stress test performed by Norges Bank,[4] by modelling how a network of Norwegian banks can amplify losses to the banking sector. The starting point is a scenario / shock in the macroeconomic model used for stress testing. Banks are linked by having direct exposures to another bank and by owning the same type of securities. Potential problems in one bank can thereby spread to other banks and amplify losses in the banking sector beyond what is covered in the stress scenario. In the contagion part, banks will start fire sales if their capital position suggests the bank is facing liquidity problems. Even though funding problems is the reason for fire sales, we do not explicitly model banks' financing. These fire sales cause losses for every bank holding the affected assets and can lead to the resolution of an institution. At this moment direct contagion becomes important and we assume that the authorities choose to use the bail-in tool. Furthermore, we include real costs connected to bail-in (e.g. lawyers and consultants).

The contagion part of the framework allows us to see the additional fall in the banking capital, if we apply the drop in bank capital resulting from the scenario in the macroeconomic model. Therefore, we use the contagion part featuring individual banks and direct as well as indirect connections to inform us about real costs due to contagion. The direct contagion part is inspired by Hüser et al. (2017) and the indirect contagion part is based on Cont and Schaanning (2017). We choose to include direct contagion because indirect contagion can lead to severe outcomes

[3] See Norges Bank (2019) for the report.
[4] See Andersen et al. (2019) for an overview of Norges Bank's framework for cyclical stress testing.

for individual banks, which in turn makes direct contagion a relevant channel in such cases. Ultimately, we are less interested in individual outcomes for banks but rather the implications for the system as a whole.

Our framework is informed by data about the current network structure, but the contagion part in particular relies on numerous critical assumptions. Since the past provides little guidance on how to model such a scenario, we choose instead to build a hierarchical model with distributions over all parameters. This allows us to conduct a sensitivity analysis across all parameters. As a consequence, we are looking at a distribution of outcomes given that we have a distribution of parameter inputs and some stochastic components. Our focus here is not the distribution of losses across banks, but the amplification due to real cost (fire sale externality and the real cost of a bail-in).

Although we have to rely on a number of critical assumptions, we can rely on data to calibrate the core of the model, the network structure, and some further parts of the model. The contagion part of the stress test framework is based on supervisory data on bank balance sheets, large exposures, loans to non-financial corporations (NFCs), and securities holdings statistics. The data reveals that the law of large numbers might not imply in the case of direct and indirect networks due to the heterogeneity across banks and the relative importance of a few banks.

We use Monte Carlo simulations to quantify the risk related to contagion in the banking sector. On average, contagion leads to a 0.5 pp drop in the CET1 ratio. There is a tail risk in the distribution of losses, the standard deviation being 0.44 pp, and contagion amplification can entail up to a 2 pp drop in the CET1 ratio. Furthermore, we find that indirect contagion is the main driver of the results. The simulation results also enable us to evaluate the importance of the mechanisms in the model. Contagion losses are high if banks quickly run into funding problems. We also find that contagion amplification is small when banks prefer to liquidate assets with high risk weights in deep markets. Furthermore, price drops on covered bonds are highly correlated with high contagion amplification.

The paper is structured as follows: Section 2 describes the data used to calibrate the model.

Section 3 gives an overview of the framework underlying our analysis, which is the same framework that was used in the FSR 2019. Section 4 analyses the outcome of the simulations and the importance of different mechanisms. Finally, Section 5 concludes the analysis.

2 Data

The data underlying our simulations come from three main sources: securities holdings and transactions statistics for Norwegian listed securities from Verdipapirsentralen (VPS), supervisory Capital Requirements Directive IV (CRD IV)[5] reporting, and supervisory reporting about exposures to NFCs - ENGA.[6] In addition, we use data on prices, average daily trading volume, issuer and Standardised Approach (SA) risk weights[7] from Reuters and Bloomberg. The scope of the analysis is determined by the availability of data across all data sources. Table 1 gives an overview of the data sources used to calibrate the model. For 2019 Q2, we have complete data for 22 banks and 1077 assets. These assets make up 35% of the total liquid assets of the banks in our sample[8] and are comprised of mostly Norwegian shares and bonds (e.g. covered bonds and government bonds). The banks in our sample do not include foreign branches and make up around 80% of the Norwegian banking sector. Furthermore, we consolidate the different data sources at the level of reporting of the CRD IV data (banking group level).

Based on the large exposures data from CRD IV reporting, we find that direct exposures that can be subject to bail-in amount to 12% of banks' CET1 capital. However, large exposures do include covered bonds, which are not subject to bail-in. We use large exposures after credit risk mitigation (CRM) and exemptions, which excludes 90% of covered bonds.[9] Furthermore, direct (large) exposures between the banks in our sample make up only 15% of the total large exposures

[5]CRD IV, which has been transposed into Norwegian law, is made up of: Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 and the Capital Requirements Regulation (CRR) - Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013.

[6]The ENGA database, collected by Finanstilsynet (Financial Supervisory Authority of Norway), contains information about collateral and internal ratings-based (IRB) parameters for all Norwegian banks.

[7]We include banks using the foundation internal ratings-based (F-IRB) approach in our sample, but due to lack of data we use SA risk weights for their liquid asset holdings.

[8]Complete coverage does not mean that the data explain 100% of the aggregate because Norwegian banks also hold non-Norwegian listed securities.

[9]See Article 400 (2)(a) CRR.

of the banks in our sample. Thereby, a large proportion of securities subject to bail-in is held by other investors. We thereby overestimate the importance of direct contagion, although in our simulations we find that direct contagion is hardly ever triggered given reasonable parameter values.

Figure 1 shows the network of indirect exposures (common asset holdings) of the 22 banks in our sample, based on VPS securities holdings data. The plot shows the exposures aggregated at sector level as a share of banks' CET1 capital. Certain banks have diversified portfolios and all banks hold relatively large shares in the financial and insurance sector (NACE sector K), as well as the public sector (NACE sector O). As Norwegian listed securities make up 118% of these banks' CET1 capital, valuation losses due to fire sales could have a significant impact on these banks' CET1 ratios.

The banks in our sample hold 19% of the amount outstanding in the securities they are invested in, and they are important actors in the markets for covered and public sector bonds. They hold 39% of the outstanding amount of the covered bonds they are invested in, and 14% of the amount outstanding of the public sector bonds. Considering risk weights, covered bonds, despite having very low risk weights, make up 51% of the risk-weighted indirect exposures of the 22 banks in our sample. The market depth of an asset used in the indirect contagion part of the model depends on trading volume and price volatility. We use transaction data from VPS going back six months from the end of 2019 Q2 to calculate the average daily trading volume. We use data from Bloomberg and Reuters for the same period to calculate daily return volatility. Calibrating the model on market data from this relatively calm period implies that the scenario unravels with a backdrop of relatively calm markets. Nonetheless, the model allows for parameterisations of less liquid markets. Yet, there is no feedback from fire sales and overall market liquidity.

Figure 2 shows the direct exposures among the 22 banks in our sample, based on CRD IV large exposures data from 2019 Q1.[10] The colour indicates how large the exposures are relative to the holder bank's CET1 capital. There are few banks that appear to have issued securities held by many other banks in our sample. Overall, the direct contagion network appears to be relatively

[10]Data for 2019 Q2 was not available at the time when we conducted the simulations for the FSR 2019.

sparse. Combining the information on direct exposures with the indirect exposures, one can see that bank 12 appears to have issued securities that are held by other banks. At the same time, bank 12 has very diversified asset holdings compared to the banks holding the securities issued by bank 12. In other words, this is an example where the exposure to different NACE sectors is not limited to the direct holder of these assets, but also affects the holder's creditors, who are indirectly exposed to these risks via direct links. The exposures shown in Figure 2 represent 12% of these banks' CET1 capital.

3 Framework

Norges Bank has developed a framework to quantify possible contagion effects. The results of the analysis can form part of a preliminary assessment of how structural conditions in the banking system affect systemic risk. The framework builds on the work done by Cont and Schaanning (2017) and Hüser et al. (2017) and analyses contagion effects caused by a drop in the value of securities and the default of large interbank exposures.

The focus of our framework is the contagion part, but the starting point of the stress test is a macroeconomic scenario. Given a scenario, a macroeconomic model quantifies the impact on the banking sector, and the fall in bank capital is what sets in motion the dynamics in the contagion part. In our case, we take the scenario from the cyclical stress test laid out in the FSR 2019. The macroeconomic model for the Norwegian economy (NEMO)[11] quantifies the impact of this scenario on the banking sector.[12] The remainder of this section describes the framework. Furthermore, Figure 3 provides an overview of the components and mechanisms of the framework and Table 2 gives an overview of the parameters.

The first step in the contagion part is to translate the loss in the banking sector to meaningful numbers for the individual banks. How we do this is potentially a critical assumption, and we will explain this and other assumptions in detail later on. If the CET1 ratio of any bank drops

[11] See Kravik and Mimir (2019) for a documentation of NEMO.

[12] Any macroeconomic model that models the banking sector and allows scenario analysis is sufficient to deliver the starting point of the contagion part of the model.

below a certain threshold, the bank is assumed to face funding problems. As a response, banks will shed assets, e.g. by engaging in fire sales of liquid assets in order to maintain their liquidity, and might be bailed-in if the bank enters into resolution. Banks in our model neither adjust their lending to the real economy, nor do they adjust their deposit and wholesale funding.

These so-called fire sales will have a price impact and will thereby impact all holders of the securities sold. This spillover effect, or indirect contagion, might lead other banks' solvency situation to deteriorate, their liquidity situation worsening in lock step, and to further fire sales by those banks. Critical assumptions at this stage are when fire sales start, what is being sold, and how prices react.

In some extreme cases a bank might have so little capital that it enters into resolution and we assume that its creditors would be bailed-in. Other banks might be creditors of the bank in resolution and would have to deduct losses and their newly converted equity holdings in the bank in resolution. Furthermore, we assume additional costs (e.g. lawyers and accountants) would be incurred in the case of bail-in. This mechanism is the direct contagion channel by which the solvency and liquidity situation at one bank can affect other banks and even amplify the initial shock. The critical assumptions for this mechanism are the point at which a bank enters resolution, the capital level after recapitalisation and the real cost.

There is a point where no more contagion occurs, and we determine the additional capital lost due to contagion. One has to be careful not to interpret the amplification as an equilibrium outcome. Instead the loss amplification is an additional exogenous shock to bank capital at the macro level.

3.1 Initial shock distribution

The starting point of the contagion part is a negative shock to the banking sector. This shock then needs to be translated into losses for the individual banks. The total initial fall in bank capital in the contagion model is:

$$\epsilon = \tilde{r} \cdot \sum_{b=1}^{N^b} C_{b,0}, \tag{1}$$

where $\tilde{r} < 0$ is the initial percentage drop in capital in the banking sector, N^b is the number of banks in the contagion model and $C_{b,0}$ is the capital of bank b before contagion. In FSR 2019, we let $\tilde{r}$ equal the first period percentage drop in capital of the banking sector in NEMO in the cyclical stress test. The next step is to distribute ϵ to each individual bank. The initial shock to bank b's capital is

$$I_b = \epsilon \cdot S_b, \tag{2}$$

where S_b is the share of the total initial fall in capital distributed to bank b.

In the following paragraphs, we will take a close look at how S_b is constructed. The main takeaway is that initial losses for a bank are partly random and partly determined by expected losses (EL) on exposures to NFCs and the CET1 ratio. S_b is given by

$$S_b = \kappa \cdot \left(\varsigma \cdot S_b^R + (1 - \varsigma) \cdot S_b^d\right), \tag{3}$$

where ς follows a beta distribution with mean of 0.15 and a standard deviation of 0.13, κ is a constant that ensures $\sum_{b=1}^{N^b} S_b = 1$,[13] S_b^R is the stochastic part of S_b and S_b^d is the part that distributes losses according to CET1 ratios and EL on loans to NFCs. S_b^d is given by

$$S_b^d = \kappa^d \cdot \frac{A_{b,0}^R \cdot \delta_b}{C_{b,0}}, \tag{4}$$

where δ_b is the EL on exposures to NFCs for bank b, $A_{b,0}^R$ is the risk-weighted assets for bank b before contagion, and κ^d is a constant that ensures $\sum_{b=1}^{N^b} S_b^d = 1$.[14]

We construct the stochastic part of S_b in equation (3), S_b^R, such that the standard deviation of $S_b^R \cdot A_{b,0}^R$ is the same across banks.

[13] Hence, $\kappa = \left(\sum_{b=1}^{N^b} \left(\varsigma \cdot A_{b,0}^R \cdot S_b^R + (1-\varsigma) \cdot S_b^d\right)\right)^{-1}$.

[14] Thus, $\kappa^d = \left(\sum_{b=1}^{N^b} \left(\frac{A_{b,0}^R \cdot \delta_b}{C_{b,0}}\right)\right)^{-1}$.

S_b^R follows a log-normal distribution with mean 1 and standard deviation proportional to banks' normalised risk-weighted assets (RWA), $\sigma_s \cdot \frac{\min\limits_{b\in\{1,\dots,N^b\}} A_{b,0}^R}{A_{b,0}^R}$. The standard deviation, σ_s, of the log-normal distribution follows a gamma distribution with mean 0.01 and a standard deviation of 0.0001.

The parameters σ_s and ς imply the following: for ς close to 1 and σ_s larger than 0 losses are distributed randomly, for ς close to 1 and σ_s close to 0 losses are distributed proportional to banks' RWA, and for ς close to 0 they are distributed proportional to EL on exposures to NFCs and the CET1 ratio of bank b. From equations (3) and (4), we observe that banks with high EL on loans to NFCs and a low CET1 ratio will incur high initial losses on average.

The initial shock to bank capital decreases the capital and RWA for each bank

$$C_{b,1} = C_{b,0} + I_b, \tag{5}$$

$$A_{b,1}^R = A_{b,0}^R + w \cdot I_b, \tag{6}$$

where w is the average risk weight for the assets that decrease in value. We assume that w is beta distributed with mean 0.6, which is the average risk weight in the Norwegian banking sector and standard deviation 0.06. The CET1 ratio for bank b after the initial shock is

$$\Xi_{b,1} = \frac{C_{b,1}}{A_{b,1}^R}. \tag{7}$$

3.2 Indirect contagion

If the initial shock brings the CET1 ratio for any bank b below a threshold $\overline{\Xi}_b$, the banks are assumed to face funding problems owing to waning creditor and investor confidence (Ellis and Flannery, 1992; Flannery and Sorescu, 1996). There is uncertainty about where the threshold $\overline{\Xi}_b$ exactly is, and we choose it to be a weighted average of the capital requirement $\underline{\xi}$ and the individual capitalisation level before contagion, $\Xi_{b,0}$,

$$\overline{\Xi}_b = \Xi_{b,0} \cdot (1 - \lambda_\Xi) + \underline{\xi} \cdot \lambda_\Xi, \tag{8}$$

where λ_Ξ is a weighting parameter that follows a beta distribution with mean 0.6 and standard deviation 0.07. This calibration assumes that on average, the threshold is closer to the capital requirement than the individual CET1 ratio before contagion.

We assume that banks facing funding problems will sell assets in order to maintain liquidity. As to how much, we assume that they will sell as many securities as they need to bring their CET1 ratio back above $\overline{\Xi}_b$. This is a simple approximation of the liquidity needs of banks facing funding problems. We assume further that they will use multiple counterbalancing measures. One of the counterbalancing measures is fire sales of liquid assets, which is the focus in the indirect contagion part. The other counterbalancing measures are not explicitly modelled and are captured by allowing for sales of other assets at a percentage haircut η.

The total amount of RWA to be sold by bank b at round r of contagion is

$$\Upsilon_{b,r} = \left(A^R_{b,r} - \frac{C_{b,r}}{\overline{\Xi}_b} \right) \cdot \mathbf{1}_{\Xi_{b,r} < \overline{\Xi}_b}, \tag{9}$$

where $A^R_{b,r}$, $C_{b,r}$ and $\Xi_{b,r}$ are RWA, capital and CET1 ratio for bank b in contagion round r, respectively. We assume that bank b sells $\lambda_\Upsilon \cdot \Upsilon_{b,r}$ liquid assets, where λ_Υ follows a beta distribution with mean 0.5 and standard deviation 0.15. Hence, bank b sells $(1 - \lambda_\Upsilon) \cdot \Upsilon_{b,r}$ of other assets. Fire sales of liquid assets lead to contagion in the banking sector, whereas sales of other assets do not.

Another critical assumption in our model is which liquid assets banks are going to sell. Previous works have considered both proportional fire sales (Cont and Schaanning, 2017; Greenwood et al., 2015) and fire sales that maximise expected liquidation value (Braouezec and Wagalath, 2018). Since the CET1 ratio is the trigger for fire sales in our model, we assume that banks take into account factors that impact the CET1 ratio. Further, we allow the fire sales to be random or proportional to a certain degree as well. For example, selling liquid assets with a high risk weight will have a large impact on the CET1 ratio. Further, since the price impact of selling an asset depends on the market depth M_a of the asset, the market depth will also impact the CET1 ratio.

Let $\mathbf{\Pi}_{a,b,r}$ be bank b's holdings of the liquid asset a. We model the share of $\mathbf{\Pi}_{a,b,r}$ being fire sold as

$$\mathbf{\Gamma}_{a,b,r} = K^l_{b,r} \cdot \Big((1 - \lambda_\Gamma) \cdot W_a \cdot M_a + \lambda_\Gamma \cdot \mathbf{\Gamma}^R_{a,b} \Big) , \tag{10}$$

where W_a is the SA risk weight of asset a and M_a is the market depth of asset a (see the next paragraph for details). In the following, N^a denotes the number of liquid assets. $K^l_{b,r}$ is a normalising constant that ensures that the total deleveraging amount of liquid assets for each bank sums to $\lambda_\Upsilon \cdot \Upsilon_{b,r}$.[15] λ_Γ is the parameter determining whether banks consider risk weights and market depth when selling. For λ_Γ close to zero, banks are more likely to sell assets with higher risk weights and assets with more liquid markets. The parameter follows a beta distribution with mean 0.15 and standard deviation 0.12, implying that banks consider to a large degree risk weights and market depth. Regarding the second part in equation (10), $\mathbf{\Gamma}^R_{a,b}$ follows a log-normal distribution with mean 1 and standard deviation σ_Γ. The standard deviation follows a gamma distribution with mean 0.01 and standard deviation 0.0001. For values of σ_Γ close to (above) zero and λ_Γ close to 1, banks deleverage proportional to their holdings (at random).

We calculate the market depth for asset a as

$$M_a = (1 - \underline{P}_a) \cdot D_a \cdot \sqrt{h}, \tag{11}$$

where $D_a = \frac{V_a}{\sigma_a}$ and $\underline{P}_a$ is the price floor of asset a which follows a beta distribution with mean 0.5 and standard deviation 0.05. V_a is the average daily trading volume for asset a and σ_a is the daily return volatility for the same asset. h is the liquidity horizon in days, which follows a log-normal distribution with mean 10 and standard deviation 2.62. This calibrated parameter is lower than the base calibration in Cont and Wagalath (2016) and implies that on average we see a relatively stronger price reaction due to less liquid markets. Since the price impact depends

[15] Hence, $K^l_{b,r} = \frac{\lambda_\Upsilon \cdot \Upsilon_{b,r}}{\sum_{a=1}^{N^a} \mathbf{\Pi}_{a,b,r} \cdot W_a \cdot \Big((1-\lambda_\Gamma) \cdot W_a \cdot M_a + \lambda_\Gamma \cdot \mathbf{\Gamma}^R_{a,b} \Big)}$.

negatively on the market depth, liquidating assets over a longer time horizon and selling assets that are frequently traded reduces the price impact when engaging in fire sales.

The total fire sales of asset a in contagion round r is

$$\Gamma_{a,r} = \sum_{b=1}^{N^b} \mathbf{\Gamma}_{a,b,r} \cdot \mathbf{\Pi}_{a,b,r}. \tag{12}$$

In the following, we deviate from the framework set out in Cont and Schaanning (2017) and introduce the notion that fire sales in one asset can have broader implications for the overall market or specific market segments. In other words, we assume other investors will rebalance their portfolios in response to a bank engaging in fire sales, because they see the asset being sold as a substitute for other assets in the same market. Our modelling approach is consistent with two specific mechanisms. First, assets are imperfect substitutes and demand for them is not perfectly elastic (Klein, 1970) and second, investors have a preferred habitat and do not necessarily diversify their risk by holding the market portfolio (Dorn and Huberman, 2010). This portfolio rebalancing or market liquidity channel is captured by "correlation matrix" $\mathbf{\Omega}_{a,\mathfrak{a}}$, which is the degree to which asset a is considered a substitute for asset $\mathfrak{a}$. More specifically, $\mathbf{\Omega}_{a,\mathfrak{a}}$ ensures that the total value being sold is the same whether other investors are present or not but the selling is spread across assets. We model the total amount of asset a being sold as

$$\widetilde{\Gamma}_{a,r} = \sum_{a=1}^{N^a} \Gamma_{a,r} \cdot \mathbf{\Omega}_{a,\mathfrak{a}}, \tag{13}$$

where $\mathbf{\Omega}_{a,\mathfrak{a}}$ is

$$\mathbf{\Omega}_{a,\mathfrak{a}} = M_{\mathfrak{a}} \cdot (\mathbf{1}_{I_a=I_{\mathfrak{a}}} \cdot \sigma_I + \mathbf{1}_{S_a=S_{\mathfrak{a}}} \cdot \sigma_S - \mathbf{1}_{I_a=I_{\mathfrak{a}}} \cdot \mathbf{1}_{S_a=S_{\mathfrak{a}}} \cdot \sigma_S \cdot \sigma_I) \cdot K_a, \tag{14}$$

where I_a and S_a are the issuer and sector of asset a, respectively. σ_I captures the degree to which assets from the same issuer are considered substitutes, and σ_S captures the same for assets belonging to the same sector. We assume that securities issued by the same issuer have a higher degree of substitutability than securities issued by companies in the same sector. We incorporate this belief by letting σ_I (σ_S) follow a beta distribution with mean 0.001 (0.0005) and standard deviation 0.005 (0.002). K_a is a normalising constant that ensures $\sum_{\mathfrak{a}=1}^{N^a} \mathbf{\Omega}_{a,\mathfrak{a}} = 1$.[16] From equation (14), we see that $\mathbf{\Omega}_{a,\mathfrak{a}}$ is high when the liquid assets a and $\mathfrak{a}$ belong to the same sector and have the the same issuer.

The modelling of price dynamics is a key part of the framework, since indirect contagion arises due to price drops on common exposures. We model, following Cont and Schaanning (2017), the percentage drop in asset a after r rounds of contagion as an exponential function of the amount sold, market liquidity and a price floor $\underline{P}_a$

$$\Delta_{a,r} = \left(1 - \frac{\underline{P}_a}{P_{a,r}}\right) \cdot \left(1 - \exp\left(-\frac{\widetilde{\Gamma}_{a,r}}{M_a}\right)\right), \tag{15}$$

where $P_{a,r}$ is the price of asset a at contagion round r.[17] The specification in equation (15) ensures that prices are higher than the price floor, and that the price of asset a is unchanged if no one (banks or other investors) sells that asset. Furthermore, the price impact of an asset in the case of a fire sale depends negatively on the market depth M_a of the asset. Since $\Delta_{a,r}$ is the percentage price drop in asset a, the price of asset a after r rounds of contagion is

$$P_{a,r+1} = (1 - \Delta_{a,r}) \cdot P_{a,r}. \tag{16}$$

Assets being fire sold decrease in value, and banks holding these assets will incur a valuation loss. The value of bank b's holdings of asset a after r rounds of contagion is

$$\mathbf{\Pi}_{a,b,r+1} = (1 - \mathbf{\Gamma}_{a,b,r}) \cdot (1 - \Delta_{a,r}) \cdot \mathbf{\Pi}_{a,b,r}, \tag{17}$$

where $1 - \mathbf{\Gamma}_{a,b,r}$ captures the volume effect of fire sales and $1 - \Delta_{a,r}$ captures the effect of the valuation change on the remaining holdings. Aggregate liquid RWA for bank b, $\Pi^R_{b,r}$ is updated as

$$\Pi^R_{b,r+1} = \sum_{a=1}^{N^a} (\mathbf{\Pi}_{a,b,r+1} \cdot W_a). \tag{18}$$

The valuation losses are the main driver of indirect contagion. In addition, we borrow from Cont

[16]Hence, $K_a = \left(\sum_{\mathfrak{a}=1}^{N^a} (M_{\mathfrak{a}} \cdot (\mathbf{1}_{I_a=I_{\mathfrak{a}}} \cdot \sigma_I + \mathbf{1}_{S_a=S_{\mathfrak{a}}} \cdot \sigma_S - \mathbf{1}_{I_a=I_{\mathfrak{a}}} \cdot \mathbf{1}_{S_a=S_{\mathfrak{a}}} \cdot \sigma_S \cdot \sigma_I))\right)^{-1}$.

[17]Prices are initialised at 1.

and Schaanning (2017) and assume that banks cannot sell all their assets at pre-fire sale prices. Instead, the price which asset a is liquidated is between the pre- and post-fire sale price. More formally and using equation (16)

$$P^l_{a,r} = (1-\alpha)\cdot P_{a,r} + \alpha \cdot P_{a,r+1}, \tag{19}$$

$$= P_{a,r}\cdot(1-\alpha\cdot\Delta_{a,r}), \tag{20}$$

where $P^l_{a,r}$ is the price at which asset a is liquidated. α follows a beta distribution with mean 0.5 and standard deviation 0.15. A higher α will increase the shortfall / losses when banks sell liquid assets. post-fire sale value of holdings and the liquidation shortfall

$$X_{b,r+1} = \sum_{a=1}^{N^a}(\Delta_{a,r}\cdot(1-\mathbf{\Gamma}_{a,b,r})\cdot\mathbf{\Pi}_{a,b,r} + \alpha\cdot\Delta_{a,r}\cdot\mathbf{\Gamma}_{a,b,r}\cdot\mathbf{\Pi}_{a,b,r}). \tag{21}$$

In addition to fire sale losses, there are losses due to sales of other assets at a haircut. In total, bank b's capital after r rounds of contagion is impacted in the following way

$$C_{b,r+1} = C_{b,r} - X_{b,r+1} - \eta\cdot(1-\lambda_\Upsilon)\cdot\Upsilon_{b,r}, \tag{22}$$

where $\eta\cdot(1-\lambda_\Upsilon)\cdot\Upsilon_{b,r}$ represents losses from selling other assets at a discount.[18] The RWA of bank b after r rounds of indirect contagion decrease due to the liquid RWA being reduced in both quantity and price and the reduction in other RWA

$$A^R_{b,r+1} = A^R_{b,r} - (\Pi^R_{b,r} - \Pi^R_{b,r+1}) - (1-\lambda_\Upsilon)\cdot\Upsilon_{b,r}. \tag{23}$$

The CET1 ratio is then

$$\Xi_{b,r+1} = \frac{A^R_{b,r+1}}{C_{b,r+1}}. \tag{24}$$

At this stage, we have concluded a round of indirect contagion. If no bank experiences further funding problems i.e. if $\Xi_{b,r+1} < \overline{\Xi}_b$ for any $b \in \{1,...,N^b\}$, contagion stops. Otherwise, there will be new rounds of indirect contagion. The losses due to fire sales may weaken the CET1

[18] Note that we assume that the haircut is paid in cash, which has a zero risk weight and therefore does not change the RWA.

ratio for one or more banks to the point where some banks enter resolution, giving rise to direct contagion.

3.3 Direct contagion

We assume that bank d enters resolution if their CET1 ratio is below a threshold, $\widetilde{\xi}$. [19] Once a debtor bank d enters into resolution, the creditor banks are subject to bail-in, and the debtor bank d is subsequently recapitalised to a CET1 ratio $\widehat{\xi}$ deemed market viable. The securities of creditor bank c subject to bail-in are converted to CET1 holdings that are deducted from creditor banks' CET1 capital. Further to this distribution mechanism, we assume real costs related to the bail-in procedures that amplify the initial loss.

The point below which a bank enters into resolution because it is failing or likely to fail, $\widetilde{\xi}$, is not defined in terms of a specific CET1 ratio in the regulation. We assume that $\widetilde{\xi}$ follows a normal distribution with mean 0.1 and standard deviation 0.01. Further, we assume that the recapitalisation level $\widehat{\xi}$ is above the resolution threshold. More specifically, we assume $\widehat{\xi} = \xi + \widetilde{\xi}$, where ξ follows a normal distribution with mean 0.04 and standard deviation 0.001. In other words, the resolution is triggered for a CET1 ratio below 10% and the bank is subsequently recapitalised to a CET1 ratio of around 14%.

The bail-in amount for debtor bank d is the difference between the capitalisation level post-bail-in and the current level, given that the bank is entering resolution. More formally,

$$B_{d,r} = \left(\widehat{\xi} \cdot A^R_{d,r} - C_{d,r}\right) \cdot \mathbf{1}_{\Xi_{d,r} \leq \widetilde{\xi}}. \tag{25}$$

Only a smaller part of the securities[20] subject to bail-in (Minimum Requirement for own funds and Eligible Liabilities (MREL)) is held by the banks in our sample. We take this into account by attributing a share $1 - \lambda_I$ of $B_{d,r}$ to creditors other than the banks in our sample. λ_I follows

[19] For the conditions triggering resolution, see Article 32 (1) CRD IV.

[20] 15% of large exposures are between the banks in our sample, but we assume that covered bonds make up for a larger share of the large exposures between the banks in our sample than between banks in our sample and other investors.

a beta distribution with mean 0.1 and standard deviation 0.02.

Creditors in the model incur losses only up to the total exposure they have towards the debtor bank in resolution. Whatever was attributed to the banks in our sample but cannot be absorbed because of a lack of exposure, will be bailed-in from other creditors. Therefore, the total amount of bail-in for a debtor bank d born by the creditor banks in our sample is

$$B^I_{d,r} = \min\left(B_{d,r} \cdot \lambda_I, \sum_{c=1}^{N^b} \boldsymbol{\Theta}_{c,d,r}\right), \tag{26}$$

where $\boldsymbol{\Theta}_{c,d,r}$ are the risk-weighted direct exposures from creditor bank c to debtor bank d.

According to the regulation,[21] bail-in is first applied to the most junior claims subject to bail-in and, once a seniority level is fully bailed-in, the next more senior level is bailed-in. Within the seniority level all creditors are treated as equal. Since we do not observe seniority in the data sources, we distribute the bail-in amount proportionally, i.e.

$$\boldsymbol{\Lambda}_{c,d,r} = \frac{B^I_{d,r} \cdot \boldsymbol{\Theta}_{c,d,r}}{\sum_{c=1}^{N^b} \boldsymbol{\Theta}_{c,d,r}}. \tag{27}$$

In addition to the write off of direct exposures, we assume that there are real costs, e.g. lawyers' and accountants' fees, related to the bail-in procedures. The real costs, $\boldsymbol{R}_{c,d,r}$, are either a share of the bail-in amount or the direct exposures between bank d and creditor bank c

$$\boldsymbol{R}_{c,d,r} = \varrho \cdot \Big((1-\lambda_R) \cdot \boldsymbol{\Lambda}_{c,d,r} + \lambda_R \cdot \boldsymbol{\Theta}_{c,d,r} \cdot \mathbf{1}_{\boldsymbol{\Lambda}_{c,d,r}=0}\Big), \tag{28}$$

where λ_R follows a beta distribution with mean 0.5 and standard deviation 0.17, and ϱ follows a log-normal distribution with mean 0.01 and standard deviation 0.002. In other words, we assume that on average real costs are 1% of the weighted average of the amount bailed-in and the affected exposure amount. After r rounds of contagion, creditor bank c's capital changes because of three components. First, capital increases if bank c has been bailed in, due to the conversion of debt to equity. Second, capital is lower because bailed-in exposures need to be

[21]See Article 48 (1) and Article 108 CRD IV for the seniority ladder relevant for bail-in.

deducted from own CET1. Third, real costs are attributed to the creditor banks. More formally,

$$C_{c,r+1} = C_{c,r} + B_{c,r} - \sum_{d=1}^{N^b} \left(\frac{\boldsymbol{\Lambda}_{c,d,r}}{w} + \boldsymbol{R}_{c,d,r} \right). \tag{29}$$

Direct exposures are reduced due to the conversion of bailed-in exposures to CET1

$$\boldsymbol{\Theta}_{c,d,r+1} = \boldsymbol{\Theta}_{c,d,r} - \boldsymbol{\Lambda}_{c,d,r}. \tag{30}$$

The same goes for RWA

$$A^R_{c,r+1} = A^R_{c,r} - \sum_{d=1}^{N^b} \boldsymbol{\Lambda}_{c,d,r}, \tag{31}$$

and the CET1 ratio of bank c becomes

$$\Xi_{c,r+1} = \frac{C_{c,r+1}}{A^R_{c,r+1}}. \tag{32}$$

Equation (32) concludes the direct contagion round and the next step depends on the CET1 ratios of all banks. If the resolution this round forced any bank into resolution, there will be another round of direct contagion. More formally, if $\Xi_{c,r+1} < \widetilde{\xi}$ for any $c \in \{1, ..., N^b\}$, a new round of direct contagion starts. Given that no other bank faces resolution at the end of this round but some banks face funding difficulties due to their CET1 ratio being below $\overline{\Xi}_b$, there will be another round of indirect contagion, which can be followed by further rounds of direct and indirect contagion. Contagion will only stop spreading if all banks either have satisfactory solvency, or there are no more direct exposures and liquid assets that can improve the banks' CET1 ratios. Last but not least, we assess the cost after r rounds of contagion measured in additional CET1 lost due to contagion.

After N^r rounds of contagion, we can calculate the contagion amplification as a percentage of CET1 capital, which we denote by $\widetilde{\epsilon}$. We calculate $\widetilde{\epsilon}$ as the percentage change of the sum of the CET1 of all banks from before to after contagion, less the initial percentage drop in CET1. Furthermore, we exclude the additional CET1 received by the banks in our sample from bailing-in exposures to creditors other than the banks in our sample. More formally,

$$\widetilde{\epsilon} = \frac{\sum_{d=1}^{N^b} C_{d,N^r} - \sum_{r=1}^{N^r}\left(\sum_{d=1}^{N^b}\left(B_{d,r} - B_{d,r}^{I}\right)\right)}{\sum_{d=1}^{N^b} C_{d,0}} - (1+\widetilde{r})\,. \tag{33}$$

In the next section, we show the distribution of contagion amplification based on a Monte Carlo simulation.

4 Results

In this section, we analyse the distribution of losses due to contagion effects, the uncertainty surrounding the parameter values and the drivers behind contagion. Based on the distributions in Table 2,[22] we simulate the model 30,000 times to get a distribution of losses due to contagion effects. The model has 18 stochastic parameters,[23] the random shock impact and the random fire sale pecking order. Furthermore, we choose to set correlation between parameters to 0.

The result of our simulations regarding the contagion amplification can be seen in Figure 4. It shows a non-parametric density function of losses due to contagion effects.[24] By visual inspection, there seems to be a tail risk in the distribution. The median being smaller than the mean also indicates a right skewed distribution. The mean of the losses is equivalent to a reduction in banks' CET1 ratio of about 0.5 pp, the standard deviation is about 0.44 pp, but in some cases, losses may be equivalent to a reduction in banks' CET1 ratio of about 2 pp. In our analysis, we find that direct contagion occurs in less than 0.1% of the simulations. Hence, most of the losses are due to indirect contagion.

We can investigate the importance of the different mechanisms in the model by looking at how the different parameter values covary with contagion effects. Since indirect contagion is the main driver of the results, we will in the following focus on stochastic parameters that matter for

[22] The moments of the parameter distributions are partly informed by data, as mentioned in the text, and weakly informative if no data is available. The nature of the exercise allows us to analyse the outcome given the choices of parameter distributions we made.

[23] See Table 2 for an overview of the parameter distributions.

[24] We use a standard normal kernel and choose the bandwidth according to the Silverman (1986) rule of thumb.

indirect contagion.

Each simulation starts with the translation of the decrease in capital of the banking sector as a whole into the change in individual bank capital. This change, together with the fire sale activation threshold, determines if and to what extent banks engage in fire sales, and is therefore an important part of the simulations. If all banks stay above the activation threshold, there will be no contagion. The distribution of the shock impact can matter, because a small drop in capital at the sector level can still trigger fire sales if it is over-proportionally distributed to one bank.

Our simulations show that the degree to which we randomly over-proportionally distribute losses to banks does not have a discernible impact on the contagion amplification. One way to explain this is that we also vary the threshold for fire sales. Another point we wanted to understand is whether a specific shock distributed according to the EL of NFC loans is associated with contagion amplification. Again we find that it is not, and we can thereby not say whether it is a particularly severe assumption or not.

The previously mentioned threshold for fire sales, $\overline{\Xi}_b$, is the starting point for indirect contagion. Obviously, this trigger point decides when the fire sale starts, but also the extent of it, as it also determines the amount of fire sales in order to reach the threshold level. Therefore, intuition tells us it should have considerable influence on the amplification and Figure 5 shows that indeed it does. The initial shock is positively correlated with the fire sale activation threshold. Furthermore, we observe a non-continuity in the distribution just above the median. There could be many reasons for this, and the bivariate plot only allows us to speculate that one or more banks are impacted by the shock on one side of the discontinuity that are not affected on the other.

Banks' fire sale strategy can also be important for contagion amplification. Figure 6 shows a positive relationship between the share of fire sales that involve liquid assets and the losses due to contagion. This is not a surprising result, considering that selling liquid assets leads to valuation losses, while selling other assets does not result in contagion to other banks. Furthermore, Figure

7 shows that contagion effects are lower when banks take market depth and RWA into account when engaging in fire sales. This is also an intuitive result, since the impact on prices of liquid assets depends negatively on the market depth, and selling risky assets improves the CET1 ratio, whereas selling assets with low risk weights might even decrease the CET1 ratio. This result is in line with the findings of Braouezec and Wagalath (2018).

Equations (11) and (15) show that the price impact of a liquid asset depends negatively on the liquidity horizon in days, h. Hence, we expect shorter liquidation horizons to increase the valuation losses. Figure 8 confirms this intuition, as it show a negative correlation between the liquidation horizon and contagion effects. Cont and Schaanning (2017) also find that the contagion amplification across a wide range of scenarios is sensitive to the liquidation horizon.

The degree of substitutability of assets, or the presence of arbitrageurs in the market, should dampen the impact of a given fire sale. Yet, it is not that simple, because on the one hand, the market for an individual asset will be more liquid, but on the other hand, arbitrage will lead to more assets being impacted. In other words, portfolio rebalancing can lead to more assets being impacted mildly, and if there are fewer arbitrageurs, fewer assets will be impacted more severely. The question is which effect is bigger, and Figures 9 and 10 show that high amplification is to a lesser degree related to assets being substitutes. Ultimately, portfolio rebalancing has more positive effects compared to fewer assets shouldering the cost of fire sales.

A higher shortfall parameter, i.e. a higher α, reduces the liquidation value when banks sell liquid assets. Even though α does not have a direct effect on contagion amplification, a higher α weakens banks' CET1 ratios, which in turn can lead to more fire sales. Figure 11 shows that α displays a low correlation with contagion effects. Hence, it seems that the indirect effects from increasing the shortfall parameter are small.

We considered the covariation between all stochastic parameters and contagion amplification. Parameters not mentioned in the discussion above showed little to no correlation with contagion amplification.

Beyond the stochastic parameters there are also fixed parameters, such as the direct and indirect network structure and the shock size. A fully robust analysis would entail varying the shock size and having endogenous network formation. This goes beyond the scope of this paper.

Banks' portfolio composition, i.e. the network structure, also matters for the results. Figure 1 shows that all banks hold a large share of their assets in the financial and insurance sector (NACE sector K) as well as in the public sector (NACE sector O). Securities in these sectors are typically covered and government bonds. Since banks have substantial exposures to these securities, relatively high losses may arise even in the event of a modest price decline. In the simulations, we find that price decreases on covered and government bonds are highly correlated with the amount of contagion amplification. Figure 12 shows a positive correlation between the average weighted price change of all securities in the financial and insurance sector with contagion amplification. Overall, prices decline by about 3.3% on average but this average hides the heterogeneity across simulations and among the different securities within NACE sector K.

Public securities play an equally important role as can be seen in Figure 13. On average, prices for these securities drop by 5.7%. One has to bear in mind that this is not the predicted price development of public securities in a crisis situation, but it is the impact of fire sales only on public securities.

Given that not all of the securities are held to maturity, the price dynamics of these securities can be an important source of systemic risk.

5 Conclusion

We propose a macroprudential contagion stress test framework, combining a macroprudential stress test with a contagion model. We use the model to assess to what extent contagion amplifies macroeconomic shock. We find that contagion most likely is not going to amplify strongly (mean losses equivalent to 0.5 pp of CET1 ratio at the banking sector level) but that extreme amplification is possible (2 pp).

The model is calibrated using data on securities holdings (VPS), large exposures (CRD IV), and loan level data (ENGA), yet there is substantial uncertainty about the remaining 18 parameters. We tackle this uncertainty by assuming distributions of these parameters and we use a Monte Carlo analysis to analyse the importance of the mechanisms. We find that several mechanisms interact. First, the threshold below which banks engage in fire sales is an important driver. The earlier banks start with fire sales, the more severe the amplification. This naturally interacts with the choice of which assets to sell. The higher the share of liquid assets, the higher the amplification. With fire sales of liquid assets being the primary source of the externality, it does matter in what pecking order assets are sold. The more banks take into account market depth and risk weights, the less severe the outcome for the whole system. Once sold, overall market liquidity plays an important role. The presence of other investors ensures that through arbitrage the shock is absorbed. We also find that the price floor and the implementation shortfall play less of an important role in our simulations, and direct contagion barely ever occurs. Beyond the importance of mechanisms, we note that covered bonds are at the heart of contagion amplification. Due to their central role in the network, they are, together with government securities, one of the main channels by which contagion spreads.

In our analysis, we limit the impact of the scenario on contagion to bank capital only. Thereby, we do not capture the influence of e.g. house price developments in the scenario on the contagion dynamics. One can imagine a scenario where house prices fall and liquidity for covered bonds might be weaker than we suggest. Our analysis does not capture that fire sales might have a stronger impact due to the reduced liquidity for covered bonds, because house prices are assumed not to have an impact on contagion dynamics. Instead, our framework does capture the impact of fire sales on covered bond prices because banks lose capital.

The analysis of the importance of mechanisms provides some guidance on where research can focus in order to improve our understanding of the critical parts of the financial system. These critical parts in our model are, when fire sales occur, in what order assets are sold and how this interacts with other investors.

The framework laid out in this paper can be extended along several lines. Regarding the measures to address liquidity concerns, we can go beyond fire sales and include other means of counterbalancing. Another natural extension is to allow for macro-feedback effects. This can be achieved by assuming that the contagion amplification is an exogenous shock to the capital of the banking sector of a macroeconomic model.

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Tables

Table 1: Parameter calibration and data sources

Parameter	Description	Dimensions	Source	Value
C	CET1 capital	Bank	CRD IV	
A	Total RWA	Bank	CRD IV	
δ	NFC expected losses	Bank	ENGA	
$\mathbf{\Pi}$	Liquid asset holdings	Bank, Asset	VPS	
W	SA risk weights	Asset	Bloomberg	
D	$\frac{\text{average daily trading volume}}{\text{price volatility}}$	Asset	VPS, Reuters	
I	Issuer of asset	Asset	Reuters	
S	Sector of asset issuer	Asset	Reuters	
$\mathbf{\Theta}$	Direct exposures	Creditor, Debtor	CRD IV	
$\underline{\xi}$	Capital requirement			13.5%

Table 2: Distributions of the stochastic parameters used in the simulations

Parameter	Description	Distribution	Mean	St. Dev.
ς	Combines random and informed impact	β	0.15	0.13
w	Risk weights on loss	β	0.6	0.06
σ_s	Variance of random shock impact	Γ	0.01	0.0001
λ_Υ	Share of deleveraging via liquid assets	β	0.5	0.15
η	Haircut on other assets	β	0.01	0.004
λ_Ξ	Fire sale activation threshold	β	0.6	0.07
σ_Γ	Variance of random pecking order	Γ	0.01	0.0001
λ_Γ	Combines random and market depth pecking order	β	0.15	0.12
σ_S	Substitutability of assets in same sector	β	0.0005	0.002
σ_I	Substitutability of assets by same issuer	β	0.001	0.005
$\underline{P}$	Price floor	β	0.5	0.05
α	Fire sale implementation shortfall	β	0.5	0.15
h	Liquidation horizon	$l\mathcal{N}$	10.0	2.62
$\tilde{\xi}$	Resolution threshold	$\mathcal{N}$	0.1	0.01
ξ	Recapitalisation: capital level increase	$\mathcal{N}$	0.04	0.001
λ_I	In scope direct contagion	β	0.1	0.02
ϱ	Real cost	$l\mathcal{N}$	0.01	0.002
λ_R	Determines reference quantity for real cost	β	0.5	0.17

Figures

Figure 1: Norwegian banks' holdings of all Norwegian registered securities at the sector level as a share of banks' CET1 in 2019 Q2. Sources: VPS, CRD IV reporting.

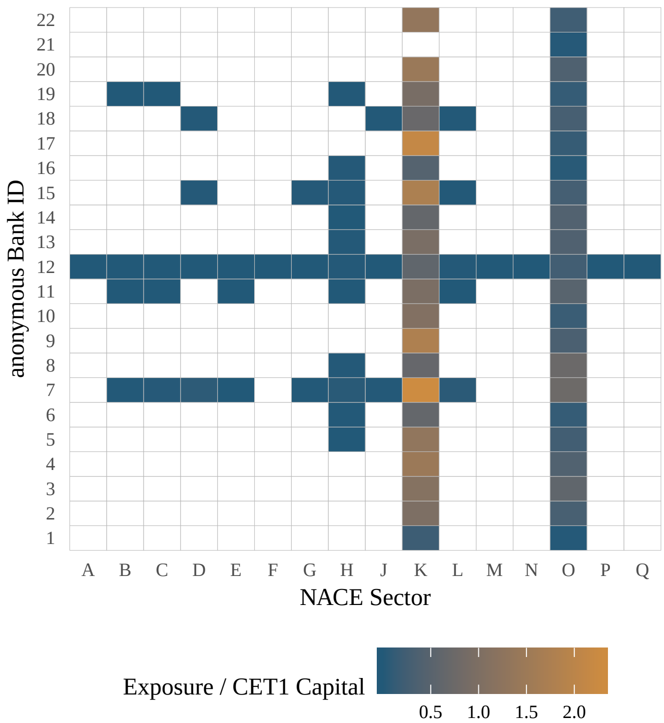


Figure 2: Exposures between Norwegian banks after exemptions and CRM. Share of the creditor banks' CET1 capital in 2019 Q1. Source: CRD IV reporting.

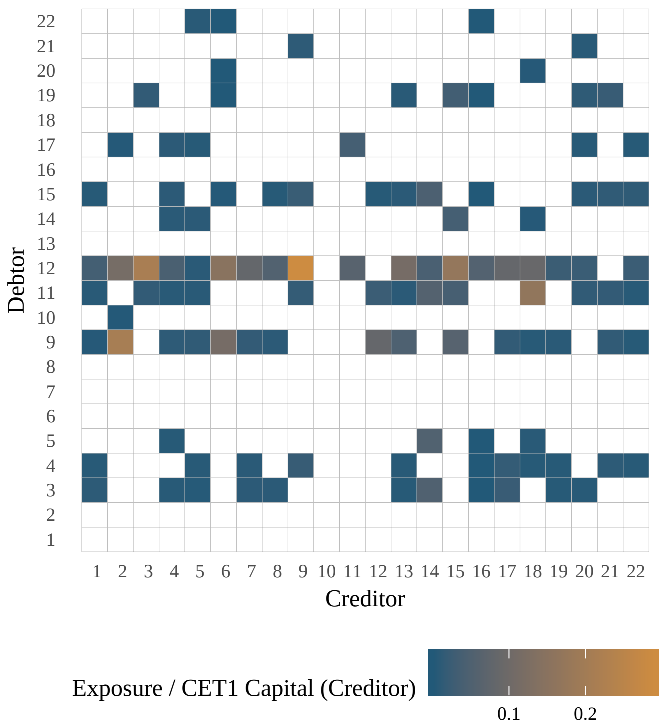


Figure 3: Bird's view of the framework.

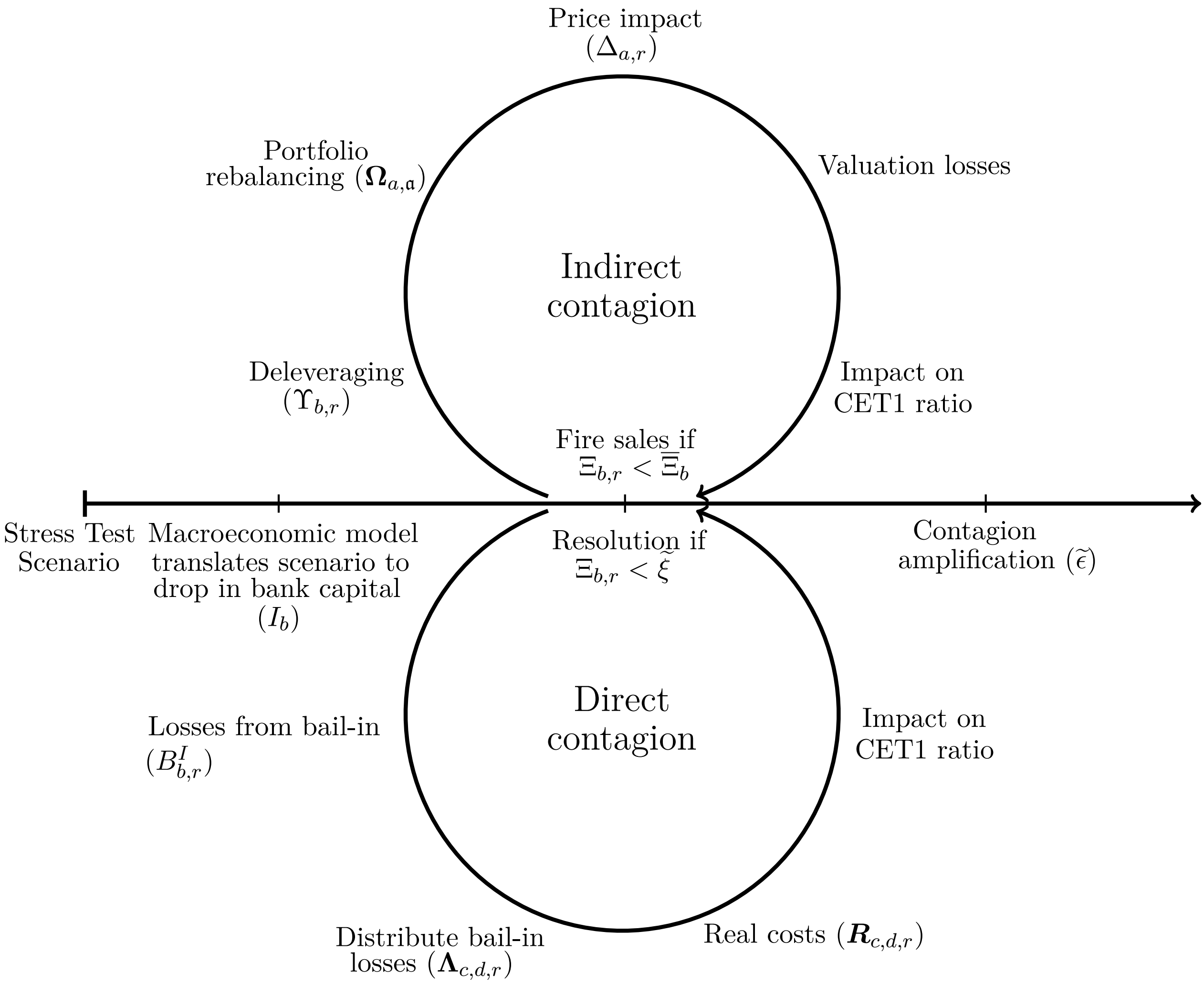


Figure 4: Estimated probability distribution of losses (pp fall in CET1 ratio) as a result of contagion in the banking sector.

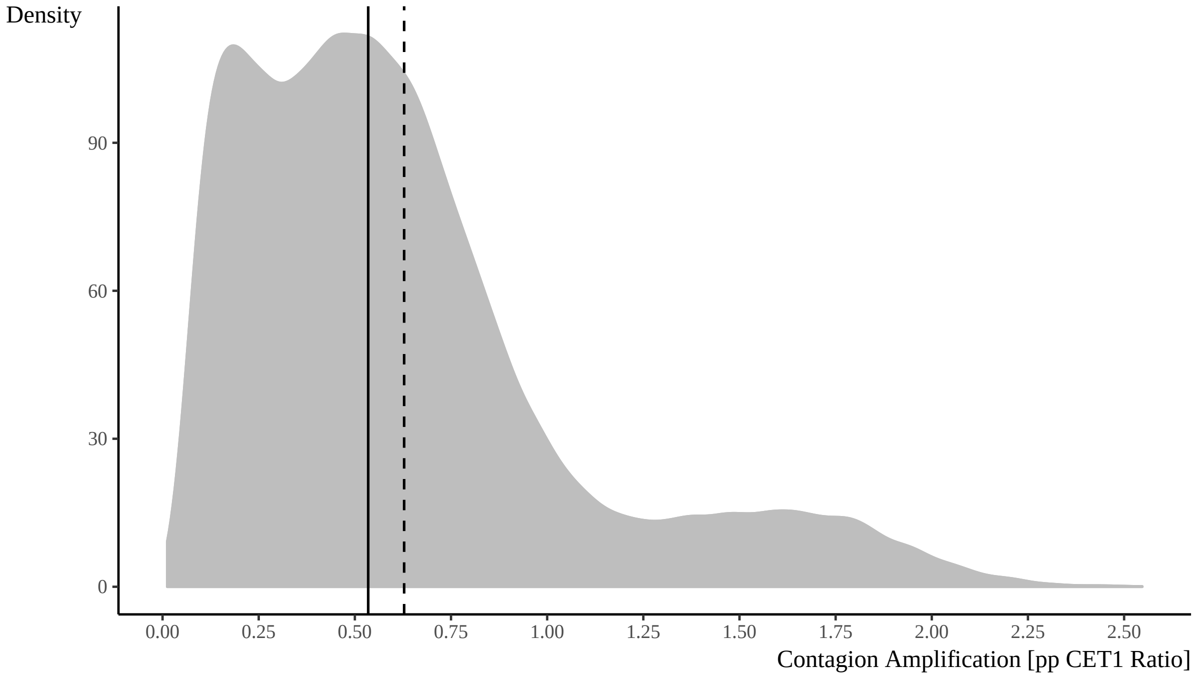


Figure 5: Relationship between the fire sale activation threshold (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

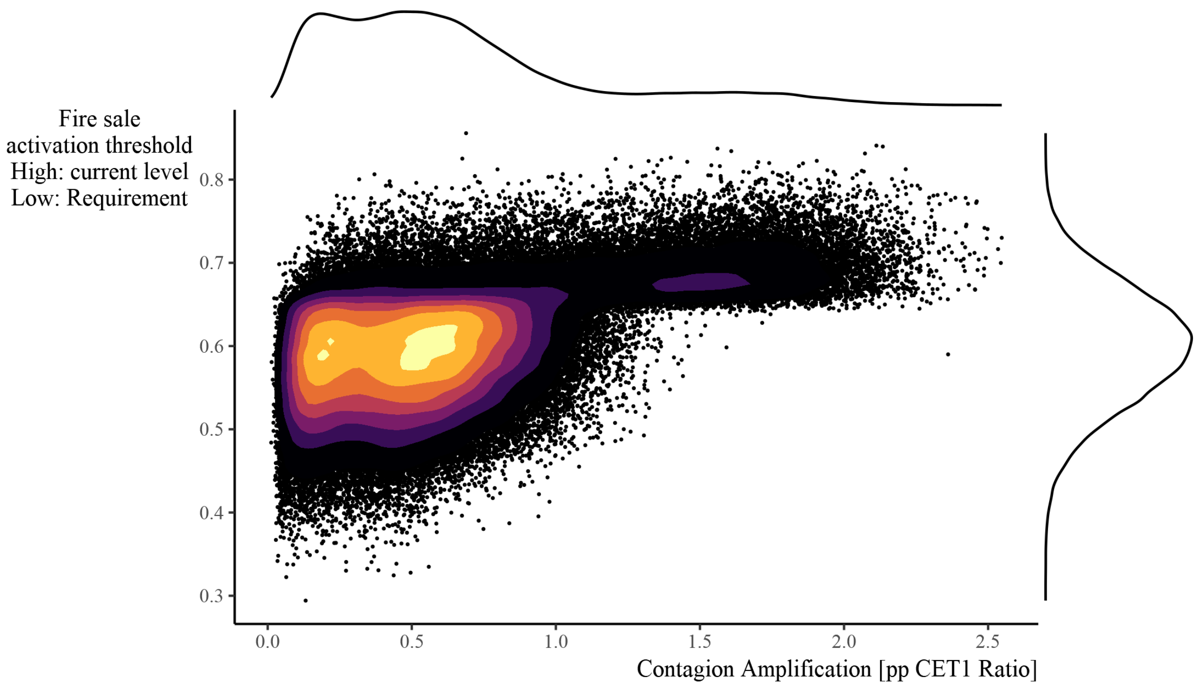


Figure 6: Relationship between the share of deleveraging done by selling liquid assets (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

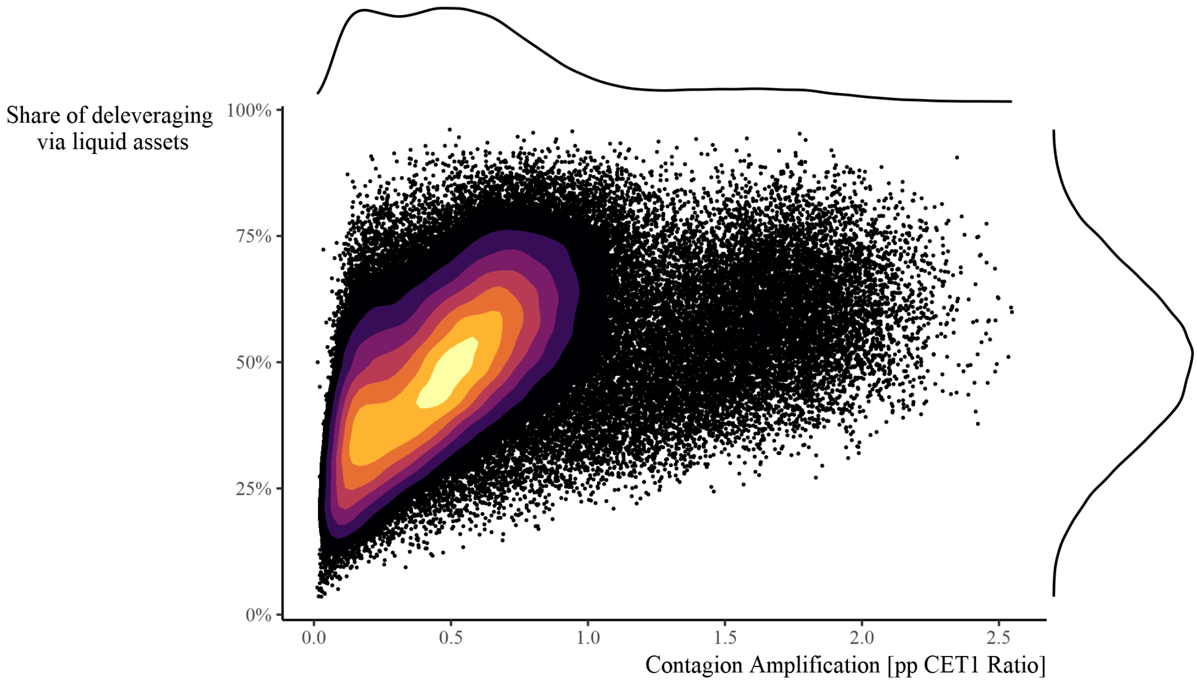


Figure 7: Relationship between the fire sale pecking order (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

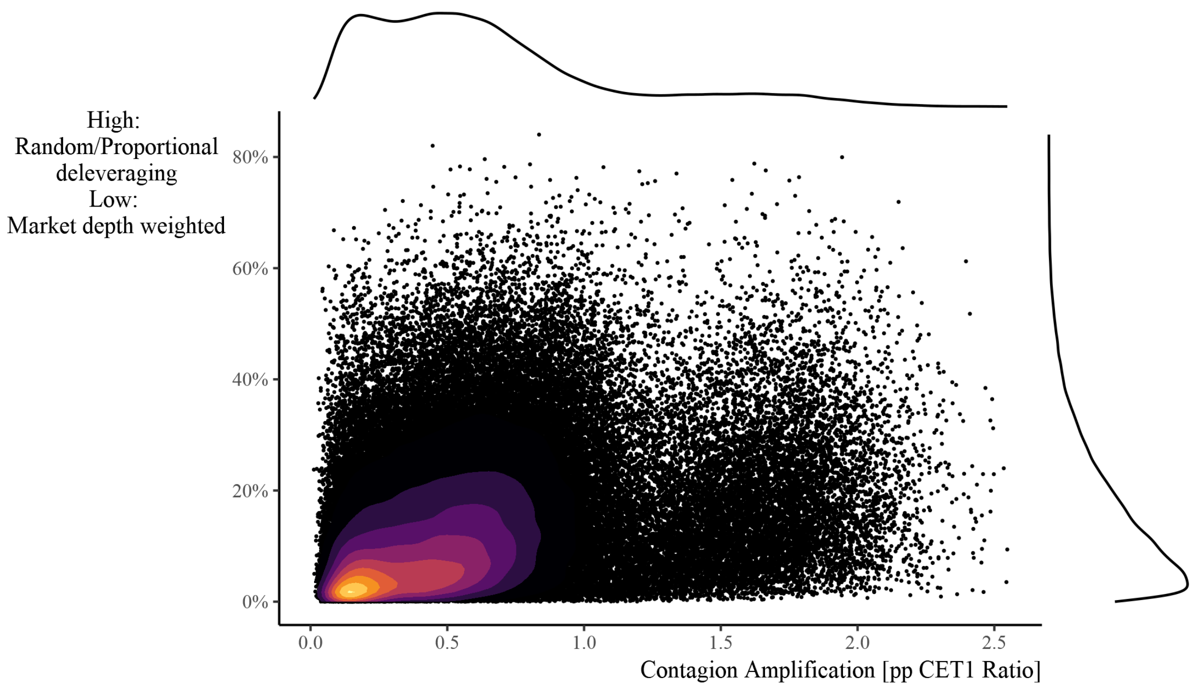


Figure 8: Relationship between the fire sale liquidation horizon in days (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

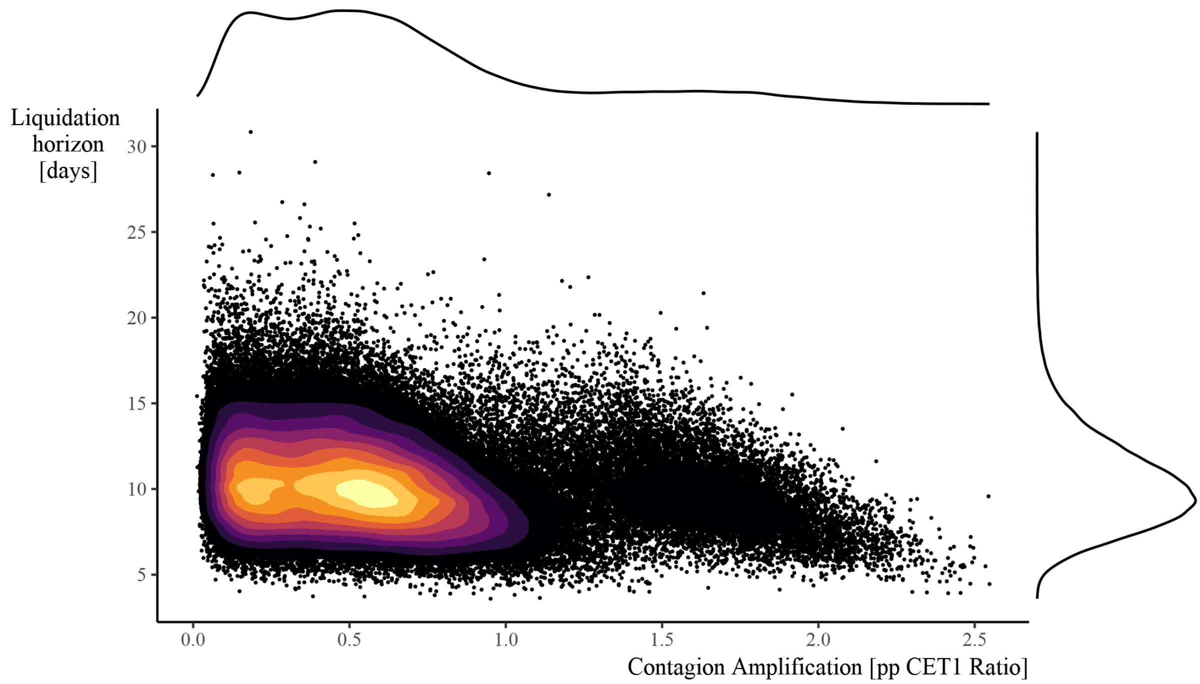


Figure 9: Relationship between the strength of portfolio rebalancing by other investors of securities of same issuer (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

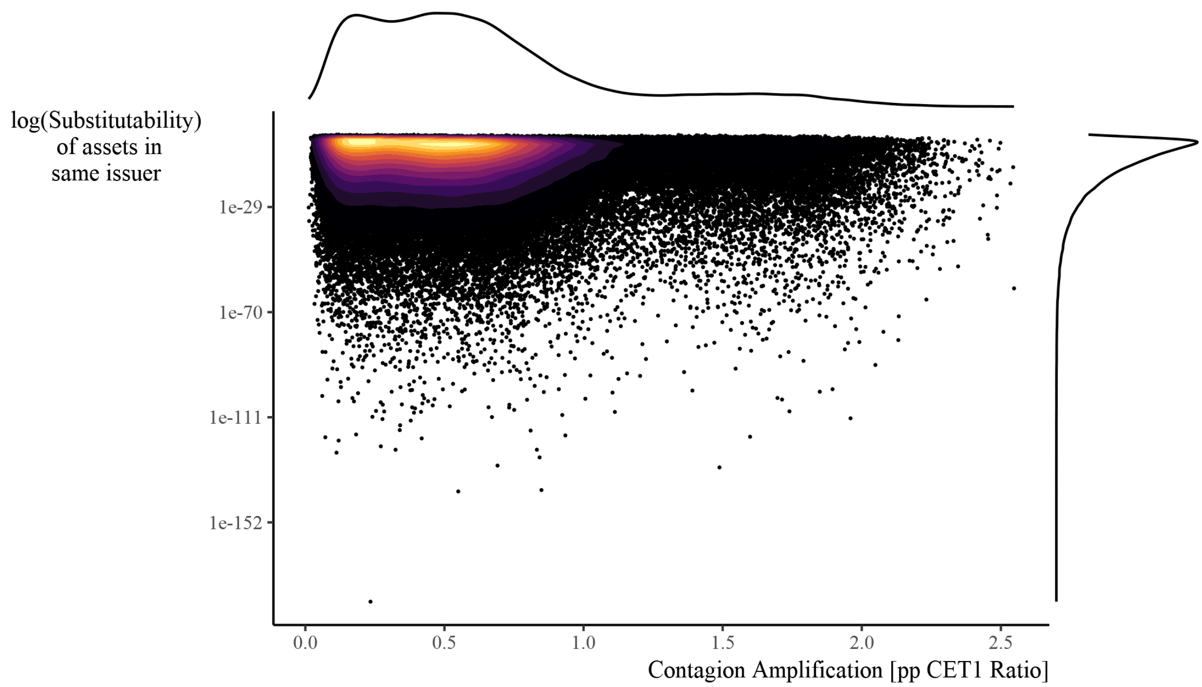


Figure 10: Relationship between the strength of portfolio rebalancing by other investors of securities within the same sector (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

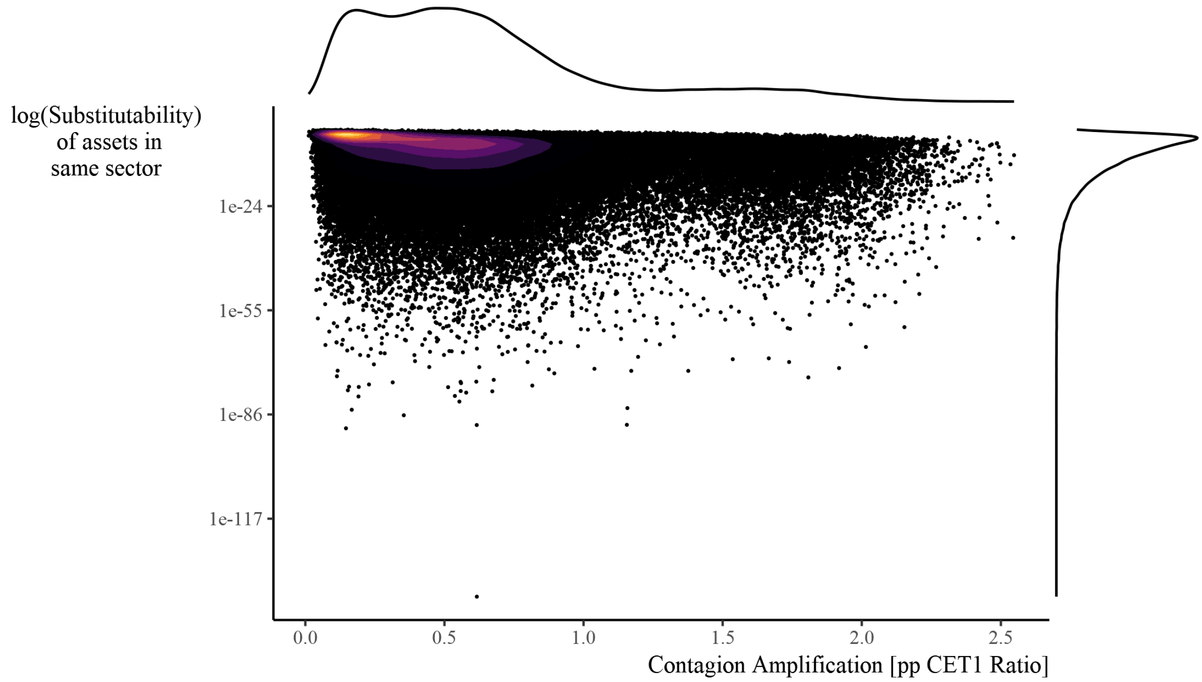


Figure 11: Relationship between the fire sale implementation shortfall (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

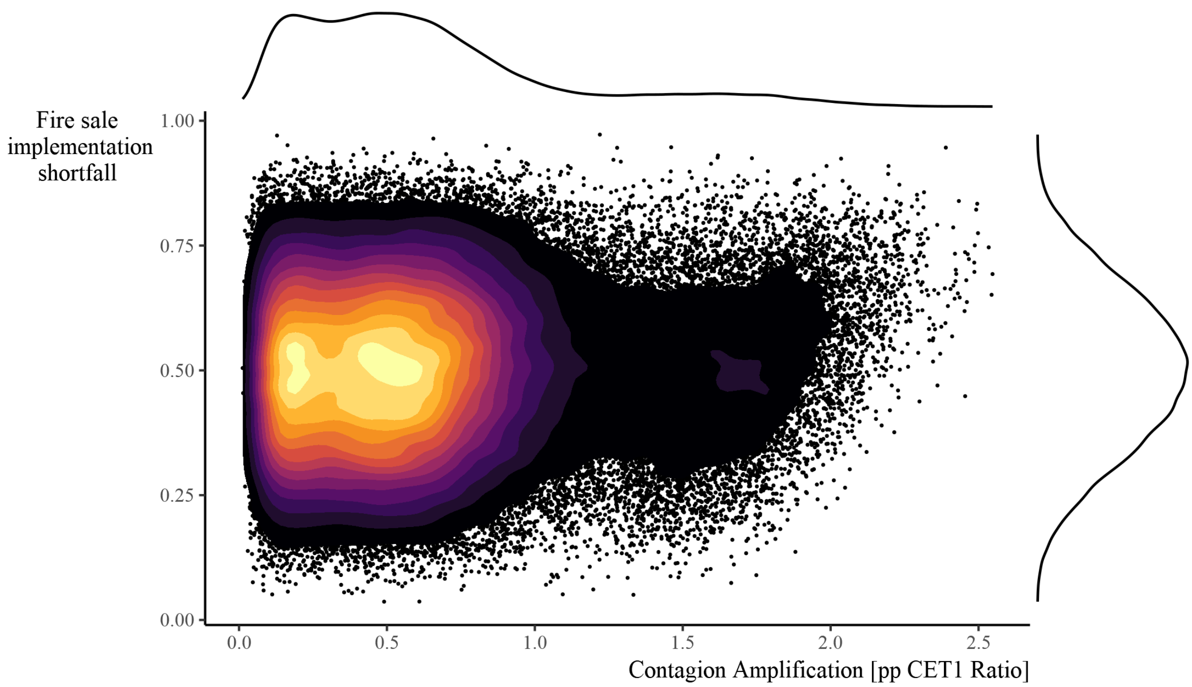


Figure 12: Relationship between weighted average price decrease of securities from NACE Sector K (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.

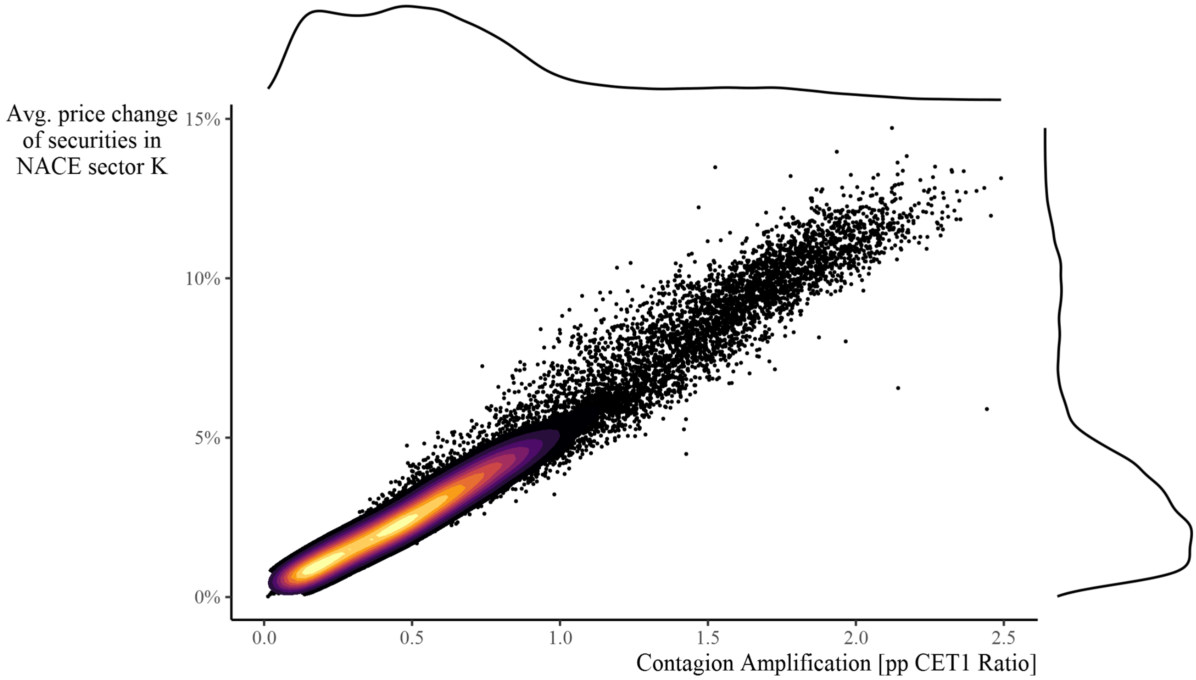
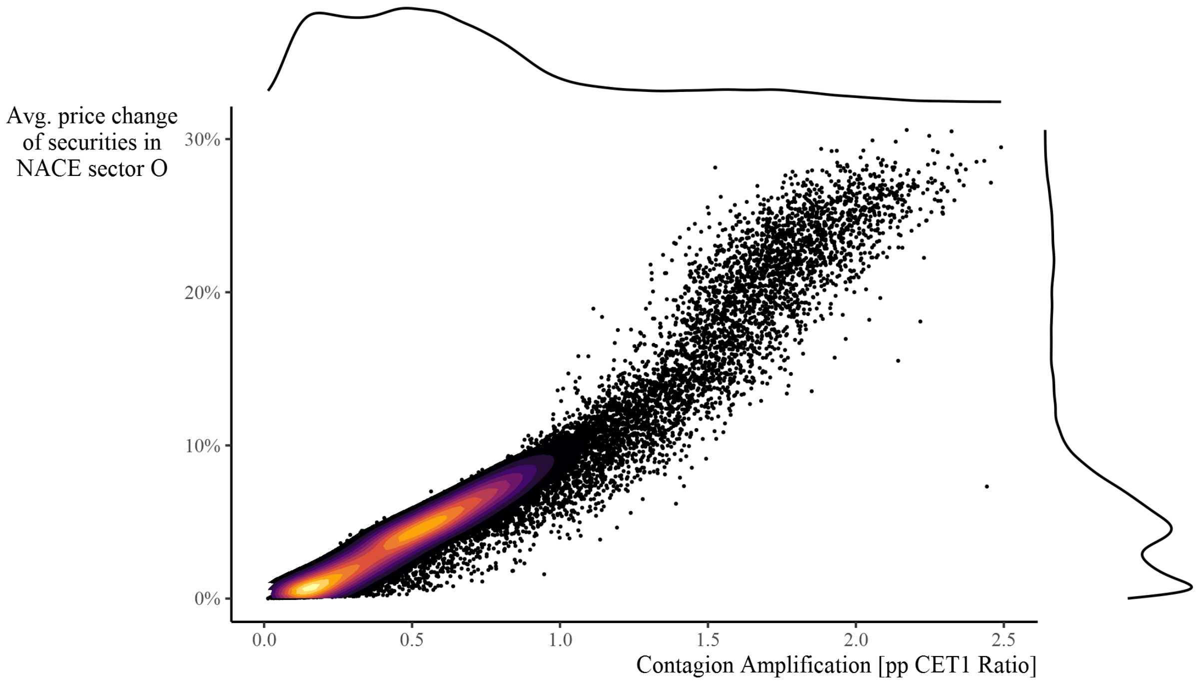


Figure 13: Relationship between weighted average price decrease of securities from NACE Sector O (vertical axis) and contagion amplification in pp of CET1 ratio (horizontal axis). The margins show estimated marginal distributions. The coloured areas are contours of a bivariate density estimate and each dot represents one simulation.



Acronyms

CET1	Common Equity Tier 1
CRD IV	Capital Requirements Directive IV
CRM	credit risk mitigation
CRR	Capital Requirements Regulation
EL	expected losses
F-IRB	foundation internal ratings-based
FSAP	Financial Sector Assessment Program
FSR 2019	Financial Stability Report 2019
GFC	Global Financial Crisis
IMF	International Monetary Fund
IRB	internal ratings-based
MREL	Minimum Requirement for own funds and Eligible Liabilities
NFC	non-financial corporation
pp	percentage points
RWA	risk-weighted assets
SA	Standardised Approach
VPS	Verdipapirsentralen