Staff Working Paper No. 878
Modelling fire sale contagion across banks and non-banks
Fabio Caccioli, Gerardo Ferrara and Amanah Ramadiah

July 2020
Abstract

We study the impact of common asset holdings across different financial sectors on financial stability. In particular, we model indirect contagion via fire sales across UK banks and non-banks. Fire sales are triggered by different responses to a financial shock: banks and non-unit-linked insurers are subject to regulatory constraints, while funds and unit-linked insurers are obliged to meet investor redemptions. We use our model to conduct a systemic stress simulation under different initial shock scenarios and institutions' selling strategies. 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.

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

JEL classification: G20, G21, G22, G23.
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 (2008); 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-banks (or more accurately non-bank financial intermediaries) on financial stability (European Central Bank (2014); International Monetary Fund (2015); Bank of England (2019); Financial Stability Board (2010)). This is mainly caused by a significant growth of the asset management sector in term of its size and importance. For example, the contribution of non-bank institutions 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).

In this paper, we study the extent to which common asset holdings across different financial sectors become the source of financial instability. In particular, we look at common asset holdings between UK banks, UK open-ended investment funds, and UK (unit-linked and non unit-linked) insurance companies. Our dataset consists of portfolio holdings of marketable assets such as equities and debt securities (corporate and government bonds) at ISIN level for the period Q1 2017. The equities and debt securities coverage accounts for 50.5% activity of the UK open-ended funds, 80% activity of the UK banks’ regulated by the Prudential Regulation Authority (PRA), and 84.6% activity of the UK insurance companies.

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 portfolios 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 (2017), we look at three different measures of systemic losses: (i) fire sale losses of the system, (ii) indirect vulnerability and (iii) systemicness of each institution and/or sector. Lastly, we explore the effectiveness of network measures in explaining the results of different stress simulations.

Our main contribution to the literature is the quantification of systemic risk using granular data of portfolio holdings of banks and non-banks. Our main findings are the following: first, we show the importance of considering multiple financial sectors in the analysis of systemic risk. 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 non-banks 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. However, we note that the waterfall liquidation may produce a higher spillover effect (indirect vulnerability) for an institution or a sector that chooses not to liquidate any of its assets during distress. Finally, we explore the effectiveness of network measures to explain the results of different stress simulations, and we find that portfolio similarity measures are useful to explain the variability in the stress simulation results.

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) 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.
assume that banks actively target their leverage ratio. Additionally, Coen et al. (2019) consider the case where banks are constrained by leverage, risk-weighted capital and liquidity regulations. Recently, the quantification of systemic risk in non-banking sectors has gained interest in the literature. For example, Cetorelli et al. (2016), Fricke and Fricke (2017) 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.

Our paper is also related to the literature on systemic risk across multiple contagion channel. 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 the similar interaction for the case of Austrian and Mexican banks. In this paper, we focus mainly on indirect contagion channel and, therefore, 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).

We also note another part in the literature that focuses on modelling system-wide fire sales across different sectors. For example, Aikman et al. (2019) and Baranova et al. (2019) simulate fire sales spillover between banks and non-banks using a general or a partial equilibrium, where they explicitly model the role of 'buy-side' investor. Our paper is different in that we look at empirical common asset holdings across different sectors. We also note that we do not explicitly model the role of 'buy-side' investor as we estimate the price impact of asset sales using historical data.
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 \( (b_1, \ldots, b_{n_1}) \), funds \( (f_1, \ldots, f_{n_2}) \), unit-linked insurers \( (uli_1, \ldots, uli_{n_3}) \) and non unit-linked insurers \( (nli_1, \ldots, nli_{n_4}) \). We take three different asset classes into account: government bonds \( (gb_1, \ldots, gb_{m_1}) \), corporate bonds \( (cb_1, \ldots, cb_{m_2}) \) and equities \( (eq_1, \ldots, eq_{m_3}) \). Hence, there are in total \( N = n_1 + n_2 + n_3 + n_4 \) financial institutions and \( M = m_1 + m_2 + m_3 \) assets in the network.

We illustrate the stylized network of common asset holdings in Figure 1. This network can be represented as a rectangular matrix \( W \) of size \( (N \times M) \), where each element

![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.](#)
$w_{ij} \geq 0$ corresponds to the sterling amount of asset $j$ owned by institution $i$. 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 $W$, 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:

$$\text{BinSimilarity}_{ik} = \sum_j \bar{w}_{ij} \bar{w}_{kj} \quad \text{(1)}$$

for the binary case, and

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

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 $k$. Matrix $W$ 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:

\[
\text{MeanBinSimilarity}_i = \frac{1}{N - 1} \sum_k \text{BinSimilarity}_{ik}
\] (3)

for the binary similarity case, and

\[
\text{MeanCosSimilarity}_i = \frac{1}{N - 1} \sum_k \text{CosSimilarity}_{ik}
\] (4)

for the weighted one.

3.2 Modelling fire sale contagion across banks and non-banks

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

\[
A_i(0) = \sum_j w_{ij}(0).
\] (5)

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

\[
A_i(1) = \sum_j w_{ij}(0)(1 - \theta_j).
\] (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.](image)

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:

$$\hat{A}_b(0) = A_b(0) + O_b.$$
Following the direct losses that bank $b$ receives (see Equation 7), its leverage ratio at $t = 1$ becomes:

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

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:

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

**Funds**  
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 at 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.](image)

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

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

where $\sigma_f$ 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) observe that some unit-linked policyholders decide to de-risk their investment in response to falling prices of risky assets.

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 $\sigma_{uli}$ 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:

$$SR_{nli}(0) = \frac{E_{nli}(0)}{SCR_{nli}(0)},$$
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\(^2\) 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. Suppose that $E_{nli}^1$ is the new equity, and $SR_{nli}^1$ is the new solvency ratio that are computed using the elasticity measure. As we assume that non unit-linked insurers target their solvency ratio: $SR_{nli}^0$, the amount of $SCR_{nli}$ that the insurer needs to reduce can be computed as:

$$\Delta SCR_{nli}(1) = E_{nli}(1) \left( \frac{SR_{nli}(0) - SR_{nli}^1}{SR_{nli}(0) \times SR_{nli}^1} \right).$$

\(^2\) https://www.bankofengland.co.uk/prudential-regulation/key-initiatives/solvency-ii
The total risky assets that the insurer sells it therefore:

\[ \Pi_{nli} = \frac{\Delta \text{SCR}_{nli}(1)}{km_{nli}}. \]

### 3.2.3 Liquidation strategy

Once the total amount to be liquidated has been computed, different liquidation strategies could be used. In what follows, there are two scenarios that we consider. 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.](image)

Some studies have suggested that the pro-rata approach is more favourable for institutions during distress (Jiang et al. (2017); Schaanning (2016)). This is based on the idea that institutions wish to preserve the liquidity of their portfolios. Suppose that \( \pi_{ij} \) 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:

\[ \text{sort } \{ \delta_1 \geq \cdots \geq \delta_M \}, \]

12
where $\delta_j$ 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 $\beta_j$ 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 $\beta_j$, we assume that:

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

where $\Psi_j$ is the price impact function of asset $j$. In particular, we consider the price impact function of Cont and Wagalath (2016)\(^3\):

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

where $\delta_j$ is the market depth of asset $j$. In Figure 7 we illustrate this function as a function of $\frac{\beta_s}{\delta}$. 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 (2017), we monitor three different measures to quantify the effect of fire sales. Firstly, we look at the aggregate fire sale losses that we define as:

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

\(^3\)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).
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:

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

Finally, we can calculate the marginal contribution of $i$ to the aggregate fire sale losses. Specifically, we assume that $i$ is the only institution that would liquidate its assets. To this end, we define the systemicness of $i$ as:

$$R^\text{systemicness}_i = \sum_i \sum_j (w_{ij}(1) - \pi_{ij}) \times \Psi_j(\beta_j) \quad \text{where} \quad \pi_{ij} \geq 0 \quad \text{and} \quad \pi_{kj,k\neq i} = 0.$$ (10)

In line with these definitions for institutions, we can define aggregate indirect vulnerability and systemicness 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\(^4\) that took part in the 2017 annual cyclical scenario, UK open-ended investment funds and 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.

- **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\(^5\).

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 trillion. Funds account for approximately 40% of the total holdings, which is twice as

\(^4\)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.

\(^5\)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.
much as the contribution of banks or insurers. This is due to the large number of funds ($n = 1865$) existing 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 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%.

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

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. Additionally, 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.

<table>
<thead>
<tr>
<th>Data for Q1 2017</th>
<th>Equities</th>
<th>Corp bonds</th>
<th>Gov bonds</th>
<th>All assets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of entity</td>
<td>19847</td>
<td>17103</td>
<td>5661</td>
<td>42611</td>
</tr>
<tr>
<td>Total shares</td>
<td>1060.80</td>
<td>413.70</td>
<td>568.61</td>
<td>2043.10</td>
</tr>
<tr>
<td>Average strength</td>
<td>53.45</td>
<td>21.49</td>
<td>100.44</td>
<td>47.95</td>
</tr>
<tr>
<td>Average degree</td>
<td>8.05</td>
<td>3.80</td>
<td>3.52</td>
<td>5.74</td>
</tr>
<tr>
<td>Density (%)</td>
<td>0.42</td>
<td>0.20</td>
<td>0.52</td>
<td>0.00</td>
</tr>
</tbody>
</table>

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.
4.2 Holdings across sectors and asset classes

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.

<table>
<thead>
<tr>
<th>All assets</th>
<th>Equities</th>
<th>Corp bonds</th>
<th>Gov bonds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>420.27</td>
<td>33.56</td>
<td>85.37</td>
</tr>
<tr>
<td>Funds</td>
<td>805.15</td>
<td>649.48</td>
<td>93.38</td>
</tr>
<tr>
<td>ULI</td>
<td>461.14</td>
<td>318.98</td>
<td>48.26</td>
</tr>
<tr>
<td>NLI</td>
<td>356.58</td>
<td>58.81</td>
<td>186.68</td>
</tr>
<tr>
<td>All sectors</td>
<td>2043.10</td>
<td>1060.80</td>
<td>413.70</td>
</tr>
</tbody>
</table>

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

4.3 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.

<table>
<thead>
<tr>
<th></th>
<th>Banks</th>
<th>Funds</th>
<th>ULI</th>
<th>NLI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>114.33</td>
<td>4.79</td>
<td>44.70</td>
<td>56.37</td>
</tr>
<tr>
<td>Funds</td>
<td>3.50</td>
<td>18.27</td>
<td>14.99</td>
<td></td>
</tr>
<tr>
<td>ULI</td>
<td>180.81</td>
<td></td>
<td>160.69</td>
<td></td>
</tr>
<tr>
<td>NLI</td>
<td></td>
<td></td>
<td>189.46</td>
<td></td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Banks</th>
<th>Funds</th>
<th>ULI</th>
<th>NLI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banks</td>
<td>0.19</td>
<td>0.02</td>
<td>0.08</td>
<td>0.11</td>
</tr>
<tr>
<td>Funds</td>
<td>0.29</td>
<td>0.07</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td>ULI</td>
<td>0.21</td>
<td>0.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NLI</td>
<td>0.18</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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. In average, we find that institutions have on average 4.42 assets in common, with an average similarity of 28% in their portfolio weights.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>MeanBinSimilarity</td>
<td>4.42</td>
<td>6.41</td>
<td>74.78</td>
<td>0.00</td>
</tr>
<tr>
<td>MeanCosSimilarity</td>
<td>0.28</td>
<td>0.20</td>
<td>0.52</td>
<td>0.00</td>
</tr>
</tbody>
</table>

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

4.4 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.

**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%).

<table>
<thead>
<tr>
<th>Total assets (£bn)</th>
<th>Leverage ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>803.57</td>
</tr>
<tr>
<td>Std</td>
<td>530.97</td>
</tr>
<tr>
<td>25th percentile</td>
<td>303.00</td>
</tr>
<tr>
<td>Median</td>
<td>677.00</td>
</tr>
<tr>
<td>75th percentile</td>
<td>1207.00</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th>Category of funds</th>
<th>Fund-flow sensitivity parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Allocation</td>
<td>0.2</td>
</tr>
<tr>
<td>Commodities</td>
<td>0.1</td>
</tr>
<tr>
<td>Convertibles</td>
<td>0.43</td>
</tr>
<tr>
<td>Equity</td>
<td>0.09</td>
</tr>
<tr>
<td>Fixed income</td>
<td>0.52</td>
</tr>
</tbody>
</table>

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. $km_{nli} = 0.5$.

<table>
<thead>
<tr>
<th></th>
<th>Equity capital (£bn)</th>
<th>SCR (£bn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>5.72</td>
<td>3.43</td>
</tr>
<tr>
<td>Std</td>
<td>5.92</td>
<td>3.07</td>
</tr>
<tr>
<td>25th percentile</td>
<td>1.98</td>
<td>1.35</td>
</tr>
<tr>
<td>Median</td>
<td>3.60</td>
<td>2.66</td>
</tr>
<tr>
<td>75th percentile</td>
<td>7.90</td>
<td>3.97</td>
</tr>
</tbody>
</table>

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

4.5 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 include 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 used straightforward in our framework. However, the shock of a corporate and government bond is provided in terms of its original yield, and therefore need to be converted. Suppose $dy$ is a change in the bond yield, the percentage change in its price ($dp/p$) can be computed as:

$$\frac{dp}{p} = -D \ast dy,$$

where $D$ is the modified duration of the bond, that is the measure of its price sensitivity to changes in its yield to maturity.\(^6\)

\(^6\)The formulae give the change in value of a bond with respect to yield.
4.6 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). We scale these values to obtain the market depths at individual instrument level.

<table>
<thead>
<tr>
<th>Asset class</th>
<th>Market depth (£bn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equities</td>
<td>338.75</td>
</tr>
<tr>
<td>Corporate bonds</td>
<td>55.46</td>
</tr>
<tr>
<td>Government bonds</td>
<td>338.75</td>
</tr>
</tbody>
</table>

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

Suppose $\delta_J$ 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:

$$\delta_j = \frac{S_j^A}{S_J^A} \delta_J.$$  \hspace{1cm} (12)

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 equities is £338.75bn, i.e. $\delta_{EQ} = £338.75bn$. Let 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. $S_{eq_1}^A = £10bn$ and $S_{eq_2}^A = £25bn$, we would then have $S_{EQ}^A = £10bn + £20bn = £35bn$. Therefore, the market depth of $eq_1$ and $eq_2$ that we would obtain are respectively $\delta_{eq_1} = \frac{£10}{£35} \times 338bn = £96.57bn$ and $\delta_{eq_2} = \frac{£25}{£35} \times 338bn = £241.43bn$.

We present the results of such rescaling in Figure 9, where we plot the distribution of the scaled market depth of each asset. Surprisingly, some government bonds seem more liquid than equities within our dataset. However, we should keep under consideration that 35.8% of our government bond are based in US, and they are extremely liquid. Additionally, we should also keep in mind that a few corporate bonds from advanced economies are much more liquid than some equities from emerging economies.
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.
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 three different measures of systemic losses: (i) aggregate fire sale losses, (ii) institution’s (sector’s) indirect vulnerability, and (iii) institution’s (sector’s) systemicness. 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. 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 the total liquidated assets in both exercise are exactly the same. The important question is, however, whether the total losses are also identical. In other words, we want to look at whether the whole is the sum of its part.

Figure 10 shows the results of the two exercises. 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.

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
Figure 10: The whole is different to the sum of its part. Stacked bar charts correspond 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.
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%.

<table>
<thead>
<tr>
<th>Shock on</th>
<th>Mean</th>
<th>Std</th>
<th>Max</th>
<th>Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>All assets</td>
<td>50</td>
<td>8</td>
<td>64</td>
<td>22</td>
</tr>
<tr>
<td>Equities</td>
<td>39</td>
<td>5</td>
<td>44</td>
<td>26</td>
</tr>
<tr>
<td>Corp. bonds</td>
<td>41</td>
<td>12</td>
<td>60</td>
<td>24</td>
</tr>
<tr>
<td>Gov. bonds</td>
<td>60</td>
<td>10</td>
<td>70</td>
<td>40</td>
</tr>
<tr>
<td>Total</td>
<td>47</td>
<td>3</td>
<td>70</td>
<td>24</td>
</tr>
</tbody>
</table>

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 and systemicness 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 the fire sale losses of 5.35% in correspondence to the direct losses of 3.63%. Note that the former is losses due to the contagion only, and exclude those resulted from the initial shock.

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
<table>
<thead>
<tr>
<th></th>
<th>Pro-rata liquidation</th>
<th>Waterfall liquidation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct losses</td>
<td>3.62% (£74.01 bn)</td>
<td>3.69% (£75.41 bn)</td>
</tr>
<tr>
<td>Total sales</td>
<td>2.60% (£53.03 bn)</td>
<td>3.09% (£56.93 bn)</td>
</tr>
<tr>
<td>Fire sale losses</td>
<td>5.35% (£109.31 bn)</td>
<td>3.69% (£119.51 bn)</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Pro-rata liquidation</th>
<th>Waterfall liquidation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct losses</td>
<td>3.72% (£76.10 bn)</td>
<td>3.58% (£75.92 bn)</td>
</tr>
<tr>
<td>Total sales</td>
<td>9.39% (£191.88 bn)</td>
<td>9.15% (£189.57 bn)</td>
</tr>
<tr>
<td>Fire sale losses</td>
<td>8.66% (£176.86 bn)</td>
<td>6.60% (£122.93 bn)</td>
</tr>
</tbody>
</table>

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

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.  

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’s 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 subsection 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.

\(^{7}\)See the coverage of each scenario in subsection 4.5.
across different asset classes, as was previously presented in Table 3. The balance sheet of banks, for instance, consists mostly of government bonds.

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

Furthermore, Figure 12 shows the corresponding aggregate fire sale losses, for the pro-rata and waterfall liquidation. Interestingly, the figure 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 this happens, some institutions 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 the non-monotonicity observed in Figure 12a and 12d.
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.
Finally, Figure 12 also shows the comparison of fire sale losses between the pro-rata and waterfall liquidation. For all types of idiosyncratic shocks, we observe that the losses for the pro-rata liquidation are always more severe than those for the waterfall liquidation. This finding is consistent with the results for the BoE and FRB CCAR stress scenario reported in Table 12 and Table 13.

5.2.2 Indirect vulnerabilities

Our previous results indicate that pro-rata liquidation leads to the highest aggregate losses. In the following, we would like to see whether this is the case for all institutions and sectors. In particular, we compare the indirect vulnerability resulted 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 the 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.

![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.](image-url)
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.\(^8\)

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

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

\(^8\)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.
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.

5.2.3 Systemicness

In addition to the vulnerability, the marginal contribution of each sector to the aggregate fire sale losses can also be studied. To this end, we assume that there is only one sector that would actively liquidate their assets. We then compute the aggregate fire sale losses of the whole network generated solely from this sector’s liquidation. In particular, we present the systemicness of banks, funds, unit-linked and non unit-linked insurers in Figure 16. Specifically, we look at the systemicness across different types of idiosyncratic shock for the pro-rata liquidation case.

In general, we see that banks become the most systemic sector. This is not surprising, especially due to the fact that banks have the strongest constraint as was previously discussed in subsection 5.2. However, we also observe that other sectors may overstep the systemicness of banks in some cases. For example, the systemicness of funds and banks intersect each other at around 20% shock on equities. Additionally, we see that the systemicness of non unit-linked insurers gets beyond banks at around 18% shock on government bonds. We note that these results are related to the inverted u-shaped plots in Figure 12 that we previously discussed in subsection 5.2. In particular, as the shock gets larger, banks would only be able to liquidate less assets that remains in their balance sheet. This then results in a smaller generated price impact.

5.2.4 The most important institutions

From a regulatory perspective, it is useful to define the most important institutions (in term of systemicness and vulnerability) in the network. In Figure 17, we present a scatter plot of the importance of each institution (normalized by the total asset holdings of all institutions: £2.04 tr). We note that the most important institutions would lie in the top right corner of the plot, as these would have high vulnerability and high systemicness.

---

9We note that the findings for the waterfall liquidation is similar, as shown in the Appendix.
Figure 16: Systemicness of different sectors across different types of idiosyncratic shocks. Results are for the case of the pro-rata liquidation.
As shown in Figure 17, institutions that belong to the same sector tend to form a cluster. In particular, we observe that the most systemically important institutions are mostly banks, followed by non unit-linked insurers. Meanwhile, funds and unit-linked insurers are relatively less important. We note that here we focus on the importance of the sector at the level of individual institutions. In fact, as was previously shown in Figure 16, funds may become more systemic in aggregate compared to non unit-linked insurers and even banks, because they are many.

5.3 Inferring the results from the network measures

We have previously discussed the results of stress simulation analysis on the UK financial system. In the following, we study the causal factors of individual institutions’ contribution to the indirect vulnerability. The main scope of this analysis is to determine whether the common asset holding characteristics are a useful indicator to explain the vulnerability of an institution within our sample. In particular, we look at the following regressions

\[ y_i = a + b \times X_i + \epsilon_i, \]

where \( y_i \) is the indirect vulnerability of institution \( i \), \( X \) is the set of explanatory variables, and \( b \) is the corresponding parameter vector. We consider the simple network measures (such as total holdings and total links) and the portfolio similarity of each institution as the explanatory variables. We also add a dummy variable that takes on the value of
1 when the institution is fund (and 0 otherwise). The reason of this special treatment for funds is illustrated in Figure 18. The figure shows the scatter plot of the total links against the (log) total holdings of each institution. In the case of banks and (unit-linked and non unit-linked) insurance companies, we observe a positive relationship between the two variables, suggesting that larger institutions tend to be more diversified. Meanwhile, in the case of funds, we find that most observations cluster around a vertical line, indicating that funds tend to be more concentrated, irrespective of their size. This is probably due to the fact that funds may often have restrictions in relation to the investment mandate. For this reason, we decided to include a dummy variable fund in each regression.

Figure 18: Scatter plot of the total links against the (log) total holdings of each institution.

We show the regression results for the Bank of England’s and Federal Reserve Board’s stress scenario in Table 14 and Table 15. In Panel A, we only take the simple network measures into account. Meanwhile, in Panel B, we also consider the portfolio similarity measure.

Firstly, we show from both tables that the $R^2$ values in Panel B are higher than those in Panel A, suggesting that the portfolio similarity measure is useful to explain more variability in the indirect vulnerability. Secondly, we find that total holdings and MeanCosSimilarity have negative coefficients, suggesting that larger and more diversified institutions would become less (indirectly) vulnerable. We note that this finding is consistent with that of Greenwood et al. (2015) and Fricke and Fricke (2017). Additionally, the variable total links have also negative coefficients, suggesting that institutions...
Table 14: The determinants of institution-specific indirect vulnerability (normalized by the total holdings of each institution). Results are shown for the Bank of England’s stress scenario, and for both pro-rata and waterfall liquidation approach.

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Panel A</th>
<th>Panel B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pro-rata</td>
<td>Waterfall</td>
</tr>
<tr>
<td>Simple network</td>
<td></td>
<td></td>
</tr>
<tr>
<td>measures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log (total holdings)</td>
<td>7.47e−05</td>
<td>−0.000497</td>
</tr>
<tr>
<td></td>
<td>(0.000159)</td>
<td>(0.000307)</td>
</tr>
<tr>
<td>total links</td>
<td>−1.45e−06**</td>
<td>−5.78e−06**</td>
</tr>
<tr>
<td></td>
<td>(8.54e−07)</td>
<td>(1.64e−06)</td>
</tr>
<tr>
<td>fund</td>
<td>−0.0144***</td>
<td>−0.0276***</td>
</tr>
<tr>
<td></td>
<td>(0.00221)</td>
<td>(0.00425)</td>
</tr>
<tr>
<td>Portfolio similarity</td>
<td></td>
<td>−0.0157***</td>
</tr>
<tr>
<td>MeanCosSimilarity</td>
<td></td>
<td>(0.00163)</td>
</tr>
<tr>
<td>constant</td>
<td>0.0407***</td>
<td>0.0757***</td>
</tr>
<tr>
<td></td>
<td>(0.00390)</td>
<td>(0.00750)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.025</td>
<td>0.022</td>
</tr>
<tr>
<td>Observations</td>
<td>1,923</td>
<td>1,923</td>
</tr>
</tbody>
</table>

Table 15: The determinants of institution-specific indirect vulnerability (normalized by the total holdings of each institution). Results are shown for the Federal Reserve Board’s stress scenario, and for both pro-rata and waterfall liquidation approach.

<table>
<thead>
<tr>
<th>Explanatory variables</th>
<th>Panel A</th>
<th>Panel B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pro-rata</td>
<td>Waterfall</td>
</tr>
<tr>
<td>Simple network</td>
<td></td>
<td></td>
</tr>
<tr>
<td>measures</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log (total holdings)</td>
<td>−0.000750</td>
<td>−0.00259***</td>
</tr>
<tr>
<td></td>
<td>(0.000599)</td>
<td>(0.000626)</td>
</tr>
<tr>
<td>total links</td>
<td>−5.56e−06*</td>
<td>−1.06e−05***</td>
</tr>
<tr>
<td></td>
<td>(3.21e−06)</td>
<td>(3.35e−06)</td>
</tr>
<tr>
<td>fund</td>
<td>−0.0566***</td>
<td>−0.0666***</td>
</tr>
<tr>
<td></td>
<td>(0.00829)</td>
<td>(0.00867)</td>
</tr>
<tr>
<td>Portfolio similarity</td>
<td></td>
<td>−0.0482***</td>
</tr>
<tr>
<td>MeanCosSimilarity</td>
<td></td>
<td>(0.00616)</td>
</tr>
<tr>
<td>constant</td>
<td>0.125 ***</td>
<td>0.183 ***</td>
</tr>
<tr>
<td></td>
<td>(0.0146)</td>
<td>(0.0153)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.025</td>
<td>0.035</td>
</tr>
<tr>
<td>Observations</td>
<td>1,923</td>
<td>1,923</td>
</tr>
</tbody>
</table>
with more assets in their portfolio are less vulnerable. It should be noted that the size of the total holdings in logarithm terms is significant only for the waterfall selling framework in the Federal Reserve board scenario, suggesting that some institutions with small portfolios may be more vulnerable when they have concentrated their investments mainly on the liquid assets (the first assets to be liquidated in a waterfall selling framework). Finally, our dummy variable fund confirms an additional and more significant vulnerability for the funds due to their lack of diversification.

6 Conclusion

In this paper, we model indirect contagion across UK banks and non-banks 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 non-banks 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, the indirect vulnerability and the systemicness of each sector. We conduct the stress simulation under different scenarios of initial shock and liquidation strategies. We find that the results are highly determined by the constraint and the portfolio composition of each sector. For example, banks become the most systemic in general, mainly because they liquidate a larger amount of assets relatively compared to other sectors. Moreover, we show that the yielded 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). Finally, we present the map of the most important institutions in the UK, in terms of systemicness and vulnerability.

Thirdly, we explore the effectiveness of network measures to explain the results of different stress simulations. Overall, we find that the portfolio similarity measure is
useful to explain more variability in the indirect vulnerability. Moreover, we find that larger and more diversified institutions would become less (indirectly) vulnerable.

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. For example, incorporating European funds that may hold similar assets to UK funds. Another important future extension is to improve the market depth calibration, such as by taking the correlations of asset prices into account.
References


39


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

In the main text, we have discussed the indirect vulnerability resulted 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.
B Appendix: Systemicness

In the main text, we have discussed the systemicness of different sectors across different types of idiosyncratic shocks, for the case of the pro-rata liquidation approach. For what follows, we discuss the similar results, for the case of the waterfall liquidation.

Figure A.3: Systemicness of different sectors across different types of idiosyncratic shocks. Results are for the case of the waterfall liquidation.