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Common asset holdings and systemic vulnerability across multiple types of financial institution☆

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ABSTRACT

One way systemic risk can crystallise is through fire sales of commonly held assets. This paper examines fire sale vulnerabilities across different types of financial institution, including non-banks. We undertake an in-depth empirical analysis of the interconnections between European open-ended investment funds and UK regulated banks and insurance companies through their common asset holdings. This research is the first to combine regulatory holding-level asset data for banks and insurers with private data for open-ended investment funds. Our results show the existence of a significant overlap between the equity and debt portfolios of different types of financial institution. We characterise financial institutions of different types in terms of their concentration profile, portfolio similarity and vulnerability to fire sales, providing evidence for the existence of a price-mediated channel of contagion between banks, insurance companies and investments funds.

1. Introduction

Fire sales occur when financial institutions are forced to sell part of their portfolios at discounted prices as a consequence of an exogenous shock. Forced liquidation of securities might happen when financial institutions face binding constraints, such as regulatory or contractual constraints. All financial institutions that hold the securities sold at discounted prices incur losses when they mark to market their portfolios. These losses can lead financial institutions unaffected from the initial exogenous shock to breach some constraints and to undertake forced sales of their portfolios. These forced sales amplify the initial fall in market prices and can lead to self-reinforcing destabilising dynamics. This contagion channel is also known as price-mediated contagion.

Fire sale risk can crystallise under different scenarios. For instance, open-ended investment funds can be forced to liquidate some of their portfolios in order to comply with investor redemptions (Coval and Stafford, 2007) and insurance companies might be forced to sell downgraded bonds in order to comply with regulatory constraints (Ellul et al., 2011). More generally financial institutions can react differently after an exogenous shock on asset prices, with some of them selling the securities whose price has been falling, thereby amplifying the initial fall in prices, and others buying them, thereby dampening the fall in prices. The former behaviour is known as pro-cyclical behaviour and the latter as counter-cyclical behaviour (Czech and Roberts-Sklar, 2019). The drivers of such behaviour can be linked to the balance sheet structure of different financial institutions (Timmer, 2018).

Price-mediated contagion has been recognised as a major driver of endogenous instability across the whole financial system as it might involve several types of financial institution and might impair market functioning (Baranova et al., 2017). However, existing work has focused either on empirically analysing the portfolio

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similarity of financial institutions of the same type (Braverman and Minca, 2014; Guo et al., 2016; Getmansky et al., 2016) or on modelling price-mediated contagion between institutions of the same type (Caccioli et al., 2014; Greenwood et al., 2015; Duarte and Eisenbach, 2014; Cont and Schaanning, 2017; Cont and Wagalath, 2013; Cetorelli et al., 2016). On the other hand, it has been found that institutions from different sectors may display strong interdependence in equity returns (Billio et al., 2012). The aim of this paper is to empirically analyse interconnections and systemic vulnerabilities related to price-mediated contagion across three types of financial institutions.

In this paper, we focus on UK banks, UK insurance companies (including unit-linked funds[1]) and European open-ended investment funds. We construct a novel dataset of common asset holdings across multiple institution types by making use of data available at the Bank of England – i.e., Capital Requirements Directive IV reports (COREP and FINREP) as well as Solvency II regulatory data, and private data from Morningstar. We use our dataset to empirically study portfolios of marketable assets across different financial institution types, providing a detailed analysis of their portfolio diversification, similarity and overlap, and to analyse vulnerabilities due to fire sales taking into account the liquidity of different asset classes. This allows us to better understand the importance of non-banks when assessing systemic risk.

For the purpose of studying common asset holdings in relation to fire sales, we focus on marketable assets such as debt and equity securities and exclude cash, derivatives, loans and illiquid assets from scope. Debt securities include both corporate and government bonds.

Each of the source datasets we make use of are subject to different reporting conventions and levels of granularity. Therefore we undertake a significant amount of pre-processing which includes use of data cleansing techniques in order to create a consistent mapping of debt and equity security holdings at issuer level across different types of financial institution. Whilst we have made a significant effort to minimise the amount of error in the sample used, the accuracy of the analysis ultimately depends on the details provided in the financial institutions' reporting. Furthermore any reporting thresholds which apply will reduce the number of items in the sample. When using this granular dataset we consider separately debt and equity holdings in order to be able to analyse differences and similarities across these two asset types and keep the volume of the data manageable.

Several factors related to asset holdings affect financial institutions' vulnerability to fire sales or price-mediated contagion, and in this paper we focus on the following[2]:

- *Portfolio concentration*. There is a trade-off on the optimal level of portfolio diversification that makes the financial system stable. On the one hand, high portfolio diversification reduces the probability of failure of individual financial institutions; on the other it could increase the likelihood of a systemic crisis (Wagner, 2010; Tasca et al., 2017). We use our dataset to empirically analyse the number of securities held in and the concentration of debt and equity security portfolios across multiple institution types. We find that most financial institutions hold heterogeneously weighted portfolios of equity and debt securities, apart from open-ended investment funds that appear to hold equity portfolios that are close to an equally weighted one.
- *Common asset holdings*. We build a network of common asset holdings where different financial institutions are connected to the securities they hold in their portfolio (Delpini et al., 2015). Specifically, this network is composed of two layers describing debt and equity security holdings, respectively. By studying how connections are distributed within the two layers of this network it is possible to study the level of commonality and concentration of debt and equity holdings within the considered financial system. By making use of an algorithm to detect communities (Newman, 2010) of financial institutions that display similar patterns in security holdings in the network, we are able to identify groups of institutions that could be more vulnerable to each other's selling behaviour in a fire sale scenario. We observe communities containing more than one type of institutions, thus showing the existence of a potential channel of contagion between different types of institution. The probability of this contagion channel to crystallise will ultimately depend on the nature and the magnitude of the exogenous shock, and on financial institution behaviour in response to the shock.
- *Portfolio similarity*. We further investigate similarities in the portfolio composition of different institution types drawing on Getmansky et al. (2016), that find correlations between their measure of portfolio similarity and asset selling behaviour for US insurers. We assess the level of similarity across debt and equity portfolios held in the system by studying the distribution of connections in the network of portfolio similarity, where financial institutions are connected to other financial institutions holding similar portfolios. Consistent with the results of the analysis of the communities in the network of common asset holdings, we find that some types of financial institutions have debt and equity investment profiles more similar to those of other institution types. We also investigate the relationship between portfolio similarity and concentration across financial institutions belonging to the identified communities of financial institutions with common asset holdings. We find a negative correlation between similarity and concentration in equity portfolios. For portfolios containing both government and corporate bonds, the relationship between similarity and concentration is less clear. However, we find that financial institutions belonging to a given community with common asset holdings display commonalities in their portfolio similarity.
- *Liquidity weighted portfolio overlap*. Finally, we consider the liquidity characteristics of the securities held in a given portfolio. Drawing on Cont and Schaanning (2017) we build the network of liquidity weighted portfolio overlap where financial institutions holding overlapping portfolios composed of less liquid assets are connected more strongly than those holding overlapping portfolios composed of more liquid assets. Following Cont and Schaanning (2017) we assess fire sale vulnerabilities by ranking financial institutions according to the importance of their connections in the liquidity weighted portfolio overlap network. We find (as one would intuitively expect) that financial institutions that have portfolios with larger holdings of marketable assets are more exposed to fire sales. We contrast this indicator with

[1] We split the insurance sector into unit-linked and non-unit-linked portfolios as their risk exposures and asset allocations should, in theory, be very different. Insurers bear risk on non-unit-linked contracts and losses in these funds will have a direct impact on available capital to meet regulatory requirements. On the other hand, unit-linked contract policyholders bear any losses. For example, losses due to market movements will reduce the value of their units. Unit-linked funds offer to their policyholders the possibility of switching between funds at short notice, so we would expect asset holdings in these funds to be sticky in the absence of switching requests and there to be liquidity buffers to accommodate withdrawals. Unit-linked fund business model shares similarities with those of open-ended funds and could lead them to rebalance their portfolios following policyholder switching requests (Bank of England, 2016).

[2] Strategic substitutability and complementarity of asset classes could also influence both portfolio allocation choices and selling and buying behaviour. However, the aim of this paper is to analyse the overlap and commonality in asset holdings mainly in relation to fire sales without taking into account the strategic decisions that drive portfolio choices. Also it is likely that strategic substitutability and complementarity of asset classes will drive financial institutions behaviour after the shock, and this is something we do not consider in our analysis.

the average portfolio similarity defined as in Getmansky et al. (2016), which does not take into account liquidity characteristics of overlapping assets, that identifies commonality across portfolio allocations of small as well as large financial institutions. As a result we find that both indicators could be useful for monitoring systemic risk due to fire sales.

Due to data limitations and in order to associate a liquidity coefficient to the assets, for our study of liquidity weighted portfolio overlap described above we switch to using a stylised portfolio which is defined at asset class level (rather than issuer level) and includes both equity and debt. We discuss the trade-off in selecting appropriate level of granularity when analysing networks of common asset holdings in Section 6.

The paper is organised as follows: in Section 2 we briefly summarise the literature on portfolio similarity, price-mediated contagion and relevant network analysis related to financial systems. In Section 3 we introduce the notation, the main quantities and methodologies that we use to analyse the asset holdings data. In Section 4 we describe the data under investigation and explain both their novelty and limitations. Finally in Sections 5 and 6 we present and discuss the results, with particular emphasis on their relevance for financial stability.

2. Literature review

There are number of relevant research papers for our empirical analysis that we here divide into four main categories: (i) empirical studies of fire sales and procyclical behaviour, (ii) models of price-mediated contagion, (iii) studies of similarity and diversification of asset holdings and (iv) indicators of fire sales vulnerabilities.

There is widespread evidence in the existing academic literature of financial institutions undertaking fire sales. Coval and Stafford (2007) and Jotikasthira et al. (2012) find evidence of fire sales by open-ended investment funds in equity markets caused by investors' redemptions. Manconi et al. (2012) find evidence of forced sales of corporate bonds during the financial crisis by open-ended investment funds and insurance companies. These fire sales were identified as a channel for the transmission of shocks from the securitised bond market to the corporate bond market. Falato et al. (2016) empirically analyse fire sale spillovers between US fixed-income open-ended funds showing the interdependence of investor redemption in funds with similar asset holdings that trigger fire sales. Ellul et al. (2011) find evidence of fire sales of downgraded bonds by insurance companies subject to regulatory constraints. More recently Timmer (2018), using granular data on debt holdings of different types of German financial institutions, finds that banks and investment funds may respond procyclically to price changes, whereas the opposite is true for insurance companies and pension funds. Using transaction level data on sterling corporate bonds, Czech and Roberts-Sklar (2019) find that during the 'Taper Tantrum' asset managers were net sellers of corporate bonds and dealers were net buyers.

Several papers have modelled fire sales contagion between the same type of financial institution. Duarte and Eisenbach (2014), Greenwood et al. (2015) and Cont and Schaanning (2017) have modelled fire sales contagion between banks due to banks deleveraging in response to an initial shock. Caccioli et al. (2014) and Levy-Carciente et al. (2015) model fire sale contagion between banks using a coupled bank-asset network (i.e., bipartite network where banks are connected to the assets that they hold).[3] Cetorelli et al. (2016), Fricke and Fricke (2017) and Baranova et al. (2017) have modelled fire sales between open-ended investment funds facing investor redemptions. Cont and Wagalath (2013) investigate the impact of fire sales caused by investor exiting investment funds on asset volatility and correlation. Less work has been done on modelling price-mediated contagion across insurance companies. However, Douglas et al. (2017) have modelled how Solvency II regulation might drive UK life insurers selling behaviour in response to different types of shocks.

Other work has focussed on modelling the interaction between multiple channels of contagion. Bookstaber and Kenett (2016) describe the financial system as a multilayer network[4] composed of three layers corresponding to three different contagion channels – i.e., funding, collateral and assets. Cifuentes et al. (2005) and Poledna et al. (2020) model the interaction between fire sale contagion and contagion due to direct exposures between banks. The same contagion channels are analysed in the agent-based model developed by Halaj (2018) that includes both banks and asset managers.

The existing research on portfolio similarity uses different approaches to analyse portfolio similarity and focuses on individual types of financial institution. For instance, Delpini et al. (2015), Braverman and Minca (2014) and Guo et al. (2016) have studied the network of common holdings between investment funds using US data. Recently, Getmansky et al. (2016) studied portfolio similarity across US insurers measuring it as the cosine similarity between portfolios of asset holdings. Getmansky et al. (2016) have also found a significant correlation between common holdings of assets among US insurance companies and their common sales suggesting that their measure of portfolio similarity might be a useful indicator of systemic risk due to price-mediated contagion.

Building on previous work (Cont and Wagalath, 2013), Cont and Schaanning (2017) have shown that second round losses of banks are driven by the network of liquidity weighted portfolio overlap. This network can be thought of as a generalisation of the portfolio similarity measure defined in Getmansky et al. (2016), which also takes into account the liquidity of common assets that is measured using market depth. Cont and Schaanning (2017) also derive an indicator of fire sales vulnerabilities called Indirect Contagion Index that corresponds to the normalised principal eigenvector associated with the network.

3. Methodology

3.1. Network of common asset holdings

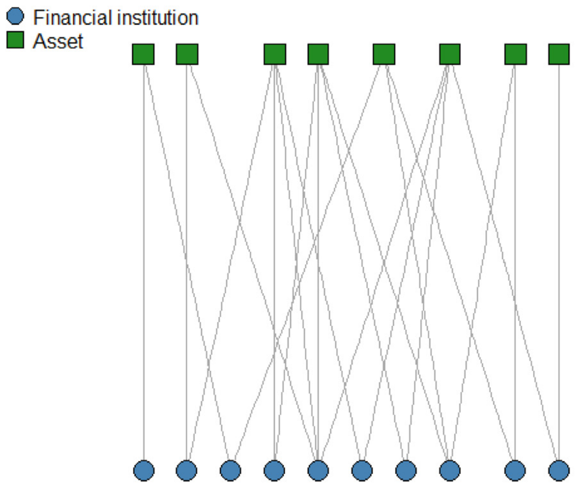
We define the network of common asset holdings as a bipartite network where vertices are divided in two sets, assets and financial institutions. If one institution holds one asset, there is a link between the corresponding vertices (one from each set) as shown in Fig. 1a. By analysing this network we can study linkages between financial institutions and issuers of debt and equity securities given the granularity of the dataset.[5]

We denote the network of asset holdings as $B = (F, A, \mathbf{H}, \alpha)$ where $F = \{F_1, \ldots, F_N\}$ is the set of vertices corresponding to financial institutions, $A = \{A_1, \ldots, A_K\}$ is the set of vertices corresponding

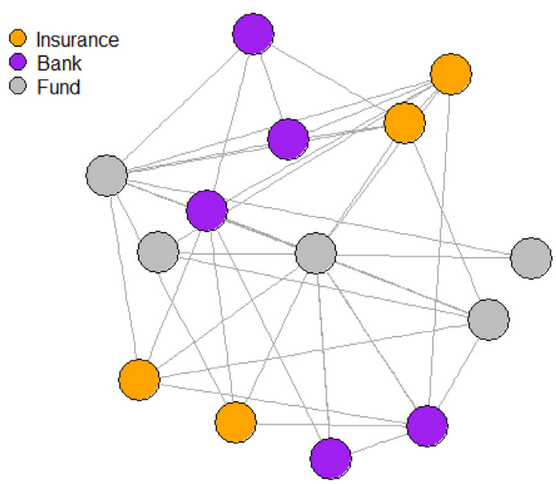
[3] Bipartite networks are useful frameworks for describing the interaction between two sets of nodes. It is possible to associate to bipartite networks monopartite networks where only one of the two sets of nodes are interconnected by projecting the bipartite network on the layer of interest. Saracco et al. (2017) develop an algorithm to obtain statistically validated projections of bipartite networks that preserve as much as possible of the original information.

[4] Multilayer networks have also been used to capture the heterogeneity within individual contagion channels. For instance, Bargigli et al. (2015) conduct an in-depth analysis of the Italian interbank market which is represented as a multilayer network where the different layers correspond to secured and unsecured debt of different maturities.

[5] See Newman (2010) for a mathematical introduction to network analysis.



(a) Stylised network of common asset holdings



(b) Stylised network of portfolio similarity

Fig. 1. Stylised representation of the network of common asset holdings (bipartite network) and network of portfolio similarity (monopartite network).

to securities at issuer level, $\mathbf{H}$ is a (rectangular) matrix in $\mathbb{R}^{N\times K}$ where the generic element H_{ik} represents the sterling amount of asset k held by financial institution i for a given layer, and α corresponds to the two different layers describing debt and equity holdings.

The total holdings of each financial institution i and the total amount held in the system for each security k in a given layer α of the network are given by the sums of the elements along the columns and rows of H_{ik}^{α} respectively

$$V_i^{\alpha} = \sum_{k=1}^{K} H_{ik}^{\alpha} \tag{1}$$

$$V_k^{\alpha} = \sum_{i=1}^{N} H_{ik}^{\alpha} \tag{2}$$

which are known in network theory as 'strengths'. The total amount held in a given layer α of the considered financial system is $V_T^{\alpha} = \sum_{i=1}^{N} V_i^{\alpha} = \sum_{k=1}^{K} V_k^{\alpha}$.

It is possible to associate with each matrix H^{α} another matrix that takes into account only the presence or absence of links. This is called an adjacency matrix $\overline{H}^{\alpha}$, where the generic element $\overline{H}_{ik}^{\alpha}$ is defined as follows

$$\bar{H}_{ik}^{\alpha} = \begin{cases} 1, & \text{if } H_{ik}^{\alpha} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Summing the elements across the rows and the columns of $\overline{H}^{\alpha}$ we obtain the degree, which measures the total number of links attached to each asset and financial institution vertex, respectively. In particular, the degree of financial institution i is

$$degree_i^{\alpha} = \sum_{k=1}^{K} \overline{H}_{ik}^{\alpha} \tag{4}$$

and corresponds to the total number of debt or equity securities held by financial institution i. Here a larger $degree_i^{\alpha}$ would indicate a portfolio that is less concentrated on a small number of debt or equity securities. We compare this measure with standard measures of portfolio concentration such as the Herfindhal–Hirschman Index (HHI), Hirschman (1945) and Herfindahl (1950)

$$HHI_i^{\alpha} = \sum_{k=1}^{K} \left(\frac{H_{ik}^{\alpha}}{V_i^{\alpha}} \right)^2 \tag{5}$$

By definition, the HHI is always between $1/degree_i^{\alpha}$ and 1, meaning that no portfolio can be more diversified than an equally weighted one or more concentrated than one composed by a single asset only.

Similarly, the degree of asset k reads

$$degree_k^{\alpha} = \sum_{i=1}^{N} \overline{H}_{ik}^{\alpha} \tag{6}$$

and corresponds to the number of financial institutions that hold a certain asset k. This can be interpreted as the concentration of asset k.

The density of the network of common asset holdings is defined as the number of total links, divided by the number of all possible links

$$\rho^{\alpha} = \frac{\sum_{k=1}^{K} \sum_{i=1}^{N} \overline{H}_{ik}^{\alpha}}{KN} \tag{7}$$

We analyse community structures within the network using bipartite modularity (Newman, 2006; Barber, 2007) and an algorithm to partition financial institutions into a minimal number of groups that cluster institutions displaying a similar pattern of asset holdings (Blondel et al., 2008). We define the market-capitalisation weighted portfolio, with portfolio weights $\tilde{\pi}_k^{\alpha} = V_k^{\alpha}/V_T^{\alpha}$, and introduce the portfolio weights $\pi_{ik}^{\alpha} = H_{ik}^{\alpha}/V_i^{\alpha}$, quantifying the fraction of the total volume of the institution i invested in the asset k.

The contribution m_{ik}^{α} to modularity of a given asset holding and financial institution assigned to the same community equals the difference between the value of the asset holding and the value corresponding to the market-capitalisation weighted portfolio, and simply reads:

$$m_{ik}^{\alpha} = V_i^{\alpha}(\pi_{ik}^{\alpha} - \tilde{\pi}_k^{\alpha}) \tag{8}$$

Modularity, which measures the total assortativity for a given partition of institutions and assets, sums over all the individual contributions m_{ik}^{α}, and reads:

$$M[c^{\alpha}] = \frac{1}{V_T} \sum_{i=1}^{N} \sum_{k=1}^{K} m_{ik}^{\alpha} \delta(c_i^{\alpha}, c_k^{\alpha}) \tag{9}$$

where $\delta(c_i^\alpha, c_k^\alpha) = 1$ if institution i and the security k belong to the same community and zero otherwise.

If a group of institutions shares a very similar pattern of asset holdings, it is likely to be assigned to the same community as it contributes positively to the modularity. As a consequence, assigning such institutions to different communities would set to zero many terms in the sum appearing in the definition of the bipartite modularity. The identification of densely connected modules is relevant as it enables us to isolate smaller subsets of the financial system more directly vulnerable to each other's selling and buying behaviour, and to analyse them together.

Optimal partitioning is found using an algorithm which maximises modularity such as the Louvain method (Blondel et al., 2008). A large number of community detection algorithms have been proposed in the last 20 years (Fortunato, 2010), here we focused on the Louvain method for its applicability to the weighted bipartite case, computational efficiency, and simple interpretability.

3.2. Network of portfolio similarity

The network of portfolio similarity is a monopartite network where all vertices are financial institutions. There is a link between two financial institutions when they hold a similar portfolio of assets as shown in Fig. 1b.

We define the network of portfolio similarity as $M = (F, \mathbf{S}, \alpha)$ where $F = \{F_1, \ldots, F_N\}$ is the set of vertices corresponding to financial institutions; $\mathbf{S}$ is a square matrix where the generic element S_{ij} denotes the similarity between portfolios i and j and corresponds to the weight attached to the link between vertices i and j; and α refers to the two different layers describing debt and equity holdings.

There are many definitions of similarity which exist (Newman, 2010) when characterising different aspects of similarity between portfolios. For instance, Delpini et al. (2015) define a similarity coefficient as the product of the Jaccard coefficient, measuring the number of overlapping assets, and an index of portfolio weight similarity which measures the similarity of portfolio weights. Alternatively Abad et al. (2017) assess the overlap in European bank exposures to shadow bank entities relative to banks' capital. In this work we use the two following definitions of portfolio similarity that can be easily applied to multiple institution types.

- Number of common assets between portfolios i and j. In this case the matrix $\mathbf{S}_1^\alpha$ is obtained as the product between the adjacency matrix of the bipartite network $\overline{H}^\alpha$ defined in Eq. (3) and its transpose

$$(S_1^\alpha)_{ij} = \overline{H}^\alpha (\overline{H}^\alpha)^T \tag{10}$$

- Cosine similarity between portfolios i and j as in Getmansky et al. (2016). In this case the matrix of portfolio similarity is

$$(S_2^\alpha)_{ij} = \frac{\sum_k H_{ik}^\alpha H_{jk}^\alpha}{||V_i^\alpha||\,||V_j^\alpha||} \tag{11}$$

where $||V_i^\alpha||$ is the norm of the vector of holdings of institution i in a given layer α. The cosine similarity accounts not only for the number of common holdings but also for the weights attached to them. Due to scaling by the norm, cosine similarity ranges between 0 and 1, where 0 means no similarity between two portfolios and 1 full similarity. Cosine similarity may assign similarity 1 both to a pair of institutions that only have one asset, which is also found to be in common, and to a pair of institutions that actually hold an entire multi-asset portfolio in common regardless of its length (i.e., level of diversification) or volume.[6]

It should be noted that under the two definitions above, S_u^α with $u = 1, 2$ are symmetric matrices associated with undirected networks, where no specified direction is associated with the links between vertices.

The weighted degree of financial institution i is obtained as

$$(W_u^\alpha)_i = \sum_{j=1}^{N} (S_u^\alpha)_{ij} \quad u = 1, 2 \tag{12}$$

and the total weighted degree is

$$(W_u^\alpha)_T = \sum_{i=1}^{N} (W_u^\alpha)_i, \quad u = 1, 2 \tag{13}$$

It is also possible to define the adjacency matrix $\overline{S}_u^\alpha$ associated with S_u^α for $u = 1, 2$. It should be noted that the adjacency matrix is the same according to the two definitions of similarity, $\overline{S}_1^\alpha = \overline{S}_2^\alpha$. This means that the degree and the density are the same in the two corresponding networks. Given that the network is undirected, the sums of the elements across the rows and the columns of the adjacency matrix are equal and correspond to the degree

$$(degree_u^\alpha)_i = \sum_{j=1}^{N} (\overline{S}_u^\alpha)_{ij}, \quad u = 1, 2 \tag{14}$$

that represents the number of portfolios similar to i. The density is now given by

$$\rho_u^\alpha = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} (\overline{S}_u^\alpha)_{ij}}{N(N-1)}, \quad u = 1, 2. \tag{15}$$

We also investigate which financial institutions occupy key positions in the network of portfolio similarity. Specifically, for each layer of the network of portfolio similarity we investigate the *strength centrality* that measures the centrality of portfolios according to their total weighted degree, as defined in Eq. (12).

3.3. Network of liquidity weighted portfolio overlap

The network of liquidity weighted portfolio overlap can be derived from a simple model of contagion through fire sales of commonly held assets that generalises Greenwood et al. (2015); Duarte and Eisenbach (2014); Cont and Wagalath (2013); Cont and Schaanning (2017). Following these studies, we make the simplifying assumption that financial institutions respond to an exogenous negative shock on their returns by selling a fraction of their various marketable assets in proportion to the pre-shock amounts held (i.e., selling a 'vertical slice' of their portfolios). If asset prices are assumed to decrease linearly following these sales, it is pos-

[6] On the other hand, avoiding the normalisation or considering the absolute distances (e.g., Euclidean distance) between portfolios may give unbounded values of similarity biased towards institutions holding larger volumes. A robust and comprehensive analysis of portfolio similarity should, in any case, also take into account the volume and the level of diversification of asset holdings which we investigate in other parts of our work.

sible to show that second-round losses[7] (in sterling) for financial institution i are

$$L_i = \sum_{j=1}^{N}\sum_{k=1}^{K} l_k h_{ik} h_{kj} b_j r_j \tag{16}$$

where l_k is the price impact coefficient for asset class k (e.g., the change in price per sterling amount of assets sold), h_{jk} denotes the (sterling) amount of asset k held by institution j, b_j is the coefficient that gives the proportion of assets sold and r_j is the change in returns of institution j after the exogenous shock. For example, b_j can be leverage for banks as in Greenwood et al. (2015) and Duarte and Eisenbach (2014), investor redemptions for open-ended investment funds as in Cetorelli et al. (2016) and Baranova et al. (2017), and can be proportional to solvency capital constraints for insurance companies. The assets included in Eq. (16) correspond to a stylised portfolio that includes both marketable debt and equity holdings and illiquid assets. The mapping of assets to these groups is described in Section 4.

The assumptions required to derive Eq. (16) are significantly simplifying as selling behaviour is likely to vary by financial institution type, and is likely to be influenced by capital coverage and other regulatory requirements or mandates. Also market prices might not change linearly after forced asset sales, particularly if these happen over a long time horizon. However, under these assumptions the liquidity weighted portfolio overlap matrix arises easily from Eq. (16) as

$$O_{ij} = \sum_{k} l_k h_{ik} h_{jk} \tag{17}$$

We define the network associated with this matrix as $N = (F, \mathbf{O})$ where $F = \{F_1, \ldots, F_N\}$ is the set of vertices corresponding to financial institutions and $\mathbf{O}$ is the square matrix of liquidity weighted portfolio overlap whose elements are defined in Eq. (17).

This is a monopartite network, as the one shown in Fig. 1b, where financial institutions are linked to each other whenever they have assets in common and these assets are weighted by a coefficient that describes their liquidity characteristics. This network can be analysed using a methodology similar to that defined in Section 3.2.

Particularly, following Cont and Schaanning (2017) we use this network to analyse fire sale vulnerabilities by ranking financial institutions according to *eigenvector centrality*. This is a centrality measure that quantifies the extent to which a vertex is connected to important vertices (Newman, 2010). It is defined as the eigenvector associated with the largest eigenvalue of the matrix of liquidity weighted portfolio overlap O_{ij}, namely $EC_i = \lambda_1 \sum_{j=1}^{N} O_{ij} EC_j$.

4. Data

In this section we provide a detailed description of the datasets we used to create the different types of networks described in the previous section.

For the purpose of studying common asset holdings and portfolio similarity as a contagion channel we control for extraneous factors which may influence the results. Thus we define the scope as direct asset holdings classified by whether they were debt or equity exposures (see Annex A for details).

4.1. Data used to construct the network of asset holdings and network of portfolio similarity

We combine granular asset data at issuer level across all three types of institutions using Q1 2016 as the reporting period. Below we provide details of the three datasets used.

- Banks: We use COREP data submitted to the Prudential Regulatory Authority (PRA) by regulated banks under European Union CRD IV legislation. COREP Large Exposures reporting provides details of banks' exposures to issuers on a quarterly basis (subject to a reporting threshold).[8] Banks should report the type of exposure they have to a specific issuer as well as other identifiers such as the Legal Entity Identifier (LEI).
- Open-ended investment funds: We extract voluntarily reported data on open-ended investment funds that are domiciled in Europe with the permission of Morningstar. 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 (TNAs) as well as meta-data about investment funds, such as information on their investment profiles.
- Insurance companies: We sample granular line-by-line asset data from PRA regulated insurance companies subject to the Solvency II directive.[9] For the networks of common asset holdings and portfolio similarity, we consider data submitted by firms which are classified as solo entities under Solvency II. Some insurance companies which are not solos are classed as groups under Solvency II. Solo level consolidation was chosen in order to match the level of consolidation of the bank and investment fund datasets and to avoid double counting. Meta data on holdings includes unique identifiers, such as ISINs and LEIs of counterparties, as well as categorisation of assets into CIC (Complementary Identification Code) types. For the purpose of this analysis we consider unit-linked and non-unit-linked portfolios.[10] The sample used includes life as well as non-life insurance companies.

In many cases the raw data described above is non-public and thus in this paper we only use anonymised or aggregated results.

4.2. Data limitations

Each of the datasets used was subject to different reporting conventions and requirements. In sampling the datasets we sought to ensure the coverage and consistency of the data used.[11]

The volume and complexity of the data from the three sources meant there was a significant amount of pre-processing to fill gaps and ensure consistency across the datasets. The main steps of the pre-processing can be found in Fig. 17. Given the free-form nature

[7] Second-round losses are defined as losses not generated by the exogenous shock to asset prices, but those due to the subsequent decline in market prices due to fire sales.

[8] Submissions must include top 10 financial and non-financial exposures as a minimum. Full details and additional rules are set out in EBA CRR Article 4 and CRR Article 394.

[9] Excluding those subject to reporting exemptions.

[10] In full these assets are described in Solvency II legislation as held in 'Unit-linked or index-linked' or 'Neither unit-linked nor index-linked' contracts respectively. We denote this split in charts as Insurers (UL) and Insurers (NL). It is possible for an insurance company to have both types of portfolios and thus be represented by two separate nodes in our analysis.

[11] For example, in order to better reflect coverage across insurers' investment portfolios and sensitivities to debt and equity markets, we included exposures to debt funds and equity funds as part of holdings of collective investment undertakings. It is possible that these holdings include also holdings of non-tradable fund shares, such as those of the open-ended funds. Unfortunately, it is hard to distinguish between tradable and non-tradable shares. We believe this is not a concern for the analysis of the networks of common asset holdings and portfolio similarity, as we have excluded holdings of non-tradable fund shares for open-ended investment funds and banks.

Table 1
Summary of the coverage of the granular dataset constructed for the network of common asset holdings and portfolio similarity. Total assets for UK insurance companies as of Q4 2015 from the Association of British Insurers; UK banks as of Q4 2015 from the PRA; European open-ended investment funds as of Q1 2016 from EFAMA.

	Insurance companies	Banks	Investment funds	Total
Number of financial institutions	139	24	1260	1423
Total debt holdings (£bn)	643.7	1509.7	1100.9	3254.3
Mapped debt holdings/ total debt holdings	0.90	0.86	0.73	0.82
Total equity holdings (£bn)	582.8	68.6	925.3	1576.73
Mapped equity holdings/ total equity holdings	0.81	0.93	0.78	0.80
Total assets (£tr)	1.6	6.5	10.2	

Table 2
Stylised portfolio used for the network of liquidity weighted portfolio overlap. For each asset class considered total holdings are reported for each institution type. Collective Investment Undertakings include shares of debt and equity funds.

	Insurers (NL)	Unit-linked funds	Banks	Open-ended funds
Cash (£bn)	44.71	16.49	391.12	249.54
Marketable assets (£bn)				
Central government bonds	152.75	79.60	75.15	44.28
General governments	55.11	9.14	493.88	345.50
Corporate bonds	243.03	36.38	182.46	349.65
Other bonds	57.33	15.33	5.90	361.44
Equity	104.63	255.91	15.09	925.28
Illiquid assets (£bn)				
Collective investment undertakings	193.95	440.38	56.11	121.54
Others	59.37	26.00	33.54	42.18
Mortgages and loans	59.00	0.39	2804.86	35.96

Table 3
Summary properties of the two layers (debt and equity) of the network of common asset holdings, such as number of total financial institutions (N), number of total securities at issuer level (K) and density.

	N	K	Density (%)				
			Total	Insurers (UL)	Insurers (NL)	Banks	Open-ended funds
Debt	1464	4899	1.25	3.24	2.45	1.93	1.04
Equity	1464	6402	1.44	10.45	3.08	0.27	1.19

and volume of the granular data on asset holdings we do not expect this process was error free, however we did take some precautions to mitigate this which are described in Annex A.

Some issuer names could not be mapped at all using the pre-processing techniques described in Annex A. This can be put down to a number of potential reasons such as the obscurity of the security issuer, the spelling by the institution or lack of identifier. Furthermore due to reliance on the firms to fill templates correctly there may be gaps or other errors in the raw data. Through various word stemming, distillation and classification techniques we were able to construct a consistent dataset of granular holdings with distilled issuer names for banks, insurance companies and open-ended investment funds. Table 1 summarises the coverage of the constructed granular dataset.

Overall we achieved a high level of coverage relative to total assets. Unknown datapoints were excluded from the analysis. The lack of metadata around these points would mean that even if random sampling was used to match the missing links, it would dilute the legitimate connections as it would not account for the idiosyncratic nature of portfolio allocation by financial institutions. Outputs of the analysis may be biased by the sample and data coverage within it. For instance, if equity had poor coverage (and thus a lower number of assets in the underlying dataset) then the number of and strength of interconnections for the network would be significantly underestimated.

4.3. Data for the network of liquidity weighted overlap

For the network of liquidity weighted portfolio overlap we use a coarser stylised portfolio to be able to associate a measure of liquidity to each asset class considered. The portfolio considered is shown in Table 2 which reports holdings split across the considered institution types. As in Cont and Schaanning (2017) we divide the portfolio into marketable assets and illiquid assets. The former excludes cash and contains those assets that are perceived as liquid in normal times – those that financial institutions are believed to liquidate at fire sale prices if forced to. The main steps of the data pre-processing used to the network of liquidity weighted overlap are shown in Fig. 18 in Annex A.

For this network, we consider insurance companies and banks at group level, and aggregate investment funds by investment strategy[12] for the reasons explained below.

- Due to the limitations of COREP data it was not possible to simply aggregate up the granular data on banks' holdings described in the previous section. In order to understand the types of assets held more widely in banks' investment portfolios, it was necessary to use FINREP data at a consolidated group level. We combine balance sheet assets with a breakdown of asset types on an IFRS basis to complete the picture. The final sample of banks and holdings used was calibrated to take into account data quality.
- As explained in Section 2, after an exogenous shock open-ended investment funds could undertake fire sales of assets to meet investor redemptions. Our aggregation of investment funds data is based on the evidence that the response of open-ended investment fund investors to an exogenous shock will be similar across individual funds with similar investment profiles (Goldstein et al., 2017).

[12] Tables 13, 14 and 15 show the mappings used to create the stylised portfolio.

Table 4
Summary statistics of the financial institution degree across the two layers (debt and equity) of the network of common asset holdings.

	Debt	Equity
Mean	61.31	92.28
St dev	116.87	253.22

- We used group level data for insurers to match the granularity of the data from banks and investment funds as close as possible. This again is split into unit-linked and non-unit-linked portfolios and both life and non-life insurers are included in the sample.

5. Results

In this section we present the results obtained from the study of the networks defined in Section 3 – namely, the networks of common asset holdings and portfolio similarity across debt and equity securities holdings, and the network of liquidity weighted overlap for a stylised portfolio. As explained in previous sections the networks of common asset holdings and portfolio similarity are constructed using granular data on holdings; whereas the network of liquidity weighted portfolio overlap uses a coarse stylised portfolio.

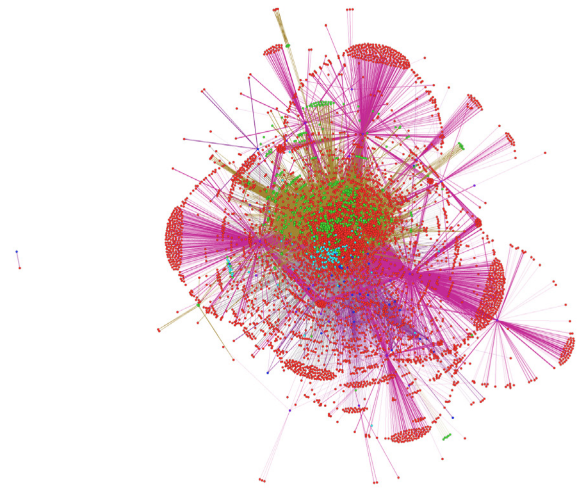
5.1. Network of common asset holdings

The debt and equity layers of the network of common asset holdings are shown in Fig. 2, where securities and different types of financial institutions are represented using different colours. At a first glance, it is difficult to discern the structural properties of the two layers, thus in the remainder of this section we present a detailed analysis of the properties of the two layers that we link to portfolio overlap in debt and equity holdings and the concentration of these holdings within portfolios. We begin by studying first order properties described in Section 3.1 – such as network density, degree and concentration – and then turn to second order properties – such as community analysis.

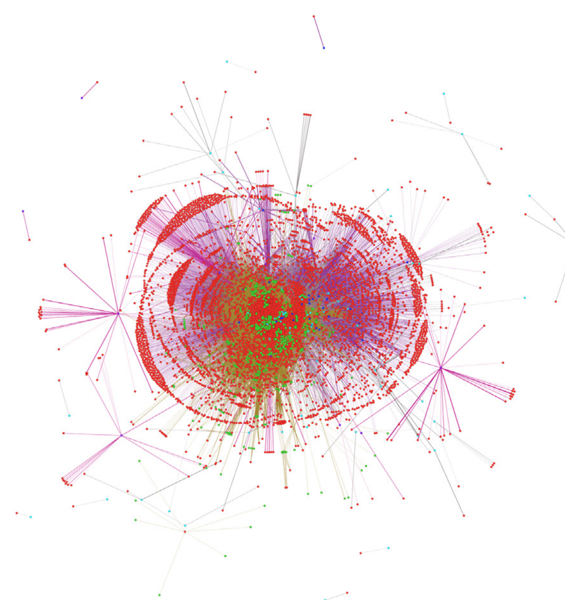
Summary characteristics of the two layers of the network of common asset holdings including the number N of total financial institutions, the number of securities K at issuer level and density statistics are shown in Table 3. The number N of total financial institutions includes separate nodes for unit-linked and non-unit-linked insurance portfolios, and therefore differs from the one reported in Table 1.

The number of identified securities in the two layers is different, with the equity layer being composed of a larger number of securities. It is found that both layers of the network have low total density, suggesting that financial institutions are far from fully diversified across the identified securities in both their equity and debt holdings: all types of financial institution invest in small subsets of the securities in the dataset. This heterogeneity in their debt and equity portfolios might reflect different factors such as risk appetite, regulatory or other constraints, geographical activities and portfolio management strategies for different types of financial institution.[13] In the following we further investigate portfolio concentration, and overlaps across holdings that might arise.

Table 4 shows that, on aggregate, financial institutions are more concentrated in their debt holdings than in their equity holdings. In particular, on average institutions hold 61 out of more than 4000 debt securities, and 92 out of more than 6000 equity securities. The number of debt holdings across different institution types show



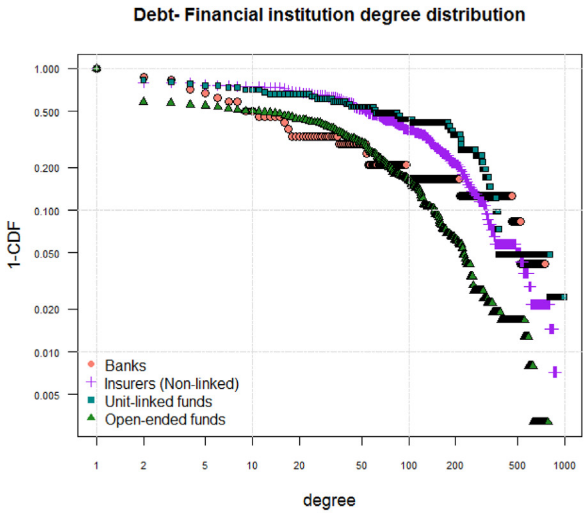
(a) Network of common asset holdings - debt layer



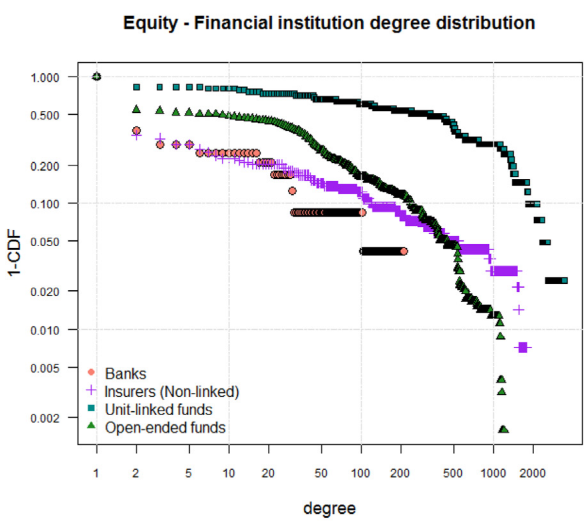
(b) Network of common asset holdings - equity layer

Fig. 2. Visualisation of asset holding network obtained applying the Yifan Hu graph drawing algorithm described in Hu (2005). Red nodes corresponds to securities (at issuer level), green nodes to open-ended investment funds, cyan nodes to unit-linked insurance funds, navy nodes to non-unit-linked insurance companies and purple nodes to banks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

[13] For instance, investment funds can have both passive and active management strategies (Cremers and Petajisto, 2009).

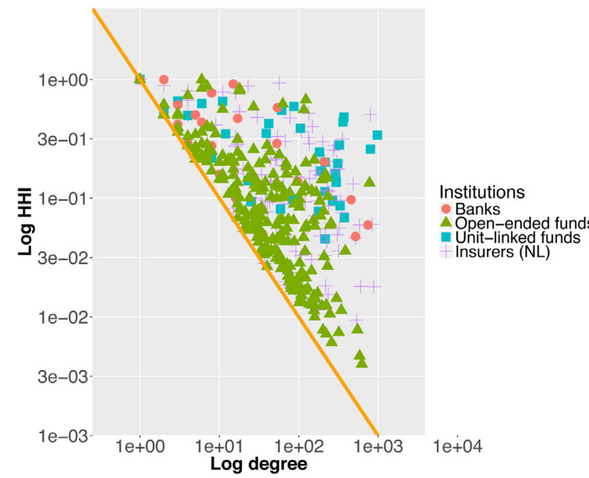


(a) Network of common asset holdings - debt layer

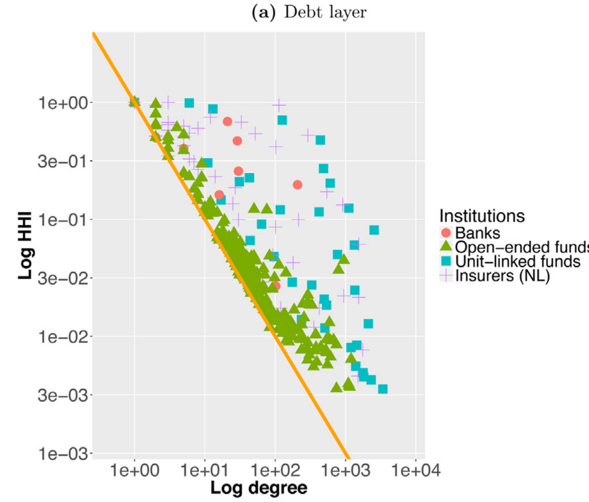


(b) Network of common asset holdings - equity layer

Fig. 3. Empirical complementary cumulative distribution of the number of securities held (financial institution degree) for both debt (top) and equity (bottom) security holdings (two layers of the network of common asset holdings) and for different institution types.



(a) Debt layer



(b) Equity layer

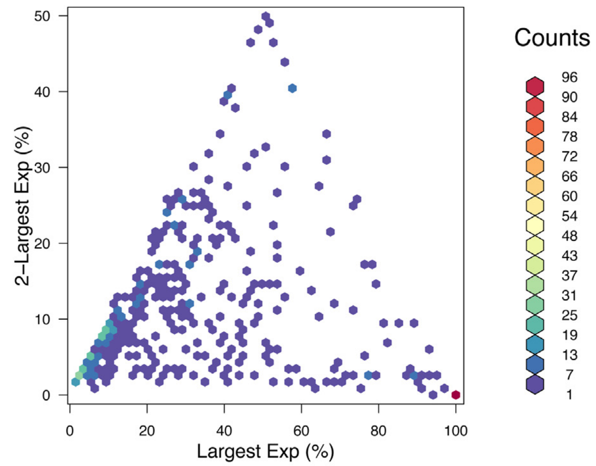
Fig. 4. Relationship between Herfindhal–Hirschman Index (HHI) and financial institution degree for the debt (top) and equity (bottom) layer of the network of common asset holdings. The charts are in log–log scale and also the 'line of equally weighted portfolios' is shown.

some similarity as illustrated by the (complementary) cumulative distribution of the financial institution degree for debt holdings in Fig. 3a. Whereas the (complementary) cumulative distribution of the financial institution degree for equity holdings of Fig. 3b reveals different equity investment profiles across institution types, with unit-linked insurance portfolios holding a larger number of equity securities than other types of financial institutions.

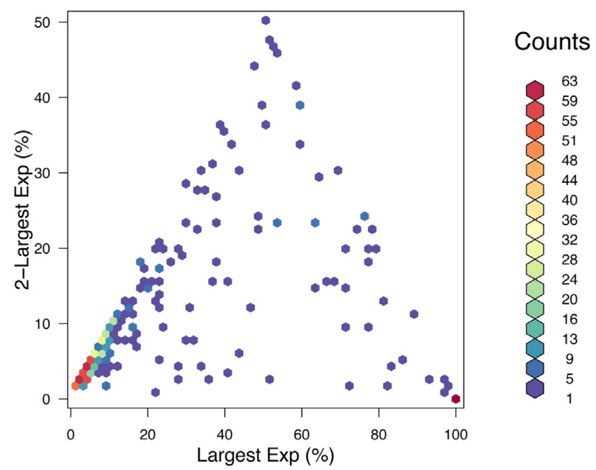
We further characterise concentration by comparing the financial institution degree with the HHI. To compare how various institutions allocate their holdings, we plot the HHI versus the financial institution degree – i.e., the number of holdings – in Fig. 4. We recognise the existence of a 'line of equally weighted portfolios' below which it is mathematically impossible to go as it corresponds to an equally distributed portfolio where each asset gets the exact same fraction of invested volume. If an individual portfolio is equally weighted, the corresponding dot will lie on the line of equally weighted portfolios. On the contrary, dots lying further above the line will correspond to more heterogeneously weighted portfolios. We find that investment funds appear to hold equity portfolios close to the equally weighted one, whereas banks, insurance companies and unit-linked funds tend to hold heterogeneously weighted equity portfolios. All financial institutions tend to hold relatively more heterogeneously weighted portfolios of corporate and government bonds.

Given that most of the portfolios appear to be heterogeneously weighted we further investigate concentration by comparing the first and second largest holdings. This is shown in Fig. 5 where dots with different colours reflect a different number of portfolios with a given combination of largest and second largest holdings. Dots are confined within a triangle given that the second largest holding will always be smaller or equal than the largest one, and the sum of the two will always be smaller than or equal to 1. Allocations are concentrated in the largest holdings if the right side of the triangle is highly populated. It is found that the top debt holdings take up a relatively large proportion of the debt portfolio compared to the equity one.

Concentration of assets is quite similar in the two layers as shown in Table 5, where the numbers of financial institutions holding a given debt and equity security have similar distributions. The average number of institutions holding a debt and equity security is 18 and 21, respectively. The complementary cumulative distribution of the asset degree, shown in Fig. 6 for the two layers, confirms



(a) Debt layer



(b) Equity layer

Fig. 5. Distribution of the two largest holdings for each institution on both the debt (top) and equity (bottom) layers. Different colours reflect a different number of portfolios with a given combination of largest and second largest holdings. Dots are confined within a triangle given that the second largest holding will always be smaller or equal than the largest one. The more populated the right side of triangle, the more concentrated holdings are. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 5
Summary statistics of asset degree across the two layers (debt and equity) of the network of common asset holdings.

	Debt	Equity
Mean	18.32	21.10
St dev	38.32	35.64

that debt and equity securities are held in a similar way across different types of financial institution – e.g., roughly 5% of debt and equity securities are held by more than 100 financial institutions. This shows that, despite the absence of complete diversification across asset holdings, there are some securities largely held in the system whose liquidation at discounted prices could affect many institutions holding it.

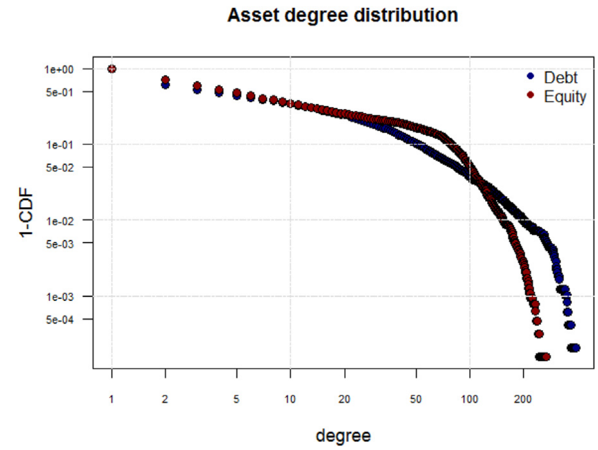


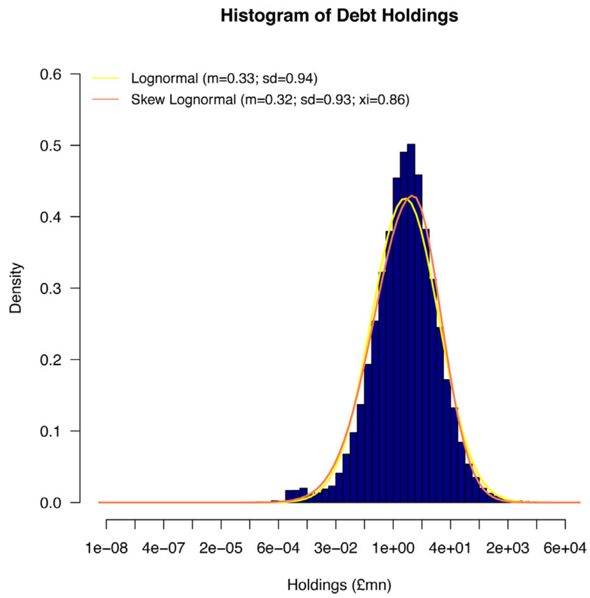
Fig. 6. Empirical complementary cumulative distribution of the number of financial institutions holding a given security (asset degree) for both equity (red) and debt (blue) security holdings (two layers of the network of common asset holdings). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

We also find that the distribution of individual debt and equity holdings is fat-tailed and well described by a log normal distribution as shown in Fig. 7. This highlights the existence of large individual holdings in some debt or equity portfolios. Vulnerabilities might arise if the larger individual debt and equity holdings belonging to the tails of the distribution were to be sold at discounted prices.

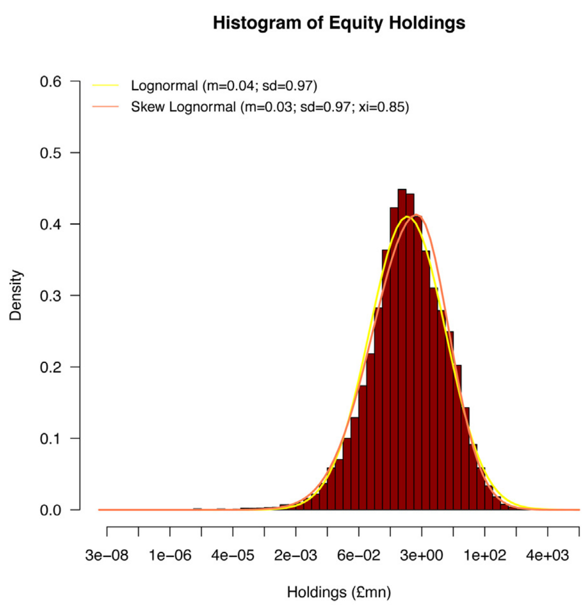
We quantify overlaps of asset holdings using community analysis. This method allows us to find subsets of institutions with maximally similar portfolios and, at the same time, obtain the corresponding set of securities on which they maximally overlap. The number of connected N and K used to compute the community analysis depended on the number of connected nodes. We find approximately 17 communities across debt holdings and 27 across the equity holdings, that we visualise using different colours in Fig. 8.

We observe a concentration in the larger communities, where the top two communities in each layer make up around 50% of holdings for debt and equity, respectively. In particular, as shown in Fig. 9a the two largest communities across debt holdings correspond to roughly £800bn and £600bn of debt holdings, respectively. Whereas the two largest communities across equity holdings correspond both to roughly £300bn of equity holdings. Given that some of the communities have a negligible size, we focus on the subset of larger communities – 10 on the debt side and 6 on the equity side.

Fig. 9a shows that in the debt layer, the largest community is composed by banks while the second largest by all other types of institution. The remaining communities are composed in large part of either banks or investment funds and to a lesser extent of unit-linked and non-unit-linked insurance companies. For debt portfolios, we also estimated the fraction of the total volume that is composed by government bonds for each community. We find that approximately half of the volume of the largest two communities corresponds to government bonds. In the equity layer, Fig. 9b shows that the five larger communities are all composed by different types of financial institution and, particularly, by open-ended funds and unit-linked funds, consistently with the intuition of open-ended funds and unit-linked funds sharing economic similarities. Overall, we find communities containing more than one type of financial institution highlighting that different types of financial institutions are interconnected through common asset holdings. Financial institutions might be more vulnerable to the

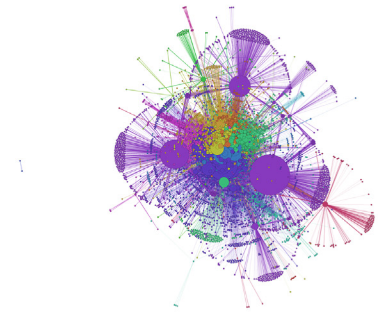


(a) Debt layer

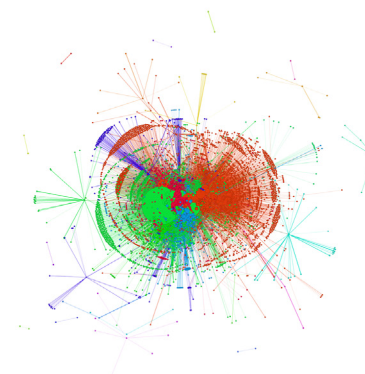


(b) Equity layer

Fig. 7. Histogram of debt (top) and equity (bottom) holdings with the result of the fit of log-normal (mean and standard deviation) and skew log-normal distributions (mean, standard deviation and skewness). A log-scale is used for the x-axis.



(a) Network of common asset holdings - debt layer - visualisation of communities



(b) Network of common asset holdings - equity layer - visualisation of communities

Fig. 8. Visualisation of communities in the asset holding network obtained using the Yifan Hu graph drawing algorithm described in Hu (2005). Vertices with different colours belong to different communities. Vertex sizes are scaled by total holdings for financial institutions and total amounts held for securities. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

behaviour of those financial institutions belonging to the same community in a fire sale scenario, compared to those belonging to other communities.

5.2. Network of portfolio similarity

The network of portfolio similarity informs our understanding of the degree of similarity between portfolios across different institution types. As explained in Section 3, two different definitions of similarity are considered in our analysis – number of common holdings and cosine similarity.

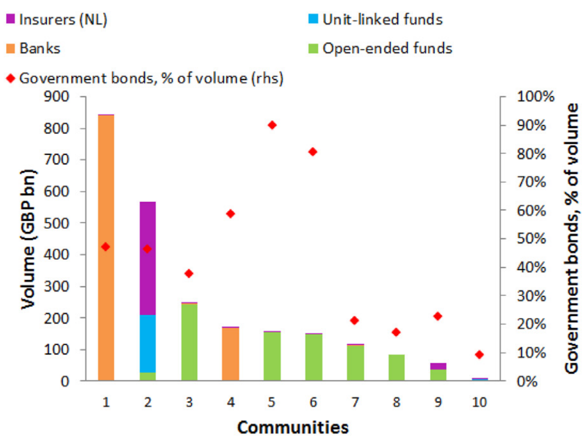
Table 6
Summary of the properties of the two layers (debt and equity) of the network of portfolio similarity. Average degree calculated as density multiplied by total number of nodes (1464).

	Debt	Equity
Density(%)	29.06	16.80
Average degree	425.44	245.95

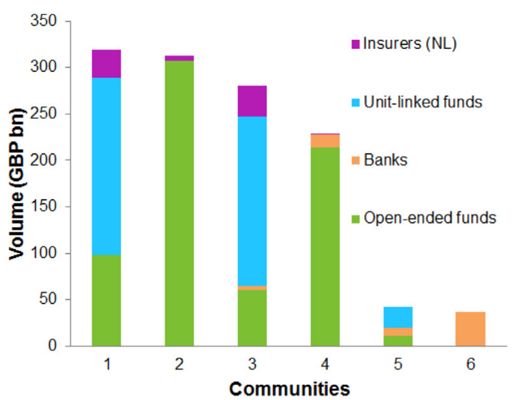
Table 6 summarises the density of the networks of portfolio similarity for debt and equity holdings.[14] In the network of portfolio similarity there is a link between two portfolios whenever they are similar. Therefore a dense network would reflect a financial system composed by financial institutions with very similar portfolios.

We analyse similarities across institution types by considering the sub-networks composed by different pairings of financial institution types. Tables 7 and 8 summarise the density of the subnetworks corresponding to different pairings of financial institution types.

[14] The density is the same for the two definitions of portfolio similarity as they lead to the same adjacency matrix as explained in Section 3.2.



(a) Debt layer- community composition



(b) Equity layer - community composition

Fig. 9. Absolute composition of the largest communities identified by the Louvain modularity maximisation algorithm in the network of common asset holdings in the debt layer (top) and equity layer (bottom).

Table 7
Density between different sub-networks corresponding to different pairs of investment types in the network of portfolio similarity in the debt layer.

	Insurers (NL)	Insurers (UL)	Banks	Open-ended funds
Insurers (non-linked)	0.72	0.59	0.51	0.37
Unit-linked funds		0.58	0.46	0.31
Banks			0.31	0.24
Open-ended funds				0.26

Table 8
Density between the different sub-networks corresponding to different pairs of investment types in the network of portfolio similarity in the equity layer.

	Insurers (NL)	Insurers (UL)	Banks	Open-ended funds
Insurers (non-linked)	0.05	0.20	0.05	0.09
Unit-linked funds		0.62	0.22	0.34
Banks			0.03	0.07
Open-ended funds				0.18

These results show that some institution types hold debt and equity portfolios more similar to those held by other types. For instance, both unit-linked and non-unit-linked insurance company debt holdings are very similar to debt holdings of each other and to those of banks, and to a lesser extent to those of investment funds. We find, as expected given their economic similarities, a high degree of similarity between equity portfolios of unit-linked and open-ended investment funds. These results are consistent with the findings of the analysis of the communities in the network of common asset holdings. It is important to note though that holding a larger number of securities will increase the likelihood of overlaps with holdings of other institution types.

The distribution of the number of common asset holdings and cosine similarity for each pair of financial institutions across the two layers of the network of portfolio similarity are shown in Fig. 10. The majority of pairs of financial institutions have less than 100 securities in common for both debt and equity securities. The distribution of cosine similarity in Fig. 10b shows that there is a low probability of portfolios being very similar. For instance, we find that only 5% of institution pairings have portfolios that are at least 20% similar.

To assess whether similarities can be simply explained by the volumes of total holdings of financial institutions and by the volumes of securities issued by a given issuer, we resolve to use a null model of iterative asset allocation (for details see Annex B) inspired by an analogous procedure in interbank networks developed by Hałaj and Kok (2013).[15] We find that the distribution of similarities cannot be explained solely by such constraints as shown in Fig. 10b, and that further mechanisms for the emergence of portfolio correlation, such as the information on the diversification strategy (Gualdi et al., 2016) or a factor model of index-tracking, should be taken into consideration. Nevertheless, it must be noted that, from a systemic vulnerability perspective, both a random overlap and a non-random one may have consequences in terms of fire sales of commonly held assets.

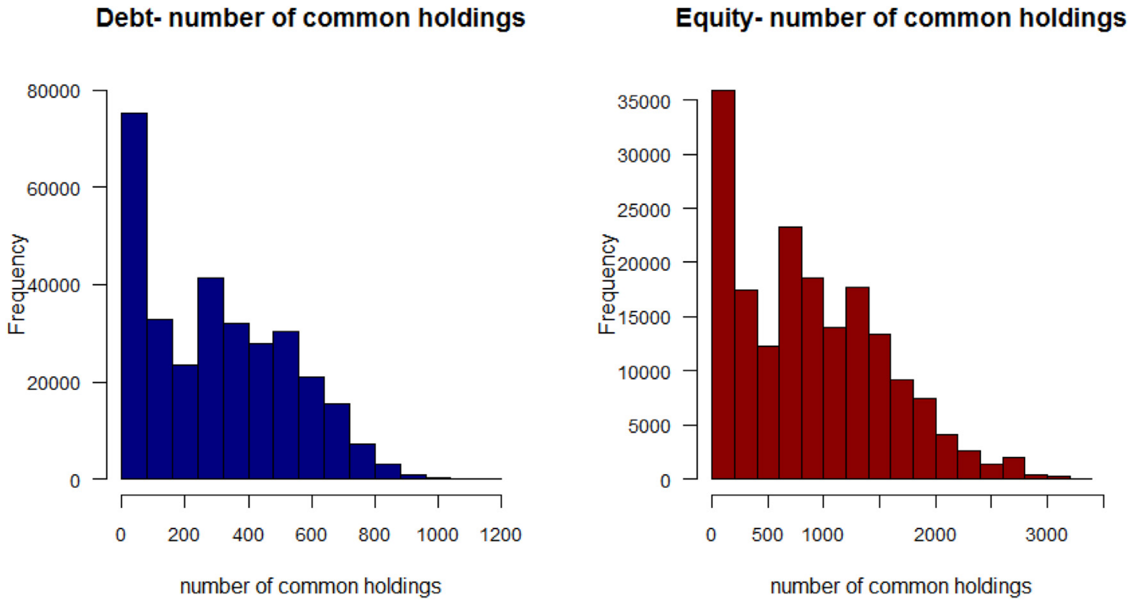
So far we have found that there are several differences across the debt and equity layers. We further investigate these differences by analysing the joint distribution of cosine similarity across the two layers. We study the frequency of a pair of similarity values on the debt and equity layers and we observe that the two layers of the network of portfolio similarity share a low and negative value of correlation as shown in Fig. 11 – i.e., similarities on the debt holding layer are slightly anticorrelated with the corresponding similarities on the equity holding layer, and vice versa. Nevertheless in Fig. 11 we observe the presence of a small subset of financial institutions that share high similarity both on the equity and on the debt layer, this is composed of open-ended investment funds only.

We analyse the centrality of different institution types using the strength centrality defined in Section 3.2, that corresponds to cosine similarity. The average cosine similarity for each type of financial institution considered is shown in Table 9 and compared with average total holdings for both debt and equity holdings.

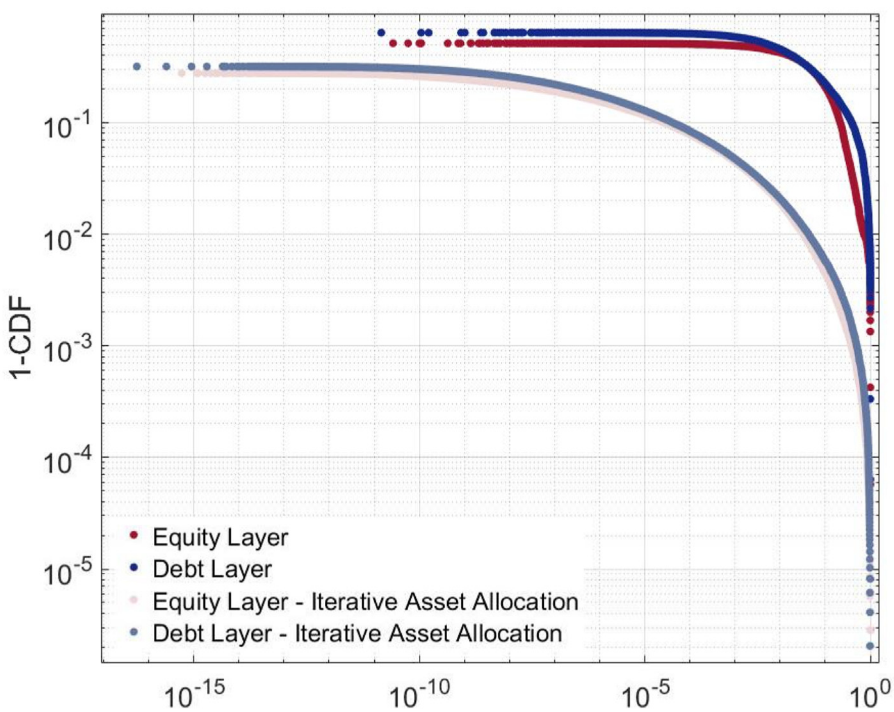
We find that the most ‘central’ institution type (in the sense of having portfolios that are more similar to those of other institutions overall) does not generally depend on the average total holdings. This is, in part, due to the fact that by definition the cosine similarity does not take into account size, but only similarity of investment profiles. Specifically we find that, on average, non-linked insurance portfolios are more ‘central’ in the portfolio similarity network for debt securities, while investment funds and unit-linked insurance portfolios are more central for equity securities. This is in line with the findings of the densities of subnetworks composed by different types of financial institutions.

Community analysis presented in Section 5.1 identifies groups of financial institutions whose portfolios are most similar to each

[15] Given the presence of a finite number of securities and financial institutions, it can be expected that similarities are simply induced by a random uncorrelated allocation. Several null models have been proposed to identify significant values of similarity (see Gualdi et al., 2016). A simple null model of similarity could be to assume that asset allocations follow the capital asset pricing model (CAPM), similarly to Di Gangi et al. (2018). However, it would only predict similarities equal to one, as can be easily shown by applying the formula for CAPM allocation – i.e., $H_{ia} = V_i V_a / \sum_i V_i$ – in the cosine similarity definition.



(a) Number of common holdings



(b) Cosine similarity

Fig. 10. Distribution of the number of common holdings (top) and cosine similarity (bottom) across both the debt and equity holdings (two layers of the networks of portfolio similarity). Empirical cumulative density functions of similarities – equity (red) and debt (blue) – are compared with the corresponding functions obtained via the null model of Iterative Asset Allocation – equity (light red) and debt (light blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 9
Average centrality measures for each institution type and each layer considered in the network of portfolio similarity.

	Debt				Equity			
	Insurers (NL)	Insurers (UL)	Banks	Funds	Insurers (NL)	Insurers (UL)	Banks	Funds
Cosine similarity	0.07	0.05	0.03	0.04	0.01	0.02	0.00	0.02
Holdings (£bn)	2.76	4.74	53.97	0.64	0.53	9.67	2.66	0.57

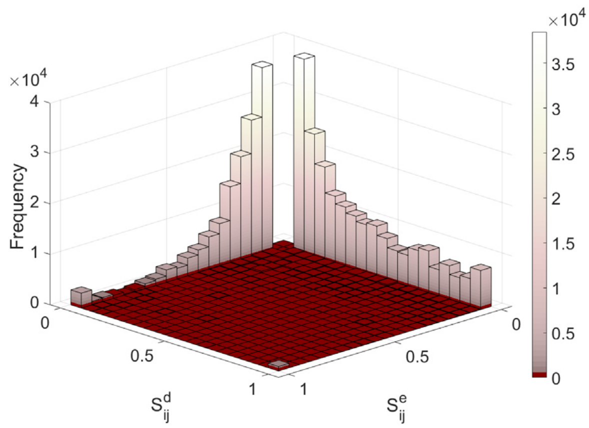
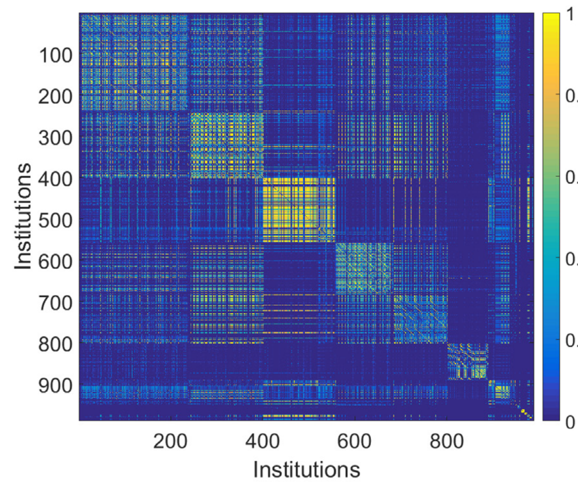
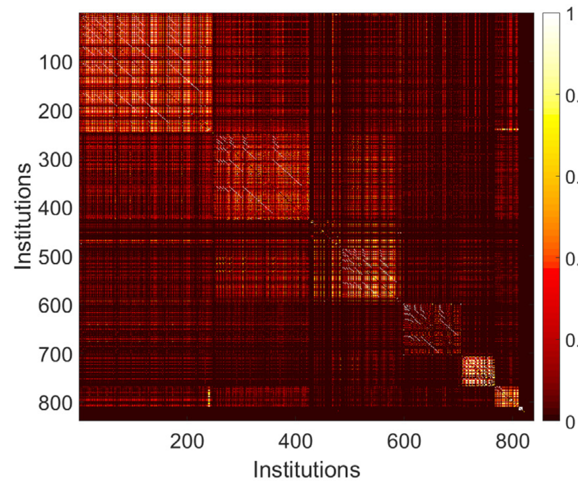


Fig. 11. Joint distribution of cosine similarities of the two layers (restricted to values larger than 0.05). Large similarities on each layers are not explained by Iterative Asset Allocation (IAA) as well as the small peak of close-to-one similarities on both layers (small column at the bottom corner of the figure). Similarity on the debt holding layer and on the equity holding layer are slightly anticorrelated as we observe high frequency values close to the two axes.



(a) Matrix of portfolio similarity - debt layer



(b) Matrix of portfolio similarity - equity layer

Fig. 12. Matrix of portfolio similarity for the debt (top) and equity (bottom) layer. Financial institutions are grouped by communities. Institutions are ordered based on the community identified by the algorithm, and communities are in order of decreasing size. We recognise the presence of a small number of large communities that account for most of the institutions on both layers.

other, and therefore more vulnerable to each other's fire-selling behaviours. In Fig. 12 we group financial institutions in the network of portfolio similarity according to the communities identified in the network of common asset holdings and we sort them in decreasing size. This allows us to recognise the presence of a small number of large sub-networks that account for most of the institutions on both layers of the portfolio similarity network, and correspond to the largest communities in the network of common asset holdings. In Fig. 13 we show the density of the different sub-networks corresponding to the groupings of Fig. 12. The higher the relative inner density of each sub-network the higher the relative vulnerability of an institution towards members of the same community compared to vulnerability towards outer institutions. Despite the modular organisation observed in Fig. 12, portfolio similarities across communities can appear and constitute a channel of possible spillovers of losses from one community to another similar one.

Finally, for each financial institution we analyse the relationship between the average cosine similarity, portfolio concentration (as measured by the HHI) and the grouping into communities shown in Fig. 9. We do so by plotting for each individual portfolio the average cosine similarity versus its concentration. Financial institutions belonging to the same community are identified using the same colour, different symbols identify different institution types and symbol sizes are proportional to total amount held in each portfolio. Any large dots in the top right corner of the chart would correspond to concentrated portfolios that are on average similar to the rest of the system. In order to identify systemic risk vulnerabilities it might be useful to identify institutions holding portfolios with these characteristics. Concentrated portfolios might be more vulnerable to external shock, and their liquidation could have widespread impact if they are large and present a high degree of similarity with the rest of the system.

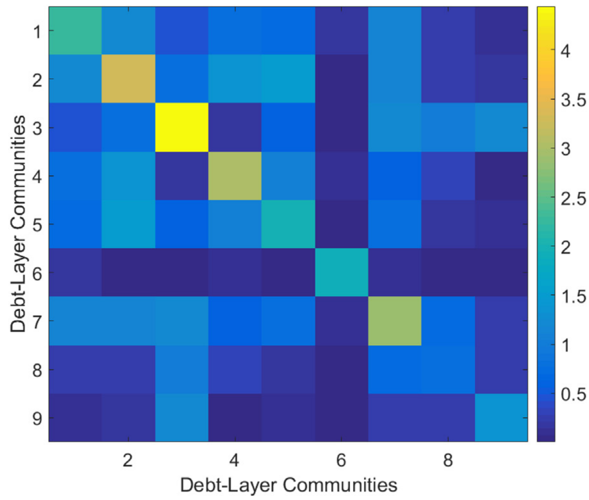
Results are shown in Fig. 14 for both debt and equity portfolios. Average cosine similarity of equity portfolios is negatively correlated with portfolio concentration. Also the average cosine similarity is larger for those belonging to the largest communities confirming that the community analysis has identified financial institutions with maximally similar portfolios. The dots aligned to the y-axis of Fig. 14b show that large financial institutions with equity portfolios that on average are similar with those of the rest of the system are also more diversified.

The relationship between debt portfolio similarity and concentration is less clear than equity. Nevertheless we still find that financial institutions belonging to the same communities display similar patterns of portfolio similarity and concentration. For instance, the horizontal line of Fig. 14a shows that both non-linked and unit-linked insurance portfolios belonging to the same community have similar average portfolio similarity and different levels of portfolio concentration. Overall this suggests that, despite portfolios might have different levels of concentration, contagion could occur between financial institutions belonging to those communities with larger portfolio similarity.

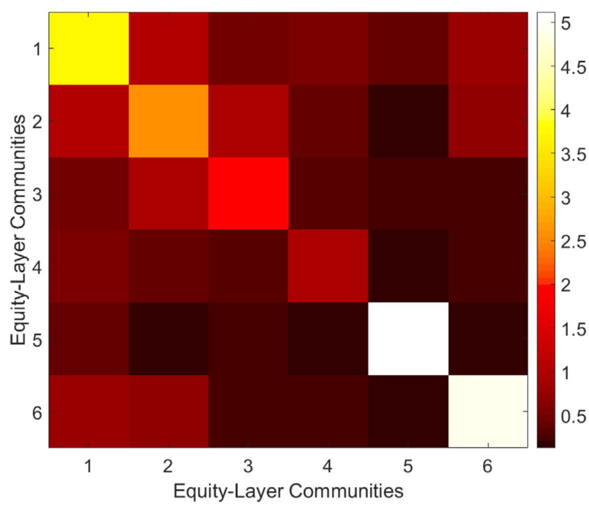
5.3. Network of liquidity weighted portfolio overlap

Finally we present results of the analysis of the liquidity weighted portfolio network. As explained in Section 3.3 this network is constructed using less granular data, consists of one layer only that describes the similarity of stylised portfolios – including both debt and equities – and takes into account the liquidity of the assets.

The stylised portfolio considered is shown in Table 2. We use market depth estimates of Cont and Schaanning (2017) as proxy

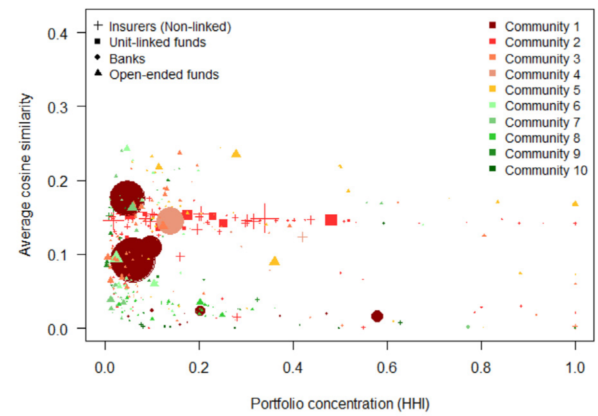


(a) Affinity matrix - debt layer

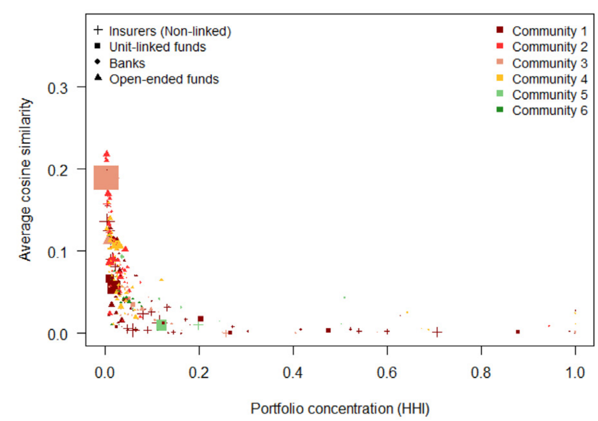


(b) Affinity matrix - equity layer

Fig. 13. Affinity matrix. Density of sub-networks corresponding to the different communities in the debt (top) and equity layer (bottom).



(a) Debt layer



(b) Equity layer

Fig. 14. Relationship between average cosine similarity, portfolio concentration and communities for debt (top) and equity (bottom) layer. Portfolio concentration is measured using HHI. Different symbols correspond to different institution types. Symbol sizes are proportional to the portfolio size. Different colours correspond to the grouping into communities shown in Fig. 9. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

for the liquidity of our asset classes, which we show in Table 12 in Annex C.[16] Intuitively a large liquidity weighted overlap between two institutions means that one institution would be more affected should the other institution be forced to liquidate its holdings.

Using the data described in Section 4.3, the network is now composed of 285 financial agents, of which 52 non-linked insurance portfolios, 20 unit-linked insurance portfolios, 21 banking groups and 192 groups of open-ended investment funds aggregated by investment strategy.

We would inherently expect this less granular network of liquidity weighted overlap (which implies by definition that overlaps will be more likely) to be more dense than the networks of common asset holdings and portfolio similarity. Therefore if our analysis was based on density alone we would not be able to produce a meaningful result. Instead, our analysis is informed by the weighted adjacency matrix. We use this to calculate metrics which give an indication of fire sales vulnerabilities.

Table 10
Density between the different sub-networks corresponding to different pairs of institution types in the liquidity weighted overlap network.

	Insurers (NL)	Insurers (UL)	Banks	Open-ended funds
Insurers (NL)	0.94	0.88	0.93	0.93
Insurers (UL)		0.80	0.90	0.89
Banks			0.97	0.96
Open-ended funds				0.95

Here we find the overall density of this network is 0.94, which is indeed much larger than the density observed in the two layers of the granular portfolio similarity network. Subnetwork densities are also larger than those in the two layers of the granular portfolio similarity network as shown in Table 10. This reflects our use of a coarser definition of granularity. We also analyse the distribution of liquidity weighted portfolio overlaps and find them to be well described by a skew log-normal distribution as shown in Fig. 15.

Cont and Schaanning (2017) define the Indirect Contagion Index (ICI) as the eigenvector centrality of the liquidity weighted portfolio overlap network which they show is correlated with fire sale losses for banks. We find that, on average, banks have the largest

[16] In this analysis, loops have been excluded as we are interested in common asset holdings across institutions and not in estimating losses due to fire sales as in Cont and Schaanning (2017). However results are very similar if loops are included.

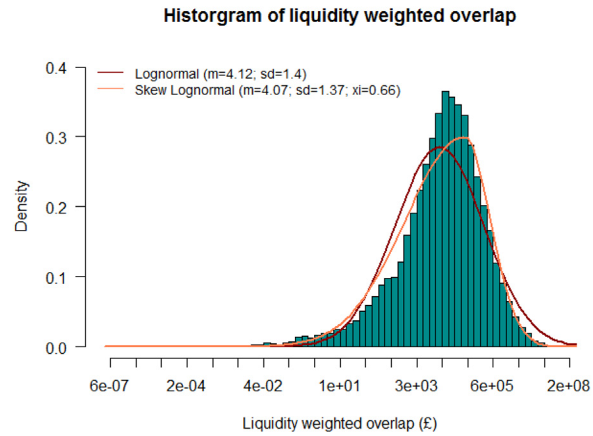


Fig. 15. Histogram of the liquidity weighted portfolio overlaps with the results of the fit of log-normal (mean and standard deviation) and skew log-normal distributions (mean, standard deviation and skewness).

Table 11
Average liquidity weighted overlap (Overlap in £mn), average holdings (Holdings) and average eigenvector centrality (Eigenvector) for each institution type considered in the network of liquidity weighted overlap.

	Insurers (NL)	Insurers (UL)	Banks	Open-ended funds
Overlap (£mn)	0.31	0.29	0.81	0.24
Holdings (£bn)	18.65	43.98	171.95	12.89
Eigenvector	0.05	0.04	0.15	0.04

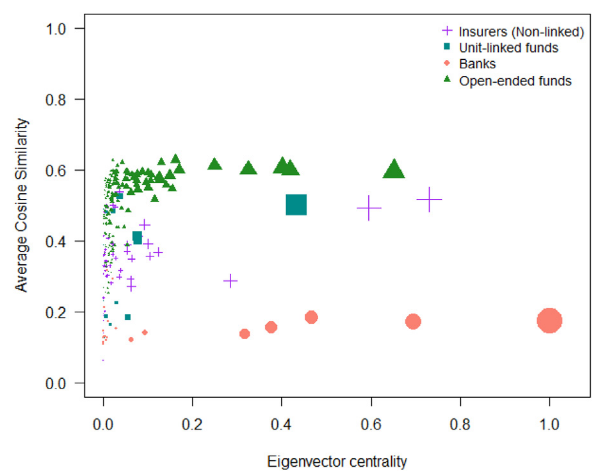


Fig. 16. Comparison between eigenvector centrality and average cosine similarity for different institution types. Symbols are proportional to total maketable assets of the corresponding institution.

eigenvector centrality, the largest liquidity weighted overlap and the largest asset holdings as shown in Table 11.

On the other hand Getmansky et al. (2016) show that average cosine similarity is a good predictor of similarity of asset sales for insurance companies. We compare these two indicators of fire sale vulnerabilities for our stylised portfolios in Fig. 16. We scaled the sizes of the symbols in proportion to holdings of marketable assets. We find that eigenvector centrality assigns large weight to those financial institutions with a large amount of marketable assets, such as banks, insurance companies, some unit-linked funds and some categories of investment funds large in size. We find that some of the insurance companies, unit-linked funds and categories of open-ended funds of larger size with a high eigenvector centrality also have a high value of average cosine similarity. On the contrary, we find that average cosine similarity is able to identify similarity of investment fund categories of smaller size with the rest of the system. We conclude that both indicators could be useful for monitoring and assessing fire sale vulnerability as they are complementary.

6. Discussion

The findings in this paper contribute to a better understanding of the extent to which different types of financial institutions hold similar debt and equity assets. We have explored the concentration, overlaps and similarities in financial institutions' asset holdings in order to assess vulnerabilities to fire sales of commonly held assets. We hope this in turn can inform how financial stability is monitored and maintained.

Our analysis shows that, despite having relatively unconcentrated portfolios, different types of financial institution can share a large amount of common asset holdings, pointing to existence of a significant channel of price-mediated contagion between banks, insurance companies and investment funds. Our findings are in line with the investment characteristics of each of the financial institution types studied. For instance, by splitting the insurance sector into unit-linked funds and non-linked funds we are able to capture the similarity and the overlap between equity portfolios of unit-linked funds and open-ended investment funds. We also find similarities between debt portfolios of banks and insurers.

The analysis of liquidity weighted portfolio overlap proposes indicators which might be useful to identify vulnerabilities due to fire sales of commonly held assets. Specifically, we compared indicators of vulnerabilities due to fire sales, such as the average cosine similarity and the eigenvector centrality in the liquidity weighted portfolio overlap network, finding that the two indicators are complementary rather than redundant. Average cosine similarity is less affected by the total invested volume of an institution, and therefore identifies investment funds with similar portfolio composition as important for systemic risk despite their holdings being of smaller size relative to banks and insurers. The liquidity weighted centrality is more correlated with the volume held (and potential losses) and consequently tends to assign greater relevance to large financial institutions, such as banks.

In light of our analysis, it is important to point out that network interconnectedness varies significantly for different levels of granularity (e.g., at issuer level for each debt or equity security, or coarser asset classes). On the one hand, granular data on security holdings could lead to an underestimation of similarity and overlaps across portfolios in the context of fire sales vulnerabilities. On the other hand, a very broad definition of asset classes might overestimate the overlap. It is therefore important when modelling fire sales to achieve a reasonable balance in this trade-off and consider including a robust measure of liquidity and correlations of asset prices. Liquidity of assets is in fact crucial to quantify the impact of fire sales of commonly held assets. Correlations between market prices of securities are key to identify the relevant level of aggregation for the estimation of the portfolio overlaps.

The dataset created in this paper by joining the granular asset holdings of insurers, banks and investment funds could have many additional applications. If in the future more detailed information at security level were available, it would be possible to understand which industry sectors (e.g., technology, financial, etc.) of debt and equity significantly contribute to overlaps. Furthermore, when a high quality time series of data on common asset holdings across different institution types is established, it might be possible to extend our analysis over time. For instance, it would be possible to evaluate the indicators of vulnerabilities due to

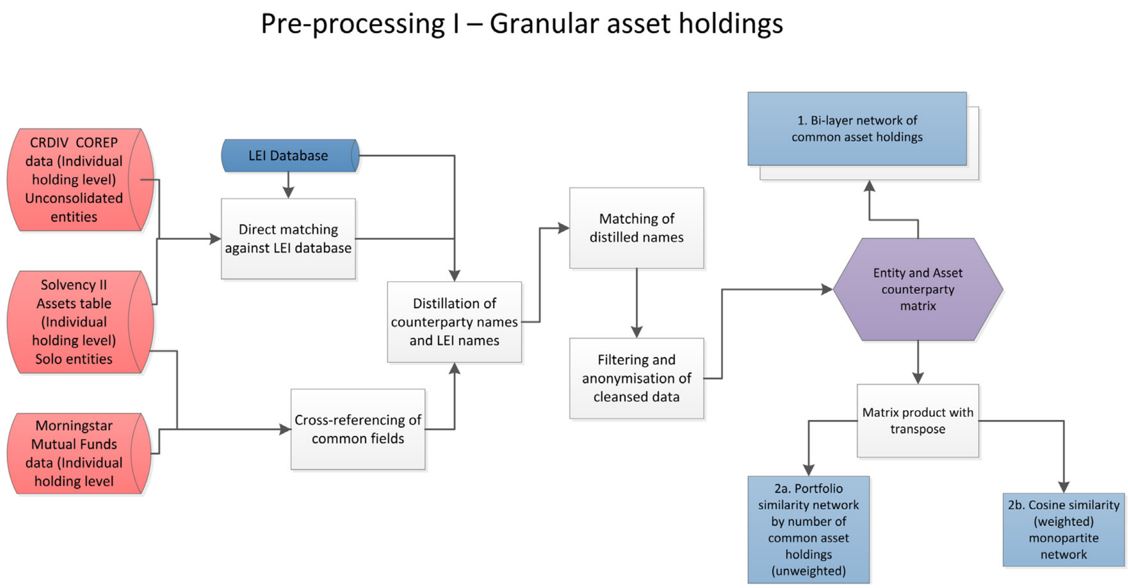


Fig. 17. High-level summary of the steps used for the pre-processing of the granular holdings data used for the networks of common asset holdings and portfolio similarity.

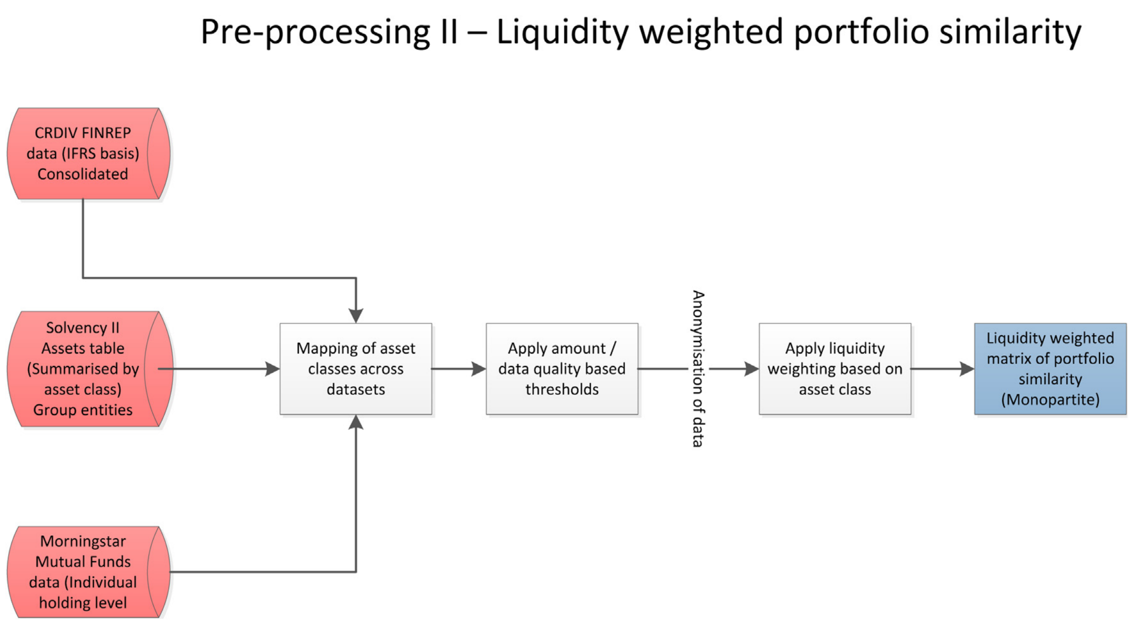


Fig. 18. High-level summary of the steps used for the pre-processing of the data used for the network of liquidity weighted portfolio overlap.

fire sales considered in this paper over time and use this to infer build-up of dangerous levels of systemic risk based on correlation with real market events. Such analysis has the potential to inform policy decisions to support the resilience of the financial system.

Financial stability under a fire sale scenario will ultimately depend on many additional factors not considered in detail in this paper, such as regulatory and market constraints that drive financial institution buying and selling behaviour under stress, and effectiveness of hedging and ability to settle transactions during stressed times. In this paper we made an important progress by creating a rich dataset for mapping common asset holdings across multiple institution types and analysing indicators of vulnerabilities due to fire sales. In the future, it would be interesting to compare the indicators and the vulnerabilities analysed in this paper with a model of fire sale contagion that accounts for all factors relevant for financial stability mentioned above.

Annex A. Data pre-processing

In this analysis we make use of and create novel datasets which have not previously been exploited for research. Therefore a number of steps have to be taken to align the datasets to be consistent and improve sample coverage for the analysis. In this annex we set out the pre-processing of the data described in Section 4.

We first define the scope of asset holdings to be studied. Derivatives, contingent assets and indirect asset holdings are out of scope of the empirical analysis as the literature in which this study is based upon is concerned specifically with transmission of losses through commonly held assets. Tables 13, 14 and 15 show how the asset classes listed in different datasets have been mapped into debt and equity holdings.

After studying the data fields contained in Solvency II and COREP reporting and identifiers used we were able to design a join between the datasets and reference data. Although there were gaps, in some cases it was possible to complete records by distilling and mapping their names using a master list of Legal Entity Identifiers (LEIs) or matching them to similar 'clean' records. Morningstar data did not include LEIs but we were able to cross-reference other fields for the same assets in the Solvency II data. We applied a distillation process to remaining unmapped asset holdings. This distillation process involved word stemming and string manipulation techniques so that issuer names couple could be matched to names of counterparties in the LEI database (rather than the actual LEIs themselves which had not been reported). We also applied a general mapping of sovereign/government exposures by country to aid uniformity. Once the distilled names were matched, assets out of scope were filtered out.

A significant challenge when preparing the data was the trade-off between increasing coverage of the mapping by stemming the original name reported by the financial institution whilst also ensuring that the mapping of an exposure to a particular counterparty is accurate. Having reviewed the accuracy of the mappings for a sample of the data, we used this to refine our data matching process several times until we reached a satisfactory level in the trade-off. As a precaution, a threshold was applied so that mapped names more than 35% different than the original name were excluded from the analysis.

The steps used for the pre-processing of the granular holdings data used for the networks of common asset holdings and portfolio similarity are described in Fig. 17.

The steps used for the pre-processing of the data used for the network of liquidity weighted portfolio overlap are summarised in Fig. 18. As this data was at the level of asset type rather than at issuer level, far less pre-processing was involved to prepare the corresponding network. We applied a common mapping of asset types as shown in Table 2 and then aggregated the data.

Annex B. Null-model for weighted bipartite networks

We generate a set of random weighted bipartite networks preserving marginal volumes for both types of nodes – i.e., the total issued holdings for each security and the total amount of holdings for each holder. This procedure, named here Iterative Asset Allocation (IAA), allows us to test whether the values of similarities found can be, at least partially, explained by the respective sizes of the different pairs of institutions, and by the limited amount of issuers present in the market. A multi-linear regression contrasting individual similarities and volumes would not take into account the interdependence of allocations between institutions and issuers, and a null model for the weighted bipartite matrix of asset holdings is needed.

Initially each institution has a capital corresponding to the sum of all her holdings, or its weighted degree, and, analogously, each issuer has an amount of securities corresponding to its weighted degree. The random network is generated via an iterative procedure that progressively populates the asset holdings until, gradually updating the remaining capital for each institution and the remaining available securities for each issuer.

The procedure is the following: an holder-issuer pair is drawn uniformly at random among institutions with non-zero capital and issuers with non-zero available securities, the value of the holding is drawn by taking a random percentage of the minimum between the total available capital of the holder and the total available securities of the issuer, i.e., $H_{ia} = f min(V_i, V_a)$.

The available buffers for both institutions and issuers are updated, and the procedure is repeated. When the available buffers, either capital or securities, fall below a given error threshold the institution or the issuer has reached convergence.

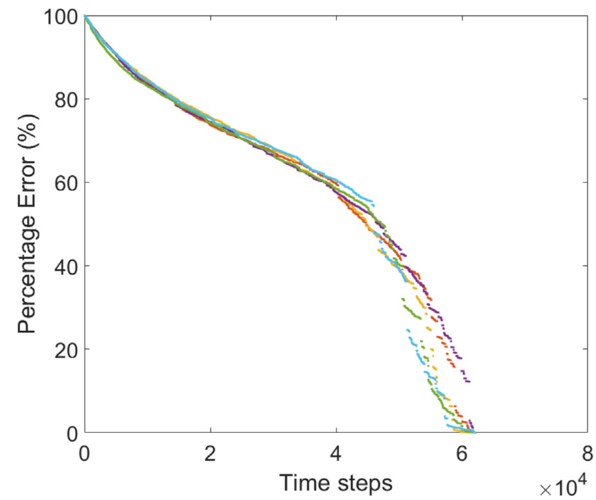


Fig. 19. Dynamics of the percentage error on the network constraints, i.e., given by the ratio between unallocated volume and total volume of the original asset holdings matix, for various random allocations sampled via the iterative asset allocation (IAA).

Table 12
Market depth proxies for the marketable asset classes of the stylised portfolio used for the liquidity weighted portfolio overlap network.

Asset class	Market depth (£bn)
Central government bonds	338.75
General governments	117.17
Corporate bonds	55.46
Other bonds	55.46
Equity	338.75

The procedure is analogous to the one defined in Hałaj and Kok (2013) for interbank networks, only here we compute the fraction after taking the minimum between the two buffers.

Buffers decrease at each step of the algorithm, reducing on average by a factor proportional to the random fraction f for each sampling, and convergence is fast and robust for different sampling procedures as shown in Fig. 19.

Annex C. Tables

Table 13
Map of the asset classes listed in the insurance dataset into debt and equity holdings. The first column corresponds to the asset classes in the source dataset, the second to the mapping into debt and equity layers (used for the network of common asset holdings and portfolio similarity), and the third to the mapping in the stylised portfolio (used for the network of liquidity weighted overlap).

Insurance CIC and CIC sub category	Mapping	Stylised portfolio
Government bonds, Central government bonds	DEBT	Central government bonds
Government bonds, Supra-national bonds	DEBT	General governments
Government bonds, Regional government bonds	DEBT	General governments
Government bonds, Municipal government bonds	DEBT	General governments
Government bonds Treasury bonds	DEBT	General governments
Government bonds Covered bonds	DEBT	General governments
Government bonds National Central banks	DEBT	General governments

Table 13 (*Continued*)

Insurance CIC and CIC sub category	Mapping	Stylised portfolio
Government bonds Other	DEBT	General governments
Corporate bonds, Corporate bonds	DEBT	Corporate bonds
Corporate bonds, Convertible bonds	DEBT	Other bonds
Corporate bonds, Commercial paper	DEBT	Other bonds
Corporate bonds, Money market instruments	DEBT	Other bonds
Corporate bonds, Hybrid bonds	DEBT	Other bonds
Corporate bonds, Common covered bonds	DEBT	Other bonds
Corporate bonds, Covered bonds subject to specific law	DEBT	Other bonds
Corporate bonds, Subordinated bonds	DEBT	Other bonds
Corporate bonds, Other	DEBT	Other bonds
Equity, Common equity	EQUITY	Equity
Equity, Equity of real estate related corporation	EQUITY	Equity
Equity, Equity rights	EQUITY	Equity
Equity, Preferred equity	EQUITY	Equity
Equity, Other	EQUITY	Equity
Collective Investment Undertakings, Equity funds	EQUITY	Collective Investment Undertakings
Collective Investment Undertakings, Debt funds	DEBT	Collective Investment Undertakings

Table 14
Map of the asset classes listed in open-ended investment fund dataset into debt and equity holdings. The first column corresponds to the asset classes in the source dataset, the second to the mapping into debt and equity layers (used for the network of common asset holdings and portfolio similarity), and the third to the mapping in the stylised portfolio (used for the network of liquidity weighted overlap).

Morningstar	Mapping	Stylised portfolio
BOND – GOV'T INFLATION PROTECTED	DEBT	Central Government bonds
BOND – SUPRANATIONAL	DEBT	General governments
BOND – GOV'T AGENCY ARM	DEBT	General governments
BOND – GOV'T AGENCY DEBT	DEBT	General governments
MUNI BOND – CASH	DEBT	General governments
MUNI BOND – GENERAL OBLIGATION	DEBT	General governments
MUNI BOND – REVENUE	DEBT	General governments
MUNI BOND – UNSPECIFIED	DEBT	General governments
BOND – GOV'T/TREASURY	DEBT	General governments
BOND – GOV'T AGENCY PASS-THRU	DEBT	General governments
BOND – CORPORATE BOND	DEBT	Corporate bonds
BOND – CORP INFLATION PROTECTED	DEBT	Corporate bonds
BOND – CONVERTIBLE	DEBT	Other bonds
CASH – COMMERCIAL PAPER	DEBT	Other bonds
BOND – COVERED BOND	DEBT	Other bonds
BOND – UNITS	DEBT	Other bonds
BOND – UNDEFINED	DEBT	Other bonds
EQUITY	EQUITY	Equity
EQUITY – UNITS	EQUITY	Equity
EQUITY – REIT	EQUITY	Equity
PREFERRED STOCK	EQUITY	Equity
EQUITY – UNDEFINED	EQUITY	Equity

Table 15
Banks' investments were already categorised as debt or equity in line with COREP reporting rules. Asset classes in FINREP reporting were used for the portfolio of liquidity weighted overlap below.

FINREP source table	Stylised Portfolio
F04.01-070-010	Central government bonds
F04.02-070-010	Central government bonds
F04.03-070-030	Central government bonds
F04.01-080-010	General governments
F04.02-080-010	General governments
F04.03-080-030	General governments
F04.01-090-010	Corporate bonds
F04.01-100-010	Corporate bonds
F04.01-110-010	Corporate bonds
F04.03-100-030	Corporate bonds
F04.02-090-010	Corporate bonds
F04.02-100-010	Corporate bonds
F04.02-110-010	Corporate bonds
F04.03-090-030	Corporate bonds
F04.03-110-030	Corporate bonds
F04.05-020-010	Other bonds
F04.02-010-010	Equity
F04.02-010-010	Equity
F04.03-010-030	Equity

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