BANK OF ENGLAND

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Modelling fire sale contagion across banks and non-banks

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Modelling fire sale contagion across banks and non-banks

Fabio Caccioli,[1] Gerardo Ferrara[2] and Amanah Ramadiah[3]

Abstract

We examine the impact of fire sales on the UK financial system through commonly held assets across different financial sectors. In particular, we model indirect contagion via fire sales across UK banks and non-banks subject to different types of constraints. We find that performing a stress simulation that does not account for common asset holdings across multiple sectors can severely underestimate the fire sale losses in the financial system. In addition, pro-rata liquidation strategy would result in a higher level of fire sale losses in the system as whole, but a waterfall strategy may produce a higher spillover effect for a passive institution (or a passive sector) that chooses not to promptly liquidate any of its assets during distress while other institutions decide to do so.

Key words: Common asset holdings, fire sales, financial contagion, systemic risk.

JEL classification: G20, G21, G22, G23.

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1 Introduction

Indirect contagion due to common asset holdings is an important source of financial instability. This can materialize for instance during fire sales, when financial institutions have to liquidate their assets at heavily discounted prices (Shleifer and Vishny, 2011). For example, banks may be forced to deleverage (Khandani and Lo, 2011; Cont and Wagalath, 2016) in response to losses, while funds may be obliged to liquidate some assets during periods of distress to meet investor redemptions (Coval and Stafford, 2007). Moreover, Ellul et al. (2011) suggest that insurance companies may need to sell their assets to comply with regulatory constraints. Other empirical evidence also show that fire sales can occur in real assets (Pulvino, 1998).

In this regard, the literature on modelling indirect contagion has proliferated. However, most of the literature to date has only looked at systemic risk within one financial sector, where most works have been devoted to the case of banks (see Caccioli et al. (2018) and Glasserman and Young (2016) for recent surveys). Recently, regulators have become concerned about the impact of non-bank financial intermediaries (NBFIs) on financial stability (European Central Bank, 2014; International Monetary Fund, 2015; Bank of England, 2019b; Bank for International Settlements, 2020). This is mainly caused by a significant growth of the asset management sector in terms of its size and importance. For example, the contribution of NBFIs in the UK to the total assets of the UK financial system has increased by 13 percentage points since 2008, as it now accounts for almost 50% of the system (Baranova et al., 2019).

Our article contributes to the literature by systematically investigating how common asset holdings across different financial sectors amplify losses within the UK financial system. To study the impact of different sector specific constraints, we look at common asset holdings between UK banks, UK open-ended investment funds, and UK (unit-linked and non unit-linked) insurance companies.

For the purpose of studying fire sale mechanisms, we first build a bipartite network of common asset holdings where institutions are connected to the assets they hold. We then show that there are portfolio similarities between the different sectors. Furthermore, we consider a model of indirect contagion, where we assume that different sectors are subject to different constraints. In particular, banks and non unit-linked insurers are forced to liquidate (some of) their assets to comply with regulatory constraints. Meanwhile, funds and unit-linked insurers are obliged to sell their assets to meet investor redemptions. The model is used to perform stress simulation exercises under different shock scenarios. Following Greenwood et al. (2015) and Fricke and Fricke (2020), we look at two different measures of systemic losses: (i) fire sale losses of the system and (ii) indirect vulnerability of each institution and/or sector.

We contribute to the literature in several ways. First, we show the importance of considering multiple financial sectors in the analysis of systemic losses by using granular data of portfolio holdings of UK banks and NBFIs. We carry out simulations for different levels of external shocks ranging between 0% and 30%, and we find that ignoring asset commonalities between different sectors may result in an underestimation of fire sale losses by 47% on average.

Second, we conduct a systemic stress simulation on UK banks and NBFIs under different types of initial shocks. In most instances, we find that fire sale losses resulting from asset liquidations are higher than direct losses from initial shocks. Moreover, we look at the case when institutions maintain their portfolio weights (pro-rata liquidation) vs. the case when institutions prefer to sell their most liquid assets first (waterfall liquidation). We show that the pro-rata liquidation approach always yields a higher level of systemic risk in aggregate. Remarkably, by analyzing the results for each institution and sector at an individual level, we find that the waterfall liquidation may produce a higher spillover effect (indirect vulnerability). This is true in particular for an institution or a sector that chooses not to promptly liquidate its assets during distress.

The remainder of the paper is organised as follows: we provide a literature review in section 2. We describe the network of common asset holdings and discuss the contagion model in section 3. We provide a statistical characterization of the dataset and describe the experimental setup in section 4. We present and discuss the results in section 5. Finally, we discuss our conclusions in section 6.

2 Literature review

This paper builds upon different strands of literature. First, we contribute to the literature on modelling indirect contagion, where most studies have focused on common asset holdings between banks. For example, Caccioli et al. (2014), Huang et al. (2013) and Ramadiah et al. (2020) model the shock amplification process by assuming that banks behave passively toward asset price changes. Meanwhile, Cont and Schaanning (2017), Greenwood et al. (2015) and Duarte and Eisenbach (2015) assume that banks actively target their leverage ratio[1]. Additionally, Coen et al. (2019) consider the case where banks are constrained by leverage, risk-weighted capital and liquidity regulations.

[1]Leverage targeting is also considered in Caccioli et al. (2014), where it is shown that dynamic deleveraging during a crisis may amplify instabilities.

Recently, the quantification of systemic risk in NBFI sectors has gained interest in the literature. For example, Cetorelli et al. (2016), Fricke and Fricke (2020) and Baranova et al. (2017) model indirect contagion across open-ended investment funds that are triggered by investor redemptions during times of distress. With respect to insurance companies, Douglas et al. (2017) study the impact of Solvency II regulation on the way that UK life insurers adjust their portfolio in periods of distress. While the above studies focus on institutions of the same type, we look at indirect contagion between different financial sectors.

Second, we contribute to the literature on networks of common asset holdings. In this respect, some studies have looked at portfolio similarity between U.S. investment funds (Georg et al., 2019; Braverman and Minca, 2018; Fricke, 2019; Delpini et al., 2019) and U.S. insurers (Girardi et al., 2018). Our work is the closest to Barucca et al. (2020), who study common asset holdings across UK banks and European funds. However, they consider portfolio holdings at the security issuer (where each asset is identified by a LEI - Legal Entity Identifier), while we focus on those at the ISIN level (where each asset is identified by using the International Securities Identification Number). Therefore, our dataset is more granular. Furthermore, while Barucca et al. (2020) focus on the structural analysis of the network of overlapping portfolios, our focus is on the quantification of fire-sale losses induced by the network.

Our paper is also related to the literature on systemic risk across multiple contagion channels. For example, Cifuentes et al. (2005) simulate a model that account for the interaction between direct and indirect contagion, while Caccioli et al. (2015) and Poledna et al. (2018) empirically study a similar interaction for the case of Austrian and Mexican banks. In this paper, we focus on indirect contagion and do not take direct contagion into account. However, we consider a richer set of financial institutions (which consists of banks, investment funds and insurance companies) and a richer set of assets (which consists of equity and debt securities). Additionally, Aikman et al. (2019) and Farmer et al. (2020) study a system-wide modelling approach and consider different types of financial institutions, However, most of the institutions in their models are representative agents. In this paper, we instead look at contagion in an empirical network of common asset holdings, which is more granular.

3 Modelling contagion in network of common asset holdings

3.1 Network of common asset holdings

We represent common asset holdings between financial institutions as a bipartite network, where nodes can be of two types (financial institution or asset), and where a link can only connect nodes of different types. A link between a node associated with a financial institution and a node associated with an asset means that the institution holds the asset in its portfolio.

We consider four different financial sectors: banks $(b_1, ..., b_{n1})$, funds $(f_1, ..., f_{n2})$, unit-linked insurers $(uli_1, ..., uli_{n3})$ and non unit-linked insurers $(nli_1, ..., nli_{n4})$. We take three different asset classes into account: government bonds $(gb_1, ..., gb_{m1})$, corporate bonds $(cb_1, ..., cb_{m2})$ and equities $(eq_1, ..., eq_{m3})$. Hence, there are in total $N = n1+n2+n3+n4$ financial institutions and $M = m1+m2+m3$ assets in the network.

We illustrate the stylized network of common asset holdings in Figure 1. This network

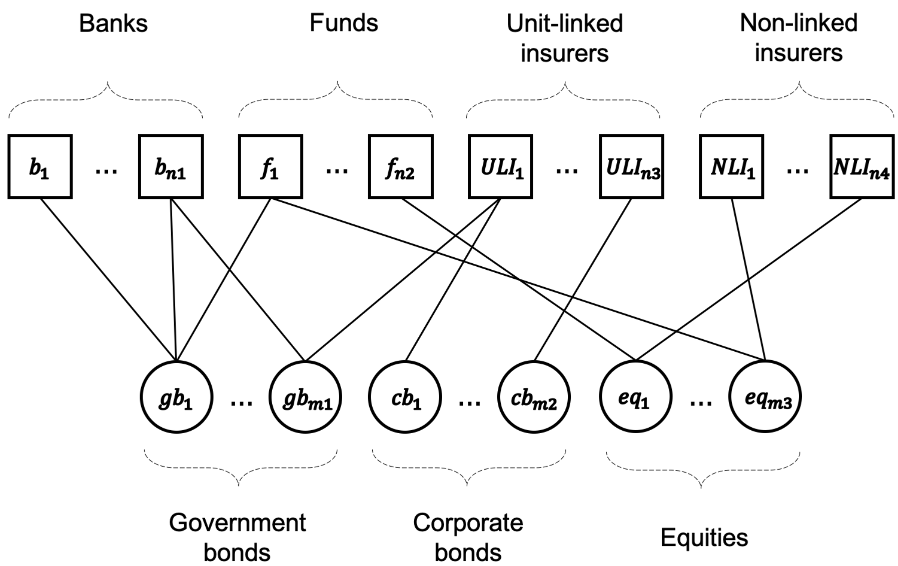


Figure 1: Stylized network of common asset holdings with four financial sectors (banks, funds, unit-linked insurers and non-linked insurers) and three asset classes (government bonds, corporate bonds and equities). A link between institution i and asset j implies that i holds j in its portfolio. The network is bipartite, which denotes the absence of inter-entity in and inter-asset links.

can be represented as a rectangular matrix $\mathbf{W}$ of size $(N \times M)$, where each element

$w_{ij} \geq 0$ corresponds to the sterling amount of asset j owned by institution i.[2] In the following, we define the *strength* of institution i as its total portfolio holdings, while the strength of asset j is the total amount of that asset owned by financial institutions in the network:

$$s_i^F = \sum_j w_{ij} \quad \text{and} \quad s_j^A = \sum_i w_{ij}.$$

We also define $\bar{W}$ as the binary adjacency matrix corresponding to $\mathbf{W}$, that is $\bar{w}_{ij} = 1$ if $w_{ij} > 0$ and zero otherwise. From this binary matrix, we can calculate the *degree* of institutions and assets, which corresponds to the number of their connections:

$$k_i^F = \sum_j \bar{w}_{ij} \quad \text{and} \quad k_j^A = \sum_i \bar{w}_{ij}.$$

We can then define the ratio between the number of existing connections and the number of potential connections in the network as *density*:

$$\text{density} = \frac{\sum_i k_i^F}{N \times M}.$$

To quantify the *portfolio similarity* between institutions i and k, we use two different measures: one is based on the binary matrix $\bar{W}$, the other on the (weighted) holdings matrix W. Following Barucca et al. (2020), we define these measures as:

$$\text{BinSimilarity}_{ik} = \sum_j \bar{w}_{ij}\bar{w}_{kj} \tag{1}$$

for the binary case, and

$$\text{CosSimilarity}_{ik} = \frac{\sum_j w_{ij} w_{kj}}{\sqrt{\sum_j w_{ij}^2} \times \sqrt{\sum_j w_{kj}^2}}. \tag{2}$$

for the weighted one. The binary version of the portfolio similarity in Equation 1 shows the number of common assets between institutions i and k. In addition to the number of common assets, the weighted measure in Equation 2 also accounts for the similarity of weights associated with those assets. We note that BinSimilarity ranges between $[0, M]$, and CosSimilarity ranges between $[0, 1]$, where for both measures higher values indicate more similar portfolios.

In what follows, we also look at the average similarity between one institution i and

[2] Matrix $\mathbf{W}$ changes over time, but we drop time subscripts in what follows.

the other institutions in the network. Following Fricke (2019), we therefore define the average portfolio overlap as:

$$\text{MeanBinSimilarity}_i = \frac{1}{N-1}\sum_k \text{BinSimilarity}_{ik} \tag{3}$$

for the binary similarity case, and

$$\text{MeanCosSimilarity}_i = \frac{1}{N-1}\sum_k \text{CosSimilarity}_{ik} \tag{4}$$

for the weighted one.

3.2 Modelling fire sale contagion across banks and NBFIs

We extend the model of fire sale contagion introduced by Greenwood et al. (2015). Our model is more comprehensive because we look at multiple financial sectors and asset classes. The main steps are as follows:

1. Initial shock. Financial institutions compute their direct losses.
2. Institutions react according to their sector-specific constraints.
3. Institutions liquidate their assets by maintaining their portfolio weight (pro-rata liquidation), or by selling their most liquid assets first (waterfall liquidation).
4. Assets liquidations generate price impact. Institutions compute their fire sale losses.

Let us describe the above steps in detail.

3.2.1 Initial shock

Suppose the initial total holdings of institution i at time $t = 0$ is

$$A_i(0) = \sum_j w_{ij}(0). \tag{5}$$

We impose a relative shock θ_j to asset j, such that the total holdings of institution i then become:

$$A_i(1) = \sum_j w_{ij}(0)(1 - \theta_j). \tag{6}$$

The amount of *direct losses* suffered by institution i following this shock is:

$$R_i^{\text{direct}} = \sum_j w_{ij}(0)\theta_j. \tag{7}$$

3.2.2 Sector-specific constraint

Observing the direct losses in its balance sheet, institution i is forced to liquidate (part of) its assets, depending on its sector-specific constraints. Banks and non unit-linked insurers are subject to regulatory constraints, while funds and unit-linked insurers are obliged to meet investor redemptions. In the following, we discuss the details of these constraints.

Banks Following Greenwood et al. (2015) and Duarte and Eisenbach (2015), we assume that banks target their leverage ratio above its regulatory minimum, that is they liquidate their assets whenever their leverage ratio is off-target. We illustrate the simplified balance sheet of a bank in Figure 2.

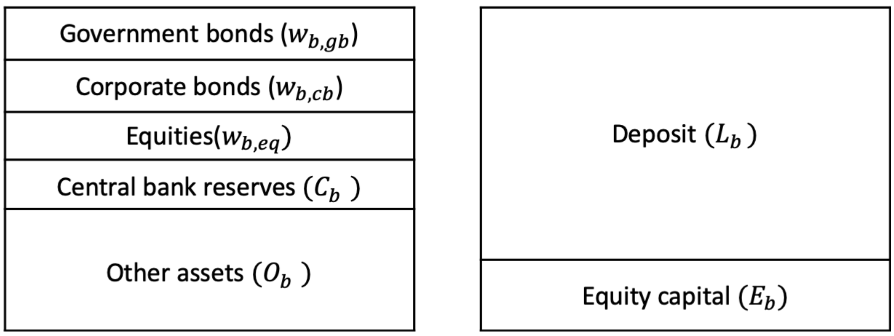


Figure 2: Bank's balance sheet. The left panel is the asset side, while the right is the liability side of the balance sheet.

In particular, the leverage ratio of bank b at time $t = 0$ is defined as:

$$LEV_b(0) = \frac{E_b(0)}{\hat{A}_b(0)}.$$

Note that $\hat{A}_b$ is the total all assets of b, and it is not the same as the total portfolio holdings that we defined in Equation 5. Here $\hat{A}_b$ also includes other assets, such as interbank assets and central bank reserves:

$$\hat{A}_b(0) = A_b(0) + O_b,$$

where we denote by O_b the value of the other assets.

Following the direct losses that bank b receives (see Equation 7), its leverage ratio at $t = 1$ becomes:

$$LEV_b(1) = \frac{E_b(0) - R_b^{\text{direct}}}{\hat{A}_b(0) - R_b^{\text{direct}}} \leq LEV_b(0),$$

which is smaller than its initial leverage. In order to maintain its leverage at $LEV_b(0)$, bank b will have to liquidate an amount:

$$\Pi_b = (\hat{A}_b(0) - R_b^{\text{direct}}) - \frac{E_b(0) - R_b^{\text{direct}}}{LEV_b(0)}$$

Funds The balance sheet of a fund is illustrated in Figure 3. Unlike banks, funds do not need to comply with any regulatory constraints. However, as it was empirically shown in Czech and Roberts-Sklar (2019), funds are pro-cyclical and liquidate their assets to meet investor redemption in periods of stress.

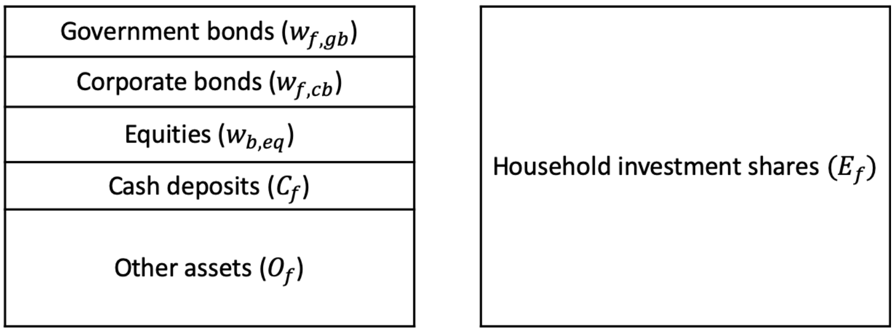


Figure 3: Fund's balance sheet. The left panel is the asset side, while the right is the liability side of the balance sheet.

Following Baranova et al. (2017) and Fricke and Fricke (2020), the amount of assets that fund f liquidates is:

$$\Pi_f = \sigma_f \frac{R_f^{\text{direct}}}{A_f(0)} A_f(1),$$

where σ_f is the fund-flow performance sensitivity parameter, which is the share of assets that investors will redeem following losses of 1%.

Unit-linked insurers The balance sheet of a unit-linked insurer is illustrated in Figure 4. The business models of unit-linked insurers and funds are similar, as they both pool policyholders/investor funds and invest them in financial assets. However, unlike funds, unit-linked insurers tend to have longer-term horizons. This means that their policyholders may be better able to accept shorter-term portfolio losses, hence unlikely to redeem their funds during distress. Nevertheless, they are given an option to switch their investments between different asset classes. In fact, in its recent survey, Bank of England (2016) observes that some unit-linked policyholders decide to de-risk their investment in response to falling prices of risky assets.

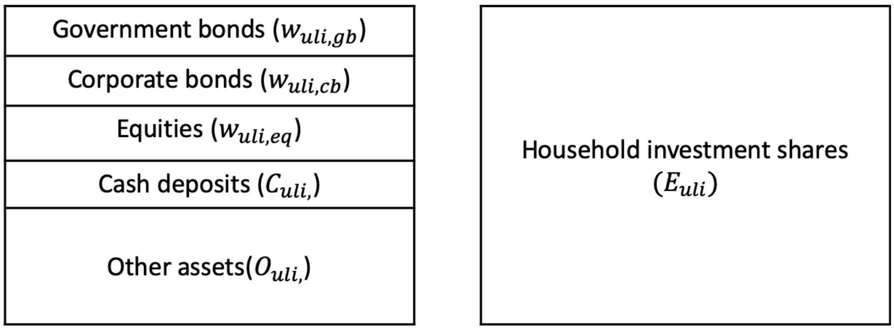


Figure 4: Unit-linked's balance sheet. The left panel is the asset side, while the right is the liability side of the balance sheet.

Following Baranova et al. (2019), the amount of total assets that unit-linked insurer uli needs to liquidate is given by:

$$\Pi_{uli} = \sigma_{uli} \frac{R_{uli}^{\text{direct}}}{A_{uli}(0)} (A_{uli,eq}(1) + A_{uli,cb}(1)),$$

where σ_{uli} is the policyholder switching sensitivity parameter, that is the share of assets that policyholders will switch following losses of 1%. Note that unit-linked insurers will only liquidate risky assets, and $A_{uli,eq}$ and $A_{uli,cb}$ are the total portfolio holdings of equities and corporate bonds.

Non unit-linked insurers Finally, we look at the case of non unit-linked insurers, and illustrate their balance sheet in Figure 5. As shown in the figure, non unit-linked insurers are similar to banks, in a way that they both hold capital and have to comply with some regulatory constraints.

In the UK, non unit-linked insurers need to comply with Solvency II regulations. Following Aikman et al. (2019), we assume that non unit-linked insurers target their solvency ratio above its regulatory minimum:

$$SR_{nli}(0) = \frac{E_{nli}(0)}{SCR_{nli}(0)},$$

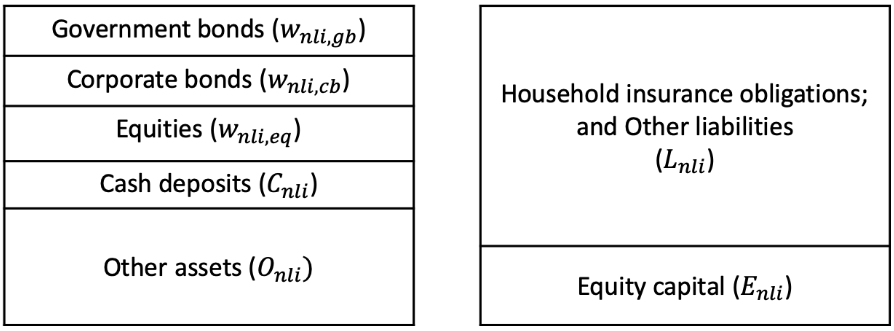


Figure 5: Non unit-linked insurer's balance sheet. The left panel is the asset side, while the right is the liability side of the balance sheet.

where $SCR_{nli}(0)$ is the regulatory solvency capital requirement:

$$SCR_{nli}(0) = kn_{nli} + (A_{nli,cb}(0) + A_{nli,eq}(0) + O_{nli})km_{nli},$$

while $A_{nli,eq}$ and $A_{nli,cb}$ are the total portfolio holdings of equities and corporate bonds. This would imply that non unit-linked insurers will only liquidate these assets but not government bonds. Meanwhile, kn_{nli} and km_{nli} are the capital charges for non- and market risks.

Following the Solvency II regulation,[3] non unit-linked insurers are reasonably well hedged in general. For example, when non unit-linked insurers sell corporate bonds, they will also lose some of the hedging benefits (or matching adjustment) in their balance sheet. This means that they would see a decrease in their liabilities, and consequently an increase in their equity and solvency ratio.

We therefore assume that non unit-linked insurers attempt to maximise the value of their equity. To this end, the total assets that they would sell are computed using a measure of post-shock elasticity that is collected by the Prudential Regulatory Authority (PRA). Suppose that $E\prime^{1}_{nli}$ is the new equity, and $SR\prime^{1}_{nli}$ is the new solvency ratio that are computed using the elasticity measure. As we assume that non unit-linked insurers target their solvency ratio: SR^{0}_{nli}, the amount of SCR_{nli} that the insurer needs to reduce can be computed as:

$$\Delta SCR_{nli}(1) = E\prime_{nli}(1)\left(\frac{SR_{nli}(0) - SR\prime_{nli}(1)}{SR_{nli}(0) \times SR\prime_{nli}(1)}\right).$$

[3] https://www.bankofengland.co.uk/prudential-regulation/key-initiatives/solvency-ii

The total risky assets that the insurer sells it therefore:

$$\Pi_{nli} = \frac{\Delta SCR_n li(1)}{km_{nli}}.$$

Non-unit linked insurers come in two types: annuity writers and with-profit insurers. The effect of shocks depends how well matched or hedged the liabilities are:

- Annuity writers benefit from falls in liability values when corporate bonds fall in value, where this is not caused by defaults or downgrades to below investment grade. Decreases in corporate bond value increase the yield, a part of which is used to discount liabilities (hence liabilities fall in value). Regulation incentivises annuity writers to match asset and liability cash flows, so they should not be fully exposed to falls in corporate bond values, unless the insurers default.

- With-profits writers share the benefits/losses of asset falls with policyholders. If insurers have given policyholders guarantees, then they can be hurt by falls in asset values if they are not hedged.

In order to increase the quality of our loss estimates, we needed to take into consideration how insurance liabilities are expected to change after a shock. We have therefore used post-shock elasticities that describe the sensitivity of each insurance liability side of the balance sheet to changes in the value of the insurer's asset portfolio and changes in interest rates. By elasticities we mean estimates of how a given percentage change in the value of the insurer's assets, or given percentage change in interest rates, results in a consequent percentage change in the value of each insurance liability. We assume the shocks, or changes in the stochastic processes, can be translated into asset, liability, eligible own funds and SCR changes using constant elasticities. The elasticities are calculated using returns from the PRA market risk sensitivities data collection.

3.2.3 Liquidation strategy

Once the total amount to be liquidated has been computed, different liquidation strategies could be used. In what follows, we consider two scenarios. The first one is the pro-rata liquidation, where banks maintain their portfolio weights constant over time. The second scenario is the waterfall liquidation, where banks liquidate assets in order of their liquidity starting from the most liquid ones. We illustrate the comparison between these two approaches in Figure 6.

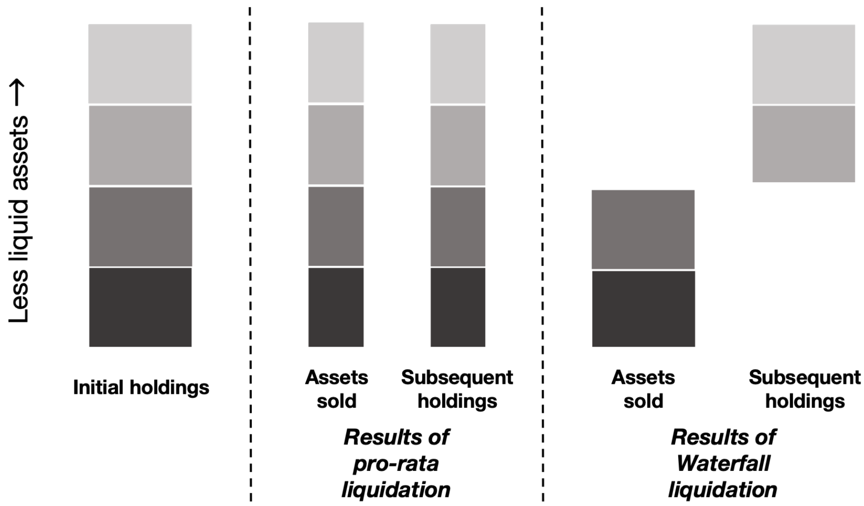


Figure 6: Illustration of pro-rata and waterfall assets liquidations.

Jiang et al. (2017) and Schaanning (2016) suggested that the pro-rata approach is more favourable for institutions during distress. This is based on the idea that institutions wish to preserve the liquidity of their portfolios. When a fund may face significant redemption pressures, if highly liquid assets are sold first, to meet redemptions requests, the remaining investors would be harmed if the fund is left with disproportionate exposure to illiquid assets. This practice could feed first mover advantages and incentivize investors to further increase redemption pressures. For this reason, Financial Conduct Authority (2016); International Organization of Securities Commissions (2018); Bank of England (2019a) recommended that divestments should ideally be performed according a pro-rate liquidation strategy aimed at keeping the fund liquidity risk profile unchanged. However, there are also some complexities around implementing such a pro-rata liquidation since it is not for granted that all assets are fungible, or transactions costs may be so high as to be to the detriment of remaining investors. subsubsection 5.2.2 provides an analysis of the vulnerability of different firms to different liquidation strategies.

Suppose that π_{ij} is the amount of asset j that institution i chooses to liquidate. In the case of pro-rata, we would have:

$$\pi_{ij} = \frac{w_{ij}(1)}{A_i(1)} \Pi_i, \quad \forall j.$$

In the case of waterfall liquidation, we assume that i liquidates its assets sequentially according the following order:

$$\text{sort}\left\{\delta_1 \geq \cdots \geq \delta_M\right\},$$

where δ_j is the market depth of asset j, that is the measure of j's liquidity to sustain relatively large transactions without impacting its price. This liquidation approach is supported by Chernenko and Sunderam (2016), who provide empirical evidence that funds use holdings cash, rather than transacting in equities and bonds, to meet investor redemptions.

3.2.4 Price impact

Assets liquidations will generate price impact. Let β_j be the total amount of asset j that has been liquidated across all institutions, that is:

$$\beta_j = \sum_i \pi_{ij}.$$

Suppose S_j is the price of asset j and $\frac{\Delta S_j}{S_j}$ is the relative price change for j. For a given value of β_j, we assume that:

$$\frac{\Delta S_j}{S_j} = -\Psi_j(\beta_j),$$

where Ψ_j is the price impact function of asset j. In particular, we consider the price impact function of Cont and Wagalath (2016)[4]:

$$\Psi_j(\Pi_j) = 0.5 \times \left(1 - \exp\left(-\frac{\beta_j}{0.5 \times \delta_j}\right)\right),$$

where δ_j is the market depth of asset j. In Figure 7, we illustrate this function as a function of $\frac{\beta}{\delta}$. As shown in the figure, this function is increasing, concave, and it leads to non-negative prices. We also note that the function is compatible with a linear specification for small volumes of liquidation. Additionally, the function assumes that the relative price change may not fall below 50%.

3.2.5 Measuring fire sale spillovers

Following Greenwood et al. (2015) and Fricke and Fricke (2020), we monitor two different measures to quantify the effect of fire sales. Firstly, we look at the *aggregate fire sale*

[4]We note that finding a correct form of price impact function is an active field of literature. We refer the interested reader to Cont and Wagalath (2016)

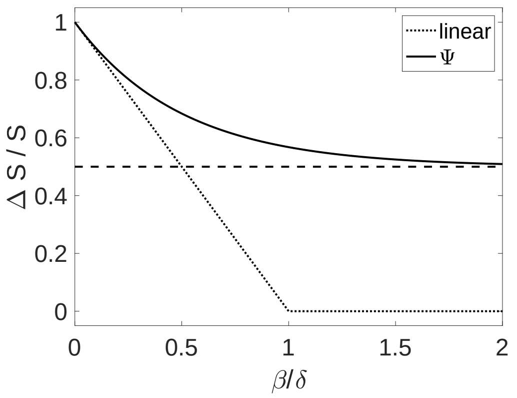


Figure 7: Price impact.

losses that we define as:

$$R^{\text{firesales}} = \sum_i \sum_j (w_{ij}(1) - \pi_{ij}) \times \Psi_j(\beta_j). \tag{8}$$

It is important to note that this formula only accounts for spillover losses and ignores losses that are incurred from initial shocks (previously defined as direct losses in Equation 7).

Secondly, we look at the *indirect vulnerability* of institution i, which is the spillover effect that i would receive, assuming it does not liquidate any of its assets, because other institutions liquidate their assets. Formally, we define the indirect vulnerability as follows:

$$R_i^{\text{vulnerability}} = \sum_j (w_{ij}(1) - \pi_{ij}) \times \Psi_j(\beta_j) \quad \text{where} \quad \pi_{ij} = 0 \quad \text{and} \quad \pi_{kj,k \neq i} \geq 0. \tag{9}$$

Finally, in line with this definition at institution level, we can then aggregate the indirect vulnerability measures for each sector.

4 Data and experimental setup

In this paper, we use granular equity and debt security holdings of the seven UK banks[5] that took part in the 2017 annual cyclical scenario, UK open-ended investment funds and

[5] The 2017 stress test covered seven major UK banks and building societies (hereafter 'banks'): Barclays, HSBC, Lloyds Banking Group, Nationwide, The Royal Bank of Scotland Group, Santander UK and Standard Chartered.

UK (both unit-linked and non unit-linked) insurance companies for Q1 2017 reporting period. Each asset in our dataset is identified by an ISIN. Let us start by describing the sources of these datasets. Below we provide details of the three datasets used. Barucca et al. (2020) use a similar type of dataset to perform an extensive study on the network of common asset holdings across financial sectors. Note that they consider an aggregated version of our data, where financial assets are grouped according to their issuers. Furthermore, they look at the network between European investment funds, UK banks and UK insurance companies for Q1 2016 reporting period, while we focus our study on the network between UK domiciled financial institutions for Q1 2017 reporting period.

- Banks: We use proprietary data submitted to the Prudential Regulatory Authority by the seven UK banks that took part in the 2017 annual cyclical stress test. Banks should report the exposure amount in the currency of the security at ISIN level.
- Open-ended investment funds: We extract from Morningstar voluntarily reported data on open-ended investment funds that are domiciled in UK. In particular we use granular data on portfolio holdings that include holding type and unique identifiers such as ISINs. We also use data on total net assets and on the funds' investment profiles.
- Insurance Companies: We sample granular line-by-line asset data from Prudential Regulatory Authority regulated UK insurance companies subject to the Solvency II directive. Our data includes unique identifiers, such as ISINs and LEIs of counterparties, as well as categorisation of assets into 'Complementary Identification Code' types. For the purpose of this analysis we consider both unit-linked and non unit-linked portfolios.[6]

We note that the data described above is non-public. Therefore, we only present results in anonymised or aggregated format.

4.1 Network of common asset holdings

We combine the datasets for different financial sectors and construct a network of common asset holdings. In the following, we describe the properties of the corresponding network. Firstly, we present the summary properties of each financial sector in the network in Table 1. As shown in the table, total holdings in the network amount at £2.04

[6] It is possible for an insurance company to be linked and non unit-linked at the same time and thus be represented by two separate nodes in our analysis.

trillion. Funds account for approximately 40% of the total holdings, which is twice as much as the contribution of banks or insurers. This is due to a large number of funds ($n = 1865$) that exist in the network. In fact, as shown in the table, the average size of each fund is relatively small. For instance, funds' average strength is only £0.43 billion, much smaller than the average strength of banks (£60.04 billion). The same is true also for the their average connectivity, as shown by the average degrees reported in Table 1. Overall, we find that the network is very sparse, with a density of only 0.30%.

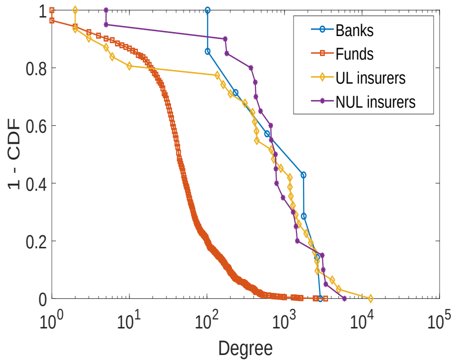
Data for Q1 2017	Banks	Funds	ULI	NLI	All firms
Number of entity	7	1865	31	20	1923
Total holdings	420.27	805.15	461.14	356.58	2043.10
Average strength	60.04	0.43	14.88	17.83	1.06
Average degree	1427	88	1499	1321	127
Density (%)	3.35	0.20	3.52	3.10	0.30

Table 1: Summary properties of each **financial sector** in the network of common asset holdings. NLI refers to non, while ULI corresponds to unit-linked insurance companies. Average strength and total holdings are presented in £bn.

We present the summary properties of each asset class in Table 2. As shown in the table, there are 42611 assets in total, each of them belonging to a particular asset class: equities, corporate bonds or government bonds. In term of the size, equities are the largest asset class in the network, accounting for up to 50% of all assets in the network. We observe that the average strength (average degree) of government bonds is the largest (smallest) compared to other sectors. This implies that the individual investment in government bonds is relatively high compared to that in equities and corporate bonds. In addition to these aggregate summary properties, we also plot the *degree distribution* of each institution and each asset in Figure 8. From the figure, we observe the variability of degree distributions among institutions and assets.

Data for Q1 2017	Equities	Corp bonds	Gov bonds	All assets
Number of entity	19847	17103	5661	42611
Total shares	1060.80	413.70	568.61	2043.10
Average strength	53.45	24.19	100.44	47.95
Average degree	8.05	3.80	3.52	5.74
Density (%)	0.42	0.20	0.52	0.00

Table 2: Summary properties of each **assets class** in the network of common asset holdings. ULI corresponds to unit-linked, while NLI to non unit-linked insurance companies. Average strength and total holdings are presented in £bn.



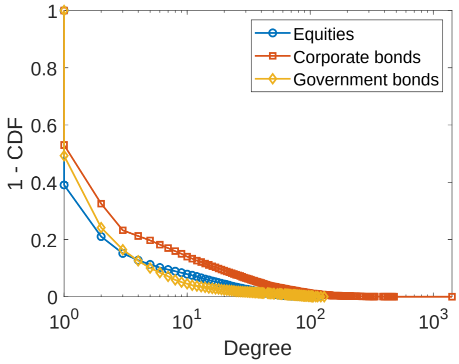


Figure 8: Degree distribution of each financial institution (left) and each financial asset (right).

Finally, we present the portfolio holdings of each financial sector across different asset classes in Table 3. Overall, we find that the relative portfolio composition varies across sectors. As shown in the table, most of the portfolio holdings of banks and non unit-linked insurers consists of bonds, while funds and unit-linked insurers hold mostly equities. This composition results in the variation of relative losses that each sector may receive following an initial shock to a particular asset class.

	All assets	Equities	Corp bonds	Gov bonds
Banks	420.27	33.56	85.37	301.34
Funds	805.15	649.48	93.38	62.29
ULI	461.14	318.98	48.26	93.90
NLI	356.58	58.81	186.68	111.09
All sectors	2043.10	1060.80	413.70	568.61

Table 3: Aggregate total holdings (in £bn) for each financial sector across different asset classes.

4.2 Portfolio similarity

We first discuss the average portfolio similarity across different pairs of institutions in specific sectors. We present the values in Table 4 and Table 5, for the binary and weighted measure respectively. First and foremost, we find that there are portfolios similarities across the different sectors. Moreover, with the exception of the binary similarity across funds, we find that the portfolio similarities across the same sector are higher compared to those across the different sectors. Additionally, we observe that the binary and weighted measure may produce different results. For example, Table 4 shows that the result across non unit-linked insurers is higher compared to that across banks, suggesting that non unit-linked insurers have a larger number of assets in common. However, Table 5 shows that the opposite is true, indicating that banks have more portfolio weight in common.

	Banks	Funds	ULI	NLI
Banks	114.33	4.79	44.70	56.37
Funds		3.50	18.27	14.99
ULI			180.81	160.69
NLI				189.46

Table 4: Average binary portfolio similarity across different sub-networks corresponding to different pairs of sectors in the common asset holdings network.

	Banks	Funds	ULI	NLI
Banks	0.19	0.02	0.08	0.11
Funds		0.29	0.07	0.03
ULI			0.21	0.11
NLI				0.18

Table 5: Average weighted portfolio similarity across different sub-networks corresponding to different pairs of sectors in the common asset holdings network.

Second, we look at the overall average portfolio similarity across all institutions in the network. In Table 6, we present the results for the binary and weighted measure. We find that institutions have on average 4.42 assets in common, with an average similarity of 28%. We observe however that the pattern of portfolio similarities between institutions is very heterogenous. The number of common assets ranges for instance between 0 and 74.8, while the cosine similarity between the vectors representing portfolio holdings ranges from 0 to 0.52. This reinforces the idea that it is useful to consider granular models, which explicitly take into account the observed heterogeneity, for a better estimation of fire-sale losses.

	Mean	Std	Max	Min
MeanBinSimilarity	4.42	6.41	74.78	0.00
MeanCosSimilarity	0.28	0.20	0.52	0.00

Table 6: Average binary and weighted portfolio similarity over all institutions in the common asset holdings network.

Portfolio similarity across different financial sector at more aggregated level (where assets are grouped according to their issuers) has been previously studied in Barucca et al. (2020). Similar to what we observe from the data, Barucca et al. (2020) also find that similarities across the same sector are higher compared to those across the different sectors. They investigate this observation further by performing community analysis on the data, and they are able to identify the existence of communities containing various types of institutions. This indicates that common asset holdings across the different sector can potentially be a channel of contagion. Finally, they show a negative relationship between the measure of similarity and concentration in equity portfolios.

4.3 Sector-specific constraint

In the following, we describe for each financial institution the constraint that may force them to liquidate their assets during periods of stress. In particular, we present the aggregate statistics of banks' leverage ratios and the calibration of fund-flow performance sensitivity parameters, unit-linked policyholders' switching parameters and non unit-linked capital charge for risky assets. NBFIs face a substantially different regulatory environment compared with banks, all of which only heightens the need of a framework to study how they react to the same shock and how they do affect each other losses.

Banks In Table 7, we present the aggregate statistics of leverage ratio and total assets (including cash reserves, derivatives and interbank assets) of banks in our dataset. As shown in the table, the average leverage ratio of banks in our datasets is 5.13%, which is above the UK minimum leverage requirement (3%).

	Total assets (£bn)	Leverage ratio (%)
Average	803.57	5.13
Std	530.97	0.66
25th percentile	303.00	4.30
Median	677.00	5.20
75th percentile	1207.00	5.70

Table 7: Aggregate statistics of banks' leverage ratio and total assets. Note that total assets here is different to the total portfolio holdings, as it also consists cash reserves, derivatives and interbank assets.

Funds We consider the fund-flow sensitivity parameters across the different categories of funds that have been calibrated previously in Baranova et al. (2017), who have run a panel regression on Morningstar European fund-level monthly data on TNA and Estimated Net Flows from January to September 2016. We present these parameters in Table 8.

Category of funds	Fund-flow sensitivity parameter
Allocation	0.2
Commodities	0.1
Convertibles	0.43
Equity	0.09
Fixed income	0.52

Table 8: Fund-flow sensitivity parameter across different categories of funds, as was previously calibrated in Baranova et al. (2017).

Unit-linked insurers In terms of the sector-specific constraint of unit-linked insurers, we consider an investor switching parameter that has been previously used in Baranova et al. (2019) and is based on the survey Bank of England (2016). In particular, we use $\sigma_{uli} = 0.3$.

Non unit-linked insurers In Table 9, we present the aggregate statistics of equity capital and solvency capital requirement (SCR) of non unit-linked insurers in our dataset. Moreover, we calibrate the average capital charge on risky assets as in Aikman et al. (2019), who assume that the capital charge for risky assets is 50% of total capital requirement, i.e. $km_{nli} = 0.5$.

	Equity capital (£bn)	SCR (£bn)
Average	5.72	3.43
Std	5.92	3.07
25th percentile	1.98	1.35
Median	3.60	2.66
75th percentile	7.90	3.97

Table 9: Aggregate statistics of non unit-linked insurers' equity capital and solvency capital requirement (SCR).

4.4 Initial shocks

We consider two types of initial shock: 1) idiosyncratic shock on each or all asset classes, and 2) regulatory stress test scenario. The latter includes the Comprehensive Capital Analysis and Review (CCAR) stress test scenario of the Federal Reserve Board 2017, and the Bank of England ACS scenario in 2017. Both regulatory scenarios provide the percentage change of each asset class across different jurisdictions. The CCAR scenario covers a broader range of jurisdictions, as it includes 80.6% of assets in our dataset.

Meanwhile, the Bank of England scenario includes 74.8% of assets in our dataset, and it focuses on more liquid markets.

Note that the shock of an equity asset in both regulatory scenarios is given in terms of its original price, and therefore can be directly used in our framework. However, the shock of a corporate and government bond is provided in terms of its original yield, and therefore needs to be converted. Suppose dy is a change in the bond yield, the percentage change in its price (dp/p) can be computed as:

$$\frac{dp}{p} = -D \, * \, dy \, , \tag{10}$$

where D is the modified duration of the bond, that is the measure of its price sensitivity to changes in its yield to maturity.[7]

4.5 Market depths

Table 10 summarised the market depth values that were previously calibrated at asset class level for Q1 2016 reporting period in Barucca et al. (2020).[8] We scale these values to obtain the market depths at individual instrument level.

Asset class	Market depth (£bn)
Equities	338.75
Corporate bonds	55.46
Government bonds	338.75

Table 10: Market depth at asset class level for Q1 2016 reporting period that was previously in Barucca et al. (2020).

Suppose δ_J is the market depth of asset class J and S_J^A is the total shares of asset class J held in the network. Let j be an instrument that belongs to class J with the total shares equal to S_j^A. The market depth of instrument j can be calculated as:

$$\delta_j = \frac{S_j^A}{S_J^A} \delta_J . \tag{11}$$

By doing such rescaling, we are assuming that an asset with a larger (smaller) value of total shares will have a larger (smaller) value of market depth, therefore the asset is more liquid (illiquid). For example, we see from Table 10 that the market depth of

[7] The formulae give the change in value of a bond with respect to yield.

[8] To compute the market depth, Barucca et al. (2020) use the method considered Cont and Schaanning (2017) which takes into account asset's volatility and traded volume.

equities is £338.75bn, i.e. δ_{EQ} = £338.75bn. Let us suppose there are only two equity assets in our network, eq_1 and eq_2. If the total shares of eq_1 and eq_2 are respectively £10bn and £25bn, i.e. $S^A_{eq_1}$ = £10bn and $S^A_{eq_2}$ = £25bn, we would then have S^A_{EQ} = £10bn + £20bn = £35bn. Therefore, the market depth of eq_1 and eq_2 that we would obtain are respectively δ_{eq_1} = £$\frac{10}{35} \times$ 338bn = £96.57bn and δ_{eq_2} = £$\frac{25}{35} \times$ 338bn = £241.43bn.

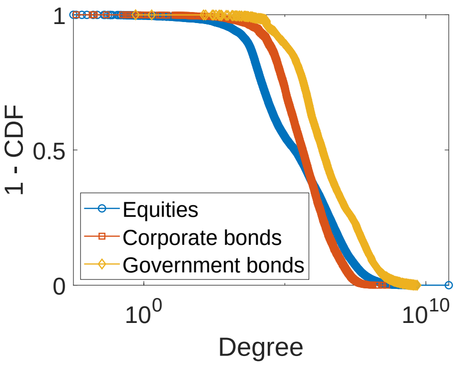
We present the results of such rescaling in Figure 9, where we plot the distribution of the scaled market depth of each asset. The plot shows that some government bonds seem to be more liquid than equities. This is related to the fact that 35.8% of government bonds in our dataset are based in the U.S., and therefore are extremely liquid. The plot also shows that a few corporate bonds are much more liquid than some equities, which is reasonable if the former are based in the advanced economies while the latter are based in the emerging markets.

5 Results

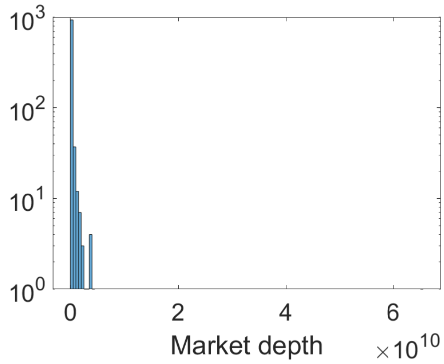
In the following, we present and discuss the results obtained from modelling fire sale contagion across different sectors. In particular, we look at two different measures of systemic losses: (i) aggregate fire sale losses and (ii) institution's (sector's) indirect vulnerability. As explained in subsection 3.2, we consider two types of initial shock: (i) idiosyncratic shock on asset class(es), and (ii) regulatory shock scenarios from the Bank of England and the Federal Reserve Board.

5.1 The importance of considering multiple sectors in the analysis

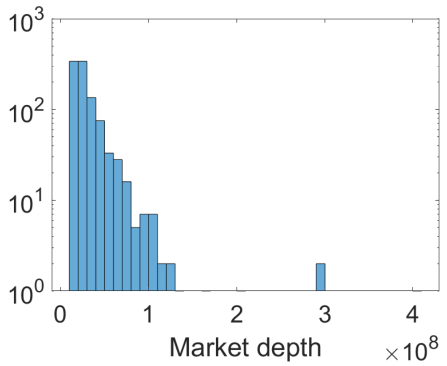
Let us start by discussing the differences between modelling contagion across sectors vs. within each sector separately. Note that the analysis in this section are conducted mainly at an aggregate level. In a later section, we will analyse the results for each institution and sector at an individual level. To obtain the aggregate fire sale losses of the former exercise, we simply run the model on the complete network of common asset holdings that consists of banks, funds and (both unit-linked and non unit-linked) insurance companies. Meanwhile, the results of the latter can be measured by running the model on each sub-network separately, where each sub-network consists only of financial institutions within the same sector. Note that, since we consider here only one round of liquidation, the total liquidated assets in both exercises are exactly the same. The important question is, however, whether the total losses are also identical. In other



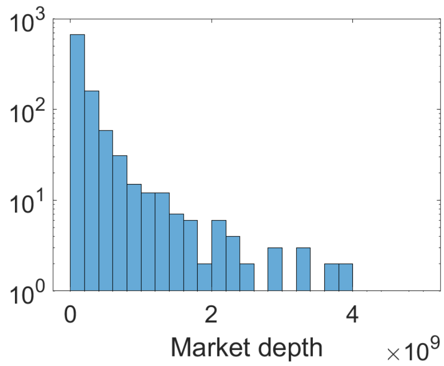
(a) All assets.



(b) Equties.



(c) Corporate bonds.

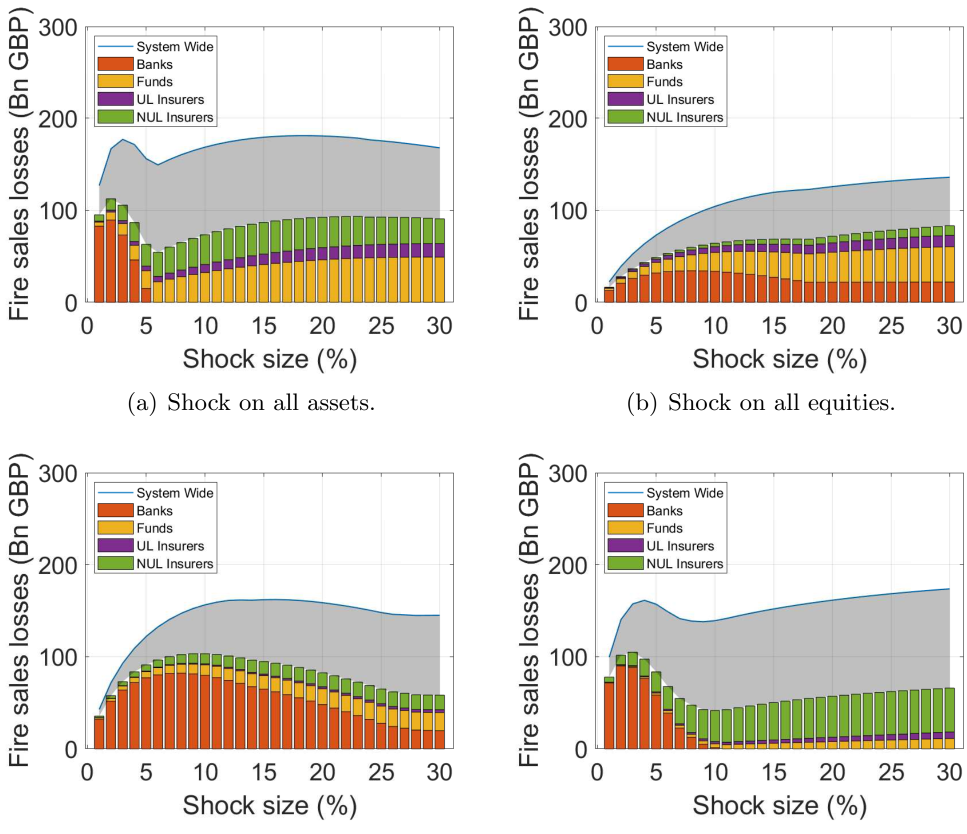


(d) Government bonds.

Figure 9: Distribution of the scaled market depth for each asset Top left: CCDF of the market depth distribution. Top right: histogram of equities, bottom right: government bonds, bottom left: corporate bonds.

words, we want to look at whether the whole is the sum of its part.

Figure 10 shows the results of the two exercises, where we assume that institutions choose to follow a pro-rata liquidation strategy. The stacked bar charts in the figure corresponds to the cumulative results for each sub-network, while the line plot is the results for the complete network. Furthermore, the grey shadow area is the differences between the two exercises, which implies that it represents the amount of losses that is due to the common asset holdings across different sectors.



(a) Shock on all assets.

(b) Shock on all equities.

(c) Shock on all corporate bonds.

(d) Shock on all goverment bonds.

Figure 10: The whole is different to the sum of its part. Stacked bar charts corresponds to the cumulative aggregate fire sale losses from modelling the contagion for each sub-networks separately, where each sub-network consists only of institutions within the same sector. A blue line plot corresponds to results for the complete network, where the network consists of institutions across multiple sectors. The differences between the two results is shown as a grey shadow area. All results are generated by assuming that institutions choose a pro-rata liquidation strategy.

The charts in Figure 10 illustrate that there are large differences between the two results. More importantly, it suggests that ignoring common asset holdings between different financial sectors can result in an underestimation of systemic risk. This occurs because, when we model one sector in isolation and compute its losses, we only account for the asset devaluation that is due to institutions of that sector liquidating their assets. This fails to account for the fact that, when the same assets are held by multiple sectors, different sectors would simultaneously liquidate their portfolios. Accounting for common asset holdings between sectors also allows us to capture the risk associated with "hidden" exposures of a sector to an asset (or asset class) they are not directly exposed to. An example of this situation would be for instance the following: Sector X invests in assets A and B, while sector Y invests in assets B and C. Sector X is not directly exposed to asset C, yet a shock to asset C would also cause a loss to sector X because institutions in Y could liquidate asset B in response to the shock. In Table 11, we compute the averages of the underestimation over different sizes of idiosyncratic shocks ($p_j \in \{0, 0.01, 0.02, ..., 0.3\}$). The table shows that the average systemic risk underestimation is around 47%, and it can reach up to 70%.

Shock on	Mean	Std	Max	Min
All assets	50	8	64	22
Equities	39	5	44	26
Corp. bonds	41	12	60	24
Gov. bonds	60	10	70	40
Total	47	3	70	24

Table 11: The amount of fire sale underestimation (in %) for ignoring the common asset holdings across different sectors. Results are computed over different sizes of idiosyncratic shock ($\theta \in \{0, 0.01, 0.02, ..., 0.3\}$) for shock on different asset class(es).

5.2 A systemic stress simulation of the UK financial system

In the previous section, we conducted stress simulations on UK financial system by applying idiosyncratic shocks on asset class(es) and considering the pro-rata liquidation. We then showed the importance of considering multiple financial sectors in the analysis. In the following, we extend the analysis by taking regulatory stress scenarios and waterfall liquidation into account. In addition to the aggregate fire sale losses, we also look at the indirect vulnerability of each institution (sector). Furthermore, we provide a map to the most systemic and the most vulnerable institutions in the system.

5.2.1 Aggregate fire sale losses

The regulatory stress scenario. We first look at aggregate fire sale losses for the case of regulatory stress scenarios. In particular, we present the results for the Bank of England (BoE) scenario in Table 12, while for the Federal Reserve Board (FRB) CCAR scenario in Table 13. Both tables show that the aggregate fire sale losses are larger than the direct losses. For example, in the case of the BoE scenario, we observe fire sale losses of 5.35% in correspondence to direct losses of 3.63%. Note that the former are losses due to the contagion only, and exclude those resulting from the initial shock.

	Pro-rata liquidation	Waterfall liquidation
Direct losses	3.62% (£74.01 bn)	
Total sales	2.60% (£53.03 bn)	
Fire sale losses	5.35% (£109.31 bn)	3.69% (£75.41 bn)

Table 12: Aggregate direct and fire sale losses for the Bank of England stress scenario.

	Pro-rata liquidation	Waterfall liquidation
Direct losses	3.72% (£76.10 bn)	
Total sales	9.39% (£191.88 bn)	
Fire sale losses	8.66% (£176.86bn)	6.60% (£122.93 bn)

Table 13: Aggregate direct and fire sale losses for the Federal Reserve Board CCAR stress scenario.

Second, we find from Table 12 and Table 13 that the aggregate fire sale losses for the pro-rata liquidation are always larger than those obtained for the waterfall case. For example, the losses for the FRB CCAR scenario is 8.66% for the former, while only 6.60% for the latter. This result is due to the fact that institutions also sell their illiquid assets during the pro-rata liquidation, which then results in a more severe price impact.

Finally, we observe that direct losses for both scenarios are relatively similar, while their fire sale losses are not. For example, the direct losses for the BoE and FRB CCAR scenario are 3.62% and 3.72% respectively, with a difference of only 0.1% (£2 bn) direct losses between the two. Meanwhile, the corresponding fire sale losses for the pro-rata case are 5.35% and 8.66% respectively, with a difference of 3.31% (£67.55 bn) fire sale losses between the two. This result corresponds to the type of assets being shocked in the two scenarios. For example, the fire sale losses is higher for the FRB CCAR case because it covers a larger number of illiquid assets.[9]

[9]See the coverage of each scenario in subsection 4.4.

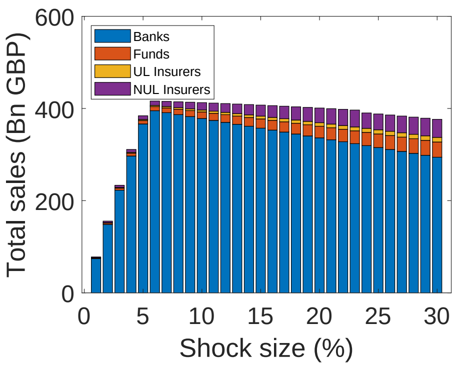
The idiosyncratic stress scenario. The previous finding suggests that fire sale losses do not only depend on the size of the initial shock, but also on the type of assets being shocked. In the following, we discuss the results for the case of idiosyncratic shocks on a particular asset class.

Let us start by looking at the total amount of liquidated assets in Figure 11. The figure shows that the amount varies across different financial sectors and types of shock. For example, banks become the sector that always liquidate the largest amount of assets. This result is due to the sector-specific constraint that was previously described in subsubsection 3.2.2. Banks, for instance, have the strongest constraint since they would need to target their leverage ratio. Moreover, Figure 11 shows that banks liquidate a larger amount of assets when the shock is imposed on bonds compared to when the shock is imposed on equities. This is due to the relative portfolio composition of each sector across different asset classes, as was previously presented in in Table 3. The balance sheet of banks, for instance, consists mostly of government bonds.

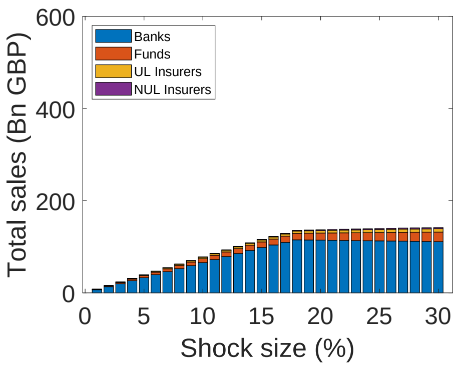
Furthermore, Figure 12 shows the corresponding aggregate fire sale losses, for the pro-rata and waterfall liquidation. For all types of idiosyncratic shocks, we observe from the figure that the losses for the former are always more severe than those for the latter. This finding is consistent with the results for the BoE and FRB CCAR stress scenario reported in Table 12 and Table 13.

We also observe from Figure 12 that equities do not seem to be the main driver of the fire sale losses, although they are representing more than 50% of the assets (see Table 2). The reason for this is because more than 90% of equities in the system are held by funds and unit-linked insurers (see Table 3). These two sectors, contrary to banks and non unit-linked insurers, do not aggressively liquidate their assets during distress as they are not subject to any regulatory constraints as was described above in Figure 11.

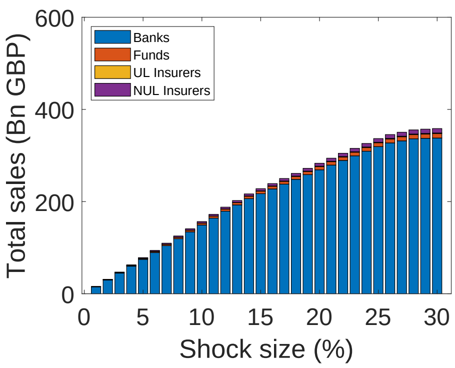
Finally, Figure 12 shows the existence of inverted u-shaped curves, when the shock is imposed on government bonds and all assets. The reason for this behaviour is that the amount that institutions liquidate increases with the size of the shock as long as they have enough assets to liquidate. When institutions run out of assets to liquidate, they do not experience fire sale losses anymore simply because they are left with no available assets to sell. So, as the shock increases, institutions move from a small shock regime where their losses are mostly due to fire sale devaluation to a large shock regime where their losses are dominated by the shock. This is the reason for of the non-monotonicity observed in Figure 12(a) and 12(d).



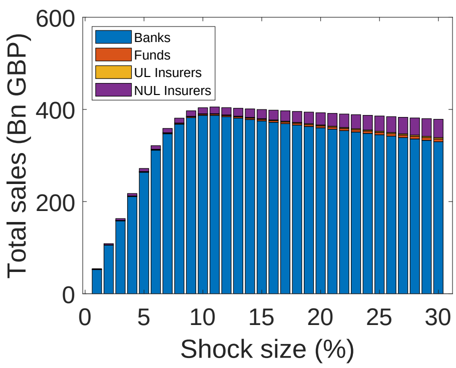
(a) Shock on all assets.



(b) Shock on equities.

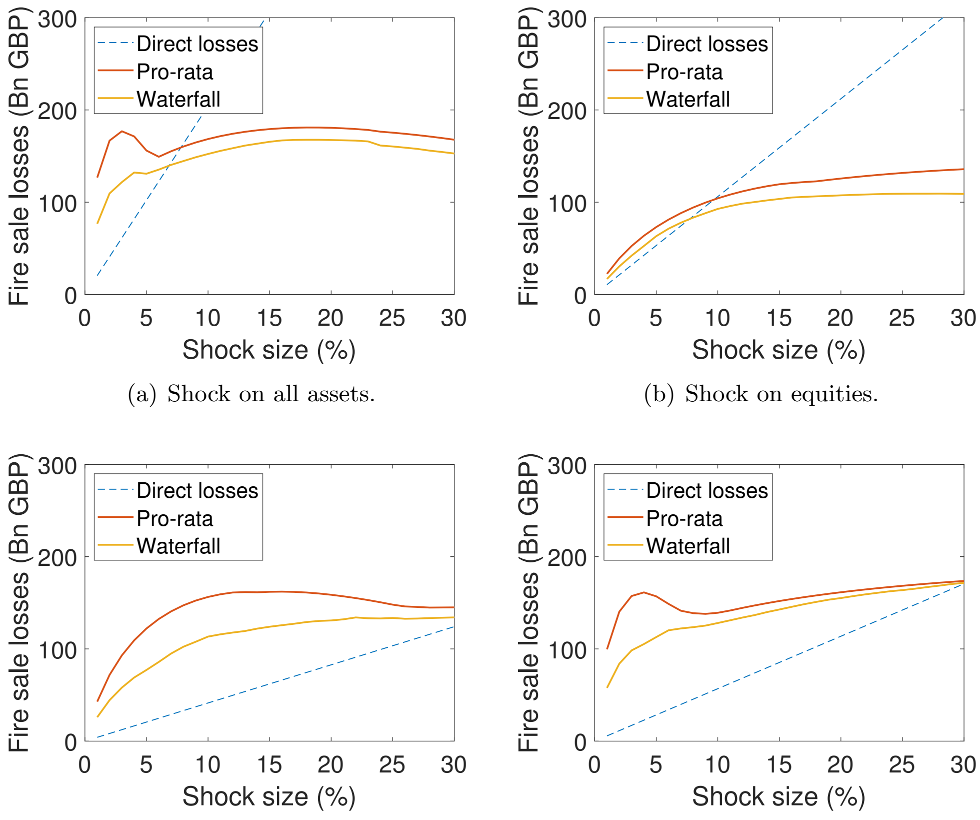


(c) Shock on corporate bonds.



(d) Shock on goverment bonds.

Figure 11: Total volume of liquidated assets across different sectors for different types of idiosyncratic shocks.



(a) Shock on all assets.

(b) Shock on equities.

(c) Shock on corporate bonds.

(d) Shock on government bonds.

Figure 12: Aggregate fire sale losses for different types of idiosyncratic shocks. Red line corresponds to the losses for the pro-rata liquidation, while yellow line refers to those for the waterfall liquidation. Blue dashed-line is the corresponding aggregate direct losses.

5.2.2 Indirect vulnerabilities

Our previous results indicate that the pro-rata liquidation leads to the highest aggregate fire sale losses. In the following, we will discuss whether a similar finding can be also observed for all institutions and sectors at an individual level. In particular, we will compare the indirect vulnerability resulting from the two liquidation approaches. The idea is to measure the spillover effect that one institution (sector) receives because other institutions are liquidating their assets, assuming that specific institution (sector) to be passive.

In Figure 13, we present the indirect vulnerability of each institution when the other institutions follow the pro-rata vs. the waterfall liquidation approach. Each dot in the figure corresponds to the calculation of the vulnerability of one institution. If the pro-rata liquidation is worse than the waterfall liquidation for all firms, then all dots should lie below the black dashed diagonal line. Figure 13 shows that this is not the case. In fact, we observe that several institutions lie above the diagonal line, suggesting that they are more vulnerable when other institutions use the waterfall approach. The figure also illustrates that the systemic risk level of institutions within a same sector can vary, which then indicates the importance of conducting stress tests at an individual level.

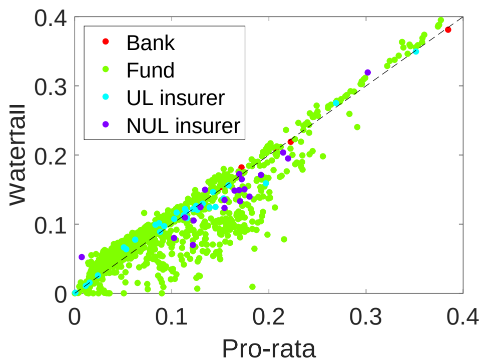


Figure 13: Indirect vulnerability that institutions receive when other institutions consider pro-rata vs. waterfall liquidation approach, for the case of 5% initial shock on all assets (relative to the total assets of the corresponding institution). Each colour in the plot corresponds to the result for different financial sectors. A dot lying above (below) the black diagonal dashed line would imply that the corresponding institution is more vulnerable when other institutions choose the waterfall (pro-rata) approach.

Furthermore, we look at the case of indirect vulnerability for each sector. In particular, we present the results for different types of idiosyncratic shocks in Figure 14 for banks, and in Figure 15 for funds. Both figures again show that banks and funds, in general, are more vulnerable if other sectors use the waterfall liquidation approach.[10] The overall vulnerability of banks is the lowest because other institutions sell fewer assets compared to what banks sell. On the contrary, the overall vulnerability of funds and insurers is significantly higher as banks sell more assets because of their regulatory constrains.

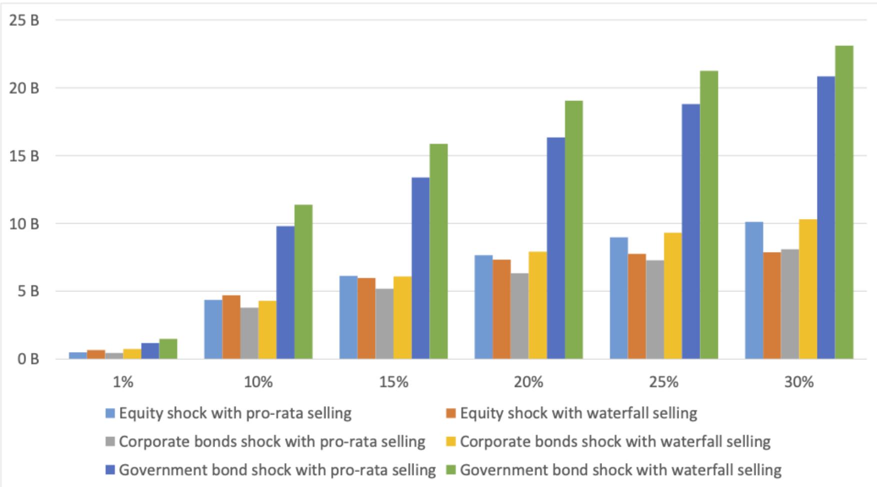


Figure 14: Indirect vulnerability of banks for different types of idiosyncratic shocks, when other sectors follow pro-rata vs. waterfall liquidation.

Overall, we find that the waterfall approach may result in more vulnerable institutions (sectors). The intuition behind this result is the following: the prices of liquid assets will fall harder if all other firms prefer to liquidate their most liquid assets. Additionally, some institution (sectors) may have more liquid assets in common. Therefore, they may be more impacted when other institutions (sectors) prefer to follow the waterfall liquidation approach. This result is also in line with the recent authorities' recommendation to ensures that a fund's portfolio retains the desired level of liquidity following a significant redemption request by using a pro-rata selling strategy, so that remaining fund investors are not left with the illiquid assets (Financial Conduct Authority, 2016; International Organization of Securities Commissions, 2018; Bank of England, 2019a).[11]

[10]We observe a similar finding for the case of both unit-linked and non unit-linked insurance companies. See Figure A.1 and Figure A.2 in Appendix.

[11]This would also remove any investor incentives to redeem early due to fear that the last investors to redeem will be left with the more illiquid assets. In short, they protect against a 'first mover advantage'.

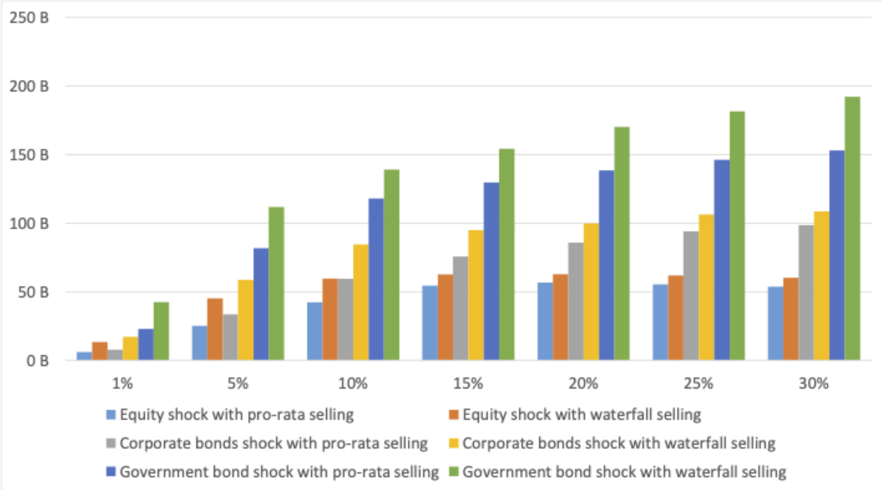


Figure 15: Indirect vulnerability of funds for different types of idiosyncratic shocks, when other sectors follow pro-rata vs. waterfall liquidation.

6 Conclusion

In this paper, we model indirect contagion across UK banks and NBFIs via fire sales of commonly held assets. Our datasets consist of equity and bond portfolios of banks, funds and (both unit-linked and non unit-linked) insurance companies at instrument level. To this end, we assume that each financial sector may be forced to liquidate (parts of) their assets in response to losses incurred in their balance sheets. In particular, banks and non unit-linked insurers are subject to some regulatory constraints, while funds and unit-linked insurers are obliged to meet investor redemptions. Overall, the findings of this paper contribute to a better understanding of the extent to which common asset holdings across different financial sectors become the source of financial instability.

Firstly, we find the importance of considering multiple financial sectors in the analysis. In particular, we show that ignoring the common asset holdings between banks and NBFI sector may lead to a significant underestimation of fire sale losses.

Secondly, we look at the stress simulation results of the UK financial system by looking at the aggregate fire sale losses and the indirect vulnerability of each institution. We conduct the stress simulation under different scenarios of initial shock and liquidation strategies. We find that the results are highly influenced by the regulatory constraints and the portfolio composition of each sector. For example, banks play a very important role in general, mainly because they liquidate a larger amount of assets relatively compared to other sectors. Moreover, we show that the aggregate losses are always higher if the institutions choose to maintain their portfolio weights when liquidating their assets (pro-rata liquidation). However, we also show that an institution (sector) may become more vulnerable if other institutions (sectors) prefer to sell their most liquid assets first (waterfall liquidation).

Our findings suggest several interesting avenues for future research. First, it is important to perform similar analysis on other datasets for different countries and/or different time periods. Additionally, it is useful to incorporate more sectors into the analysis. A natural progression of this work is to study the tradeoff between pro-rata and waterfall liquidation across different sectors.

References

Aikman, D., Chichkanov, P., Douglas, G., Georgiev, Y., Howat, J., and King, B. (2019). System-wide stress simulation. *Bank of England Staff Working Paper No. 809.*

Bank for International Settlements (2020). BIS Quarterly Review: Cross-border links between banks and non-bank financial institutions.

Bank of England (2016). Financial stability report - November.

Bank of England (2019a). Financial Conduct Authority and Bank of England statement on joint review of open-ended funds.

Bank of England (2019b). Financial stability report - July.

Baranova, Y., Coen, J., Lowe, P., Noss, J., and Silvestri, L. (2017). Simulating stress across the financial system: the resilience of corporate bond markets and the role of investment funds. *Bank of England Financial Stability Paper No. 42.*

Baranova, Y., Douglas, G., and Silvestri, L. (2019). Simulating stress in the uk corporate bond market: investor behaviour and asset fire-sales. *Bank of England Staff Working Paper No. 803.*

Barucca, P., Mahmood, T., and Silvestri, L. (2020). Common asset holdings and systemic vulnerability across multiple types of financial institution. *Journal of Financial Stability*, Forthcomin.

Braverman, A. and Minca, A. (2018). Networks of common asset holdings: aggregation and measures of vulnerability. *Journal of Network Theory in Finance*, 4(3):53–78.

Caccioli, F., Barucca, P., and Kobayashi, T. (2018). Network models of financial systemic risk: a review. *Journal of Computational Social Science*, 1:81–114.

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

Caccioli, F., Shrestha, M., Moore, C., and Farmer, J. D. (2014). Stability analysis of financial contagion due to overlapping portfolios. *Journal of Banking & Finance*, 46:233–245.

Cetorelli, N., Duarte, F., and Eisenbach, T. M. (2016). Are asset managers vulnerable to fire sales? *Federal Reserve Bank of New York, Liberty Street Economics.*

Chernenko, S. and Sunderam, A. (2016). Liquidity transformation in asset management: evidence from the cash holdings of mutual funds. *ESRB Working Paper Series No 23.*

Coen, J., Lepore, C., and Schaanning, E. (2019). Taking regulation seriously: fire sales under solvency and liquidity constraints. *Staff Working Paper No. 793.*

Cont, R. and Schaanning, E. (2017). Fire sales, indirect contagion and systemic stress testing. *Norges Bank Working Paper*, 2.

Cont, R. and Wagalath, L. (2016). Fire sales forensics: measuring endogeneous risk. *Mathematical Finance*, 26(4):835–866.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512.

Czech, R. and Roberts-Sklar, M. (2019). Investor behaviour and reaching for yield: evidence from the sterling corporate bond market. *Financial Markets, Institutions and Instruments*, 28(5):347–379.

Delpini, D., Battiston, S., Caldarelliid, G., and Riccaboni, M. (2019). Systemic risk from investment similarities. *PLoS ONE*, 14(5).

Douglas, G., Noss, J., and Vause, N. (2017). The impact of solvency ii regulations on life insurers' investment behaviour. *Bank of England Staff Working Paper No. 664.*

Duarte, F. and Eisenbach, T. M. (2015). Fire-sale spillovers and systemic risk. *Federal Reserve Bank of New York Staff Reports No. 645.*

Ellul, A., Jotikasthira, C., and Lundblad, C. T. (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, 101:596–620.

European Central Bank (2014). Structural and systemic risk features of euro area investment funds. *Financial Stability Review.*

Farmer, J. D., Kleinnijenhuis, A. M., Nahai-Williamson, P., and Wetzer, T. (2020). Foundations of system-wide financial stress testing with heterogeneous institutions. *Bank of England Staff Working Paper No. 861.*

Financial Conduct Authority (2016). Liquidity management for investment firms: good practice.

Fricke, C. and Fricke, D. (2020). Vulnerable asset management? the case of mutual funds. *Journal of Financial Stability*, Forthcomin.

Fricke, D. (2019). Are specialist funds "special"? *Financial Management*, 48(2):441–472.

Georg, C.-P., Pierret, D., and Steffen, S. (2019). Similar investors. *SSRN Electronic Journal.*

Girardi, G., Hanley, K. W., Nikolova, S., Pelizzon, L., and Getmansky Sherman, M. (2018). Portfolio similarity and asset liquidation in the insurance industry. *SAFE Working Paper No. 224.*

Glasserman, P. and Young, H. P. (2016). Contagion in financial networks. *Journal of Economic Literature*, 54(3):779–831.

Greenwood, R., Landier, A., and Thesmar, D. (2015). Vulnerable banks. *Journal of Financial Economics*, 115(3):471–485.

Huang, X., Vodenska, I., Havlin, S., and Stanley, H. E. (2013). Cascading failures in bi-partite graphs: model for systemic risk propagation. *Scientific Reports*, 3(1219).

International Monetary Fund (2015). Global financial stability review. *Technical report.*

International Organization of Securities Commissions (2018). Open-ended Fund Liquidity and Risk Management: Good Practices and Issues for Consideration.

Jiang, H., Li, D., and Wang, A. W. (2017). Dynamic liquidity management by corporate bond mutual funds. *Available at SSRN: https://ssrn.com/abstract=2776829.*

Khandani, A. and Lo, A. (2011). What happened to the quants in august 2007? evidence from factors and transactions data. *Journal of Financial Markets*, 14(1):1–46.

Poledna, S., Martínez-Jaramillo, S., Caccioli, F., and Thurner, S. (2018). Quantification of systemic risk from overlapping portfolios in the financial system. *arXiv:1802.0031.*

Pulvino, T. C. (1998). Do asset fire sales exist? an empirical investigation of commercial aircraft transactions. *Journal of Finance*, 53(3):939–978.

Ramadiah, A., Caccioli, F., and Fricke, D. (2020). Reconstructing and stress testing credit networks. *Journal of Economic Dynamics and Control*, 111.

Schaanning, E. F. (2016). Fire sales and systemic risk in financial networks. *PhD thesis, Imperial College London.*

Shleifer, A. and Vishny, R. (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives*, 25(1):29–48.

A Appendix: Indirect vulnerability of unit-linked and non unit-linked insurers

In the main text, we have discussed the indirect vulnerability resulting from the pro-rata vs. waterfall liquidation approach, for the case of banks and funds. For what follows, we present the similar results, for the case of unit-linked and non unit-linked insurance companies.

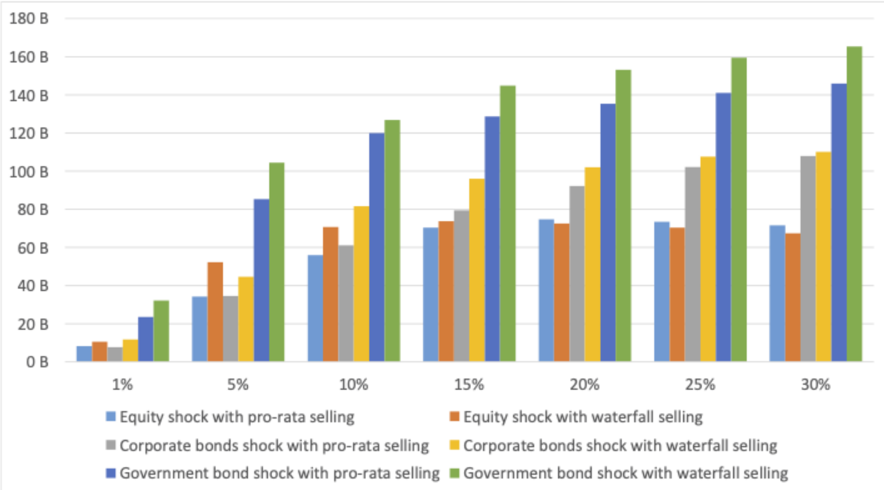


Figure A.1: Indirect vulnerability of unit-linked insurers for different types of idiosyncratic shocks, when other sectors follow pro-rata vs. waterfall liquidation.

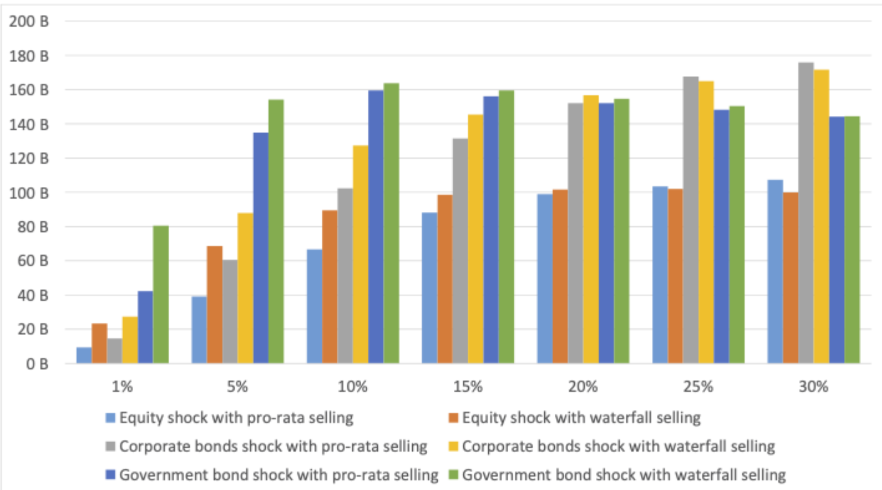


Figure A.2: Indirect vulnerability of non unit-linked insurers for different types of idiosyncratic shocks, when other sectors follow pro-rata vs. waterfall liquidation.