The UK Banking System's Global Network of Granular Exposures

Covi Giovanni*, Brookes James**, and Raja Charumathi***

Abstract

In this paper we construct and analyse the UK banking system's Global Network of granular exposures which captures roughly 92% of the UK banking system's total assets for the period Q1-2018 to Q3-2021. We thus study the microstructure of UK banking system focusing on the role played by concentration risk and interconnectedness across sectors. We then estimate the quarterly evolution of expected losses (*Capital at Risk)* for the UK banking sector, and via Monte Carlo simulations the stochastic distribution of UK banks' losses to study the severity and likelihood of tail-events (*Conditional Capital at Risk*). In the end, we provide insights on the impact of the Covid-19 crisis on UK banking system's financial stability as well of climate-related financial risks.

Keywords: Financial Network, Systemic Risk, Stress Testing, Covid-19, Climate Change.

JEL Classification: D85, G21, G32, L14

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* Stress Test Strategy Division, Bank of England; Email: giovanni.covi@bankofengland.co.uk

** Advance Analytics Division, Bank of England; Email: james.brookes@bankofengland.co.uk

*** Banking Capital Policy Division, Bank of England; Email: charu.raja@bankofengland.co.uk

"Mapping the networks between financial institutions is a first step towards gaining a better understanding of modern financial systems. A network perspective would not only account for the various connections within the financial sector or between the financial sector and other sectors, but would also consider the quality of these links. We need this work to guide the development of new theories that can help us understand events such as the August 2007 crisis, as well as design new regulations that better meet the challenge of an increasingly networked world" (Allen and Babus, 2009: 13).

1. Introduction

The Great Financial Crisis and the economic crisis that followed has highlighted how the economic system's functioning is strongly intertwined with the financial system's functioning. Input-output linkages among non-financial corporations affect the productive structure of our economic system, whereas contractual relationships among financial institutions determine the microstructure of the financial network. In the end, the financial system by proving funding via loan exposures and by allocating capital in the form of debt and equity security exposures to the real economy shapes the financial-economic nexus, binding together the two systems' return and risk cycle. Hence, the way these contractual relationships are distributed within and between the two systems - interconnectedness and concentration risk - has relevant implications for business cycle fluctuations and financial stability.

On the one hand, Gabaix (2011) has first shown how concentration risk in the economic system such as shocks to large non-financial corporations may lead to remarkable fluctuations in economic activity - the granular origins of aggregate fluctuations. On the other hand, Acemoglu et al. (2016) showed how interconnectedness in economic activity such as a high level of interdependency in the intersectoral input-output firms' linkages - network origins - may explain aggregate fluctuations in output. These results are extremely relevant also in light of the Covid-19 crisis which has caused bottleneck problems in the global supply chain (Rees and Rungcharoenkitkul, 2021). To what may concern the financial system's functioning Acemoglu et al. (2015) has shed light on how it relates with the economic system's functioning. Financial stability and the level of systemic risk in financial networks depend on the size of the initial shock stemming from the real economy and on the financial network structure. More dense (sparse) financial networks tend to amplify (dampen) real economic shocks when the initial shock is sizeable, whereas more dense financial networks enhance financial stability by reducing financial contagion when shocks are less sizeable.

The financial network literature (Glasserman and Young, 2016) has focused on modelling and quantifying those contagion channels at play that determine financial amplification mechanisms usually relying on an exogenous trigger like a bank default event. Contrary, not much emphasis in the literature has been devoted on measuring the severity and probability of the trigger event, which according to Acemoglu et al. (2015), is the variable together with the network structure determining the system's propensity to instability.

Levering-up these key insights from the literature our work investigates empirically the financial instability economic nexus by looking at how UK banks' exposures are globally distributed and concentrated on a counterparty basis across all sectors of the economy (private and public sectors) and by quantifying the potential severity of the initial shock in £ amounts as well as in probabilistic terms.

To achieve this, we construct the most comprehensive granular exposure-based dataset for the UK banking sector by merging different supervisory datasets available at the Bank of England. In this respect, the resulting Global Network of UK banks' loan and security exposures covers roughly £ 11 trillion or 92% of the UK banking system' asset side. Out of this £ 11 trillion of exposures, 60.3% is captured with a bank-to-counterparty relationship, whereas the remaining 39.7% is composed by aggregated exposure with a bank-to-country/sector relationship. Overall, the Global Network which is quarterly updated, spans between Q1-2018 and Q3-2021, and is composed on average by 125 UK reporting banks, 14,000 counterparties and 31,000 contractual relationships distributed across six major sectors (non-financial corporates, financial corporates, credit institutions, governments, central banks, and households) and across more than 170 countries.

Hence, Section 3 and Section 4 contribute to the study on the microstructure of financial systems and on comparative financial systems led by the seminal paper of Allen and Gale (2001). We thus present detailed network statistics across time, sectors and exposure types in order to provide a footprint for the microstructure of the UK banking system and so moving a step forward in the mapping of the Global Banking System. Our key results highlight that the UK banking network is composed of: i) a core-double periphery structure, that is, an additional periphery which is an exclusive market for certain key players; ii) a highly fat-tailed distribution of exposures with roughly the top-10% of exposures and counterparties capturing 90% of the total exposure amounts.

Next, Section 5 exploits the microstructure of the Global Network to quantify UK banking system's *Capital at Risk* (CaR) and *Conditional Capital at Risk* (CCaR), that is, respectively potential expected loss estimates and tail loss estimates before and during the Covid-19 crisis. In this respect, the UK banking system's CaR estimate in Q1-2021 (peak of the Covid-19 crisis) was close to £56.7 billion, up by 36% (£42 billion) relative to Q4-2019 (pre-crisis period).

Most of this increase comes from exposures towards the non-financial corporate sector, up to £29.4 billion losses or by 70% between Q4-2019 and Q1-2021. Next we compute *Conditional Capital at Risk* (CCaR), that is, tail-loss estimates so as to model scenario uncertainty and factor-in into the loss calculation the degree of concentration risk and interconnectedness of the UK banking sector's network of exposures. Overall, this approach allows us to assess not only the severity of extreme events, but also to measure their likelihood. In this respect, we estimate that a *severe distress* scenario (97.5th percentile of the estimated loss distribution) would produce roughly £240 billion of median losses in Q1-2021 up from £132 billion in Q4-2019. Moreover, we estimate that due to the Covid-19 crisis the likelihood of the UK banking sector experiencing a severe distress event above £132 billion losses increases from 1% in Q4-2019 to 5.4% in Q1-2021 (one severe stress every 18 years). Instead if we consider the probability of experiencing a *medium stress* event (90th percentile) above £76 billion losses the probability increases up to 13.2% in Q1-2021 from 5.1% in Q4-2019 (one every 7.5 years). In the end, we show that a tightening in the correlation structure of banks' counterparty defaults lead to an increased severity and likelihood of tail events, thereby corroborating empirically Acemoglu et al. (2015)'s findings.

Finally, Section 6 provides new insights on the UK banking sector's share of exposures subject to climate related transition risk and its green asset ratio following the methodology of Battiston et al. (2017). In this respect, we show that the UK banking sector's share of total assets subject to climate-related transition risk is close to 4.2%, whereas its green asset ratio is close to 3.8%, both lower than for the EA banking sector.

In the end, Section 7 provides a synopsis, contextualizing the contributions of the paper in relation to the existing literature, and discusses the limitations and potential further extensions of the work.

2. Literature Review

Granular data collection such as the large exposures framework were introduced by the Basel Committee on Banking Supervision in order to measure and monitor concentration risk and interconnectedness of credit institutions (BCBS, 2014). These data collections contributed to foster empirical research on financial network which before that relied on imputing bilateral linkages based on optimization methods such as maximum, minimum or relative entropy solutions (Sheldon and Maurer 1998, Degryse and Nyguyen, 2007; Elsinger et al. 2006; Upper, 2011, Van Lelyveld and Liedorp, 2006), or by generating random networks consistent with partial information (Halaj and Kok, 2013; Anand et al., 2014). As emphasized by Glasserman and Young (2016) empirical work in this field was and is still limited by the confidentiality of interbank transactions which were available only to central bankers and supervisors. Given these data limitations, most of empirical analyses tend to be country-specific or market-specific and focused on studying interbank network relationships[1].

To what may concern the UK financial network, our jurisdiction of interest, Gai et al. (2011) exploited the large exposure data to study concentration and contagion in the UK interbank market focusing on liquidity risk. Bardoscia et al. (2019a) by exploiting large exposure data and interbank security and derivative exposures studied how solvency contagion may propagate in the UK interbank market. Other UK-based studies investigated specific market segment such as Coen et al. (2019) which focused on UK banks' security holdings and fire-sales spillovers, and Huser et al. (2021) on interbank and CCPs repo market relationships in times of stress, as well as Bardoscia et al. (2019b) who studied the UK OTC derivative market.

In this respect, the construction of the Global Network dataset, to our knowledge the most comprehensive exposure-based dataset for the UK banking sector, allows us to complement this stream of literature: i) by adopting a multi-sector perspective, thereby going beyond contractual relationships in the interbank market; ii) by covering an extended sample of UK reporting banks, not limiting our analysis to the largest institutions as it was the case in Bardoscia et al. (2019a) and Coen et al. (2019), iii) by embracing a multilayer perspective of loan and security exposures, not limiting the analysis to a single market segment or a set of largest exposures, thus almost covering the complete asset side of the UK banking sector.

Moreover, we contribute to the study on the microstructure of financial systems and on comparative financial systems. In this regard, we document the degree of interconnectedness between UK banks and financial corporates, non-financial sector corporations, governments and central banks as well as the degree of concentration risk on an exposure and counterparty level. We then provide a comparison between the UK and EA banking networks by leveraging up the work of Montagna et al. (2021) and Sydow et al. (2021) on the EA banking sector, the only two studies sharing a similar granular multilayer coverage of banks' loan and security exposures across sectors and countries.

In regards to the stream of literature on measuring systemic risk, similarly to the SRISK measure of Bronwlees and Engle (2017) as well as the Covar approach of Adrian and Brunnermeier (2019), we derive an unconditional and conditional measure of Capital at Risk. Differently from these works we use a balance-sheet based network approach to quantify the

[1] See Huser (2015) for a review of the financial network literature.

severity and likelihood of tail events in the UK banking sector. Similarly to the stress testing stream of the systemic risk literature we use a balance-sheet based methodology (Montagna et al. 2021; and Sydow et al. 2021) to compute losses stemming from direct granular exposures towards all the counterparty sectors, though without modelling contagion and amplification mechanisms taking place in the interbank market. We prefer to leave this modelling extension for future work.

This modelling choice allows us to focus the analysis on the role played by the distribution of exposures across sectors, instead of within the interbank network as the financial network literature has investigated (Glasserman and Young, 2016). Hence, we follow Acemoglu et al. (2015) and we measure the level of systemic risk in the UK banking sector in relation to the size of the initial shock stemming from exposures towards the real economy and the financial network structure so as to highlight how concentration risk and the degree of interconnectedness matters for the level of systemic risk. Thus, we test our results to a variation in the correlation structure of defaults of UK banks' counterparties, thereby modelling explicitly intersectoral input-output firms' linkages as in Acemoglu et al. (2016). In this respect, the work provides empirical evidence and implications for financial stability on the role of asset correlations in exacerbating severity and likelihood of systemic crises (Schmieder, 2013; Taleb et al. 2012; Dullmann et al. 2008; and Lopez 2004). Finally our estimates on the likelihood and severity of tail events also contribute to shed lights on the economic and financial impact of the Covid-19 Pandemic. We so relate to the following stream of research led by some recent studies on the Covid-19 crisis (Gease and Haldane, 2020; BIS, 2021; Huser et al., 2021; Schrimpf et al., 2020 and Abuzayed et al. (2021).

In the end, the last contribution of the paper refers to the growing financial stream of climate change literature using a granular network approach to sizing climate-related financial exposures such as Roncoroni et al. (2021) and Battiston et al. (2017), among others. In this respect, our paper focus on sizing climate-related financial exposures vis-à-vis climate policy relevant sectors (CPRS) and the green asset ratio as defined by the Taxonomy Alignment Coefficient approach (TAC) introduced respectively by Battiston et al. (2017) and Alessi et al. (2019). Hence, we size UK banks' exposures towards Climate Policy Relevant Sectors (CPRSs) and the UK banking system' green asset ratio, respectively amounting to 4.2% and 3.8% of total exposures. By leveraging up the work carried out by Alessi et al. (20119) and by the European Banking Authority (2021) on the EU banking system, we show that the UK banking sector seems to be less exposed than the EU banking sector to CPRS sectors as well as less exposed to those sectors identified as green sectors.

3. Dataset

The first contribution of our work is the construction of the UK banking system's asset side using a granular approach (Appendix A).[2] The resulting Global Network of UK banks' exposures is composed by six supervisory data sources covering loan and debt and equity security exposures as well as secured and unsecured exposures. As shown in Table 1, the Global Network captures £11 trillion of gross exposures out of £12.1 trillion of total assets in Q3-2021, roughly 92% of the UK banking system' asset side. The dataset is divided into two main set of exposures. On the one hand, the granular component accounts for 60.3% of total exposure amounts (£6.6 trillion) and can be split between loan exposures 44.4% and debt and equity security exposures (15.8%)[3]. On the other hand, when the granular component is not available, we add aggregated exposures by country and sector of the counterparty as residual component, and it contributes to 39.7% of the total coverage (or £4.3 trillion)[4].

The total number of entity-to-entity relationships (edges) that we capture are almost 32,258 in Q3 2021 and they are spread across 15,334 counterparties (Nodes_B) and 127 reporting banks (Nodes_L). Overall, the network shows an average edge exposure of £0.32 billion and almost £0.72 billion per counterparty. Remarkably and consistently with the financial network literature, exposures are power-law distributed, thereby highlighting a high degree of concentration risk (See Section 4)[5].

Furthermore, by looking at the average path length[6], we notice that the coefficient is quite small averaging around 2.82, implying a quite fast-connected network of relationships, that is, shocks may propagate quickly affecting multiple entities. Nevertheless, the network is not a complete fully-connected network. Its diameter, i.e. the shortest distance between the two most distant nodes in the network is 37, whereas the density parameter[7] is equal to 0.06% emphasizing the UK banking centric perspective of our dataset[8].

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[2] In Appendix A we provide a description of the supervisory datasets, an overview of the methodology to map security and counterparty information, and additional complementary statistics,

[3] Granular exposures are defined as bank to counterparty relationships.

[4] Aggregated exposures are defined as bank to country-sector relationships. For instance, granular exposures towards households are not available, so we complement the dataset using aggregated statistics.

[5] In this respect, we fit a power law distribution to our network, and we find that the alpha coefficient average around 1.67 across time. For this value of alpha ($\alpha \leq 2$) we can state that our network follows a power-law distribution for which the value of the mean is dominated by the largest exposures in the network (Newman, 2004)[5]. For instance a coefficient of alpha equal to 2.1, which is used to approximate wealth distributions, implies that roughly 80% of total exposure amounts is concentrated in the top 20% exposures.

[6] It is defined as the average number of steps along the shortest paths for all possible pairs of network nodes.

[7] The ratio of the number of edges to the number of possible edges in the network.

[8] We need to recall that the Global Network is composed only by UK banks' exposures, implying that by construction every counterparty which is not a UK bank can't be connected to any another non-UK bank entity.

Table 1: Summary Global Network Statistics Over Time

Time	TOT	Unsecured	Granular	Security	Aggregate	Edges	Nodes	Nodes_L	Nodes_B	Avg_Edge	Avg_NL	Avg_NB	avg_path	diameter	density	power_law
Q1-2018	9786	52%	5984	1530	3801	33313	14421	139	14332	0.29	70	0.68	2.57	21	0.06	1.67
Q2-2018	9488	55%	5719	1520	3769	33086	14356	138	14269	0.29	69	0.66	2.65	18	0.06	1.68
Q3-2018	9456	55%	5709	1521	3747	33073	14343	138	14256	0.29	69	0.66	2.69	20	0.06	1.64
Q4-2018	9422	55%	5710	1528	3711	33047	14367	138	14280	0.29	68	0.66	2.80	24	0.06	1.68
Q1-2019	9404	57%	5530	1600	3873	33748	14815	137	14727	0.28	69	0.64	2.79	23	0.06	1.66
Q2-2019	9597	57%	5670	1636	3927	33702	14663	137	14573	0.28	70	0.66	2.83	57	0.06	1.67
Q3-2019	9728	57%	5644	1566	4083	31891	13853	138	13762	0.31	70	0.71	2.72	55	0.06	1.69
Q4-2019	9503	57%	5541	1506	3962	31071	13924	137	13835	0.31	69	0.69	2.88	52	0.06	1.69
Q1-2020	10430	55%	5892	1531	4538	27137	12406	137	12321	0.38	76	0.85	2.93	26	0.07	1.68
Q2-2020	10279	53%	5950	1484	4328	26924	12895	134	12811	0.38	77	0.8	2.89	26	0.08	1.68
Q3-2020	10436	52%	6098	1530	4338	28434	13432	133	13351	0.37	78	0.78	2.85	26	0.07	1.66
Q4-2020	10810	54%	6407	1823	4404	30545	14051	132	13969	0.35	82	0.77	2.89	101	0.06	1.65
Q1-2021	10950	55%	6617	1925	4333	30810	14318	132	14236	0.36	83	0.77	2.93	39	0.06	1.66
Q2-2021	10714	53%	6371	1602	4343	32193	15063	130	14980	0.33	82	0.72	2.99	17	0.06	1.65
Q3-2021	11020	53%	6646	1761	4374	32258	15413	127	15334	0.34	87	0.72	2.91	44	0.06	1.64
Average	10068	55%	5966	1604	4102	31415	14155	135	14069	0.32	75	0.72	2.82	37	0.06	1.67

Note: Values are reported in £ billion for columns (2) to (6). Column "TOT" refers to the total original amount of exposures captured, while column "Unsecured" reports the % of Gross Unsecured exposures. Granular exposures "Granunal" refer to the exposure amount mapped with exposure-specific information, whereas "security" refer to the exposure amount mapped with ISIN information, and aggregate exposures "Aggregate" refer to the exposure amount mapped on aggregate sector-country counterparty basis. AVG_EDGE refers to the average exposure amount per edge, while AVG_NODE reports the average exposure amount per lender bank (NL) and per counterparty entity (NB). Avg_path refers to the average path length of the network, whereas the power_law reports the numeric scalar and exponent of the fitted power-law distribution.

3.2 Sectoral Decomposition

Next, we further investigate the topology of the network by sub-setting the dataset according to the sectoral classification of the counterparty so as to assess the degree of heterogeneity in sector-specific networks as set out in Table 2. In Q3-2021, the most relevant counterparty sector is non-financial corporations (NFC) capturing 26.9% of total gross exposure amounts. Then follow exposures to financial corporations (FC) with 22.8%, and, after that, exposures to general governments (GG) with 17.7%, to the household sectors (HH) with 16.7%, to credit institutions (CI) with 11.7%, and finally to central banks (CB) with 4.2%.

By comparing the UK banking sector's asset decomposition by sector with one provided for the Euro Area in Montagna et al. (2021), we can notice that the share of UK banks' exposures towards the various sectors is quite aligned. The share of exposures towards FC sector is 22.8% vs 25.4% among the two banking systems, and the same is true for governments 17.7% vs 20.7%. Differences come from exposures towards NFC and HH sectors, respectively 26.9% instead of 15.1% in the Euro Area, and 16.7% versus 22.8% for the household sector. Finally, interbank exposures (CI) account for slightly less in the UK than in the Euro Area (11.7% vs 15.5%).

Next, we notice that 77% of the edges (23,854) in the network are directed towards NFCs, which account for roughly 85.4% (13,165) of the total number of counterparty entities (15,413). On average an exposure towards a NFC is roughly £0.1 billion, which represents the smallest average exposure amount across all sectors. The highest average edge value of £ 5.2 billion is vis-à-vis the household sector, although we should note that for this sector we deal with exposures aggregated at the country level since we do not have information on granular loan exposures to households. Next, edge exposures towards central banks (CB) and governments (GG) show the second and the third highest average edge value, £4.69 and £2 billion respectively. Finally, the average amount per edge towards financial sector entities (FC and CI) tend to be larger, respectively £0.9 and £0.4 billion, than the average amount per edge towards NFC. Apart from the household sector for which we do not have granular information, we can state that exposures to the public sector on average tend to be larger than exposures toward financial and non-financial corporates[9].

Overall, both the average amount per edge and the average size of counterparty borrowing seem to be aligned, although with some differences, to the Euro Area network metrics described in Montagna et al. (2021). In fact, the smallest average edge exposure is also reported in the EA network towards the NFC sector (€ 0.2 billion). CI and FC sectors follow with also a very similar average edge exposure of €0.4 billion and €0.8 billion, respectively. Also statistics for exposures to households are aligned between the two banking sectors, with an average edge exposure of € 6.5 billion. In contrast, the average edge amount vis-à-vis the GG sector is larger for the UK than for the EA, with the latter reporting an average amount per edge of €1 billion. This second comparison in terms of banking systems highlights that, although the UK and EA banking systems differ in size, with the latter roughly two times bigger than the former, the network of relationships across sectors are similar. Banks appear to diversify their exposures similarly across sectors, and across entities belonging to the same sector, independently of their jurisdiction.

Table 2: Sectoral Decomposition Q3-2021

Sector	TOT	Unsec	Gran	Sec	Agg	Edges	Nodes	Nodes_L	Nodes_B	Avg_Edge	Avg_Node_L	Avg_Node_B
CI	1293	63%	1267	544	0	3262	736	120	659	0.4	10.8	2.0
GG	1955	17%	1952	515	0	976	245	79	166	2	24.8	11.8
NFC	2961	67%	2227	593	725	24854	13165	82	13083	0.1	36.1	0.2
FC	2505	33%	691	64	1813	2712	1335	79	1258	0.9	31.7	2.0
CB	469	7%	469	7	0	100	90	59	31	4.69	8.0	15.1
HH	1837	0%	0	0	1837	354	169	32	137	5.2	57.4	13.4
Total	11020	53%	6608	1724	4374	32258	15413	127	15334	0.34	86.8	0.7

Note: Values are reported in £ billion for columns (2) to (6). Column "TOT" refers to the total original amount of exposures captured, while column "Unsecured" reports the % of Gross Unsecured exposures. Granular exposures (Gran.) refer to the exposure amount mapped with exposure-specific information, securities (Sec.) refer to the exposure amount mapped with ISIN information, while aggregate exposures (Agg.) refer to the exposure amount mapped on aggregate sector-country counterparty basis. AVG_EDGE refers to the average exposure amount per edge, while AVG_NODE reports the average exposure amount per lender bank (L) and per counterparty (B).

[9] We must highlight that there is a high degree of heterogeneity across reporting bank, since the size of exposures is among other variables, a function of the size of a bank's balance sheet.

3.3 The Global Network

We now proceed with the visualization of our Global Network in its entirety. Figure 1 aims to highlight three main network perspectives of the Global Network, namely relationships by sector, region and community. To produce these network graphs, we assign to each node a colour according to the sector or region the entity belongs to, respectively panel (a) and panel (b), and to the community according to the modularity scores calculated for each entity as in panel (c). Then we colour the edges according to the node's colour receiving the exposure (target node), except for panel (c) for which we assign the colour by type of exposures, blue for loan exposures and red for security exposures. The size of the nodes is proportional to their eigenvector centrality scores in order to highlight the role played by connectedness rather than size in the network.

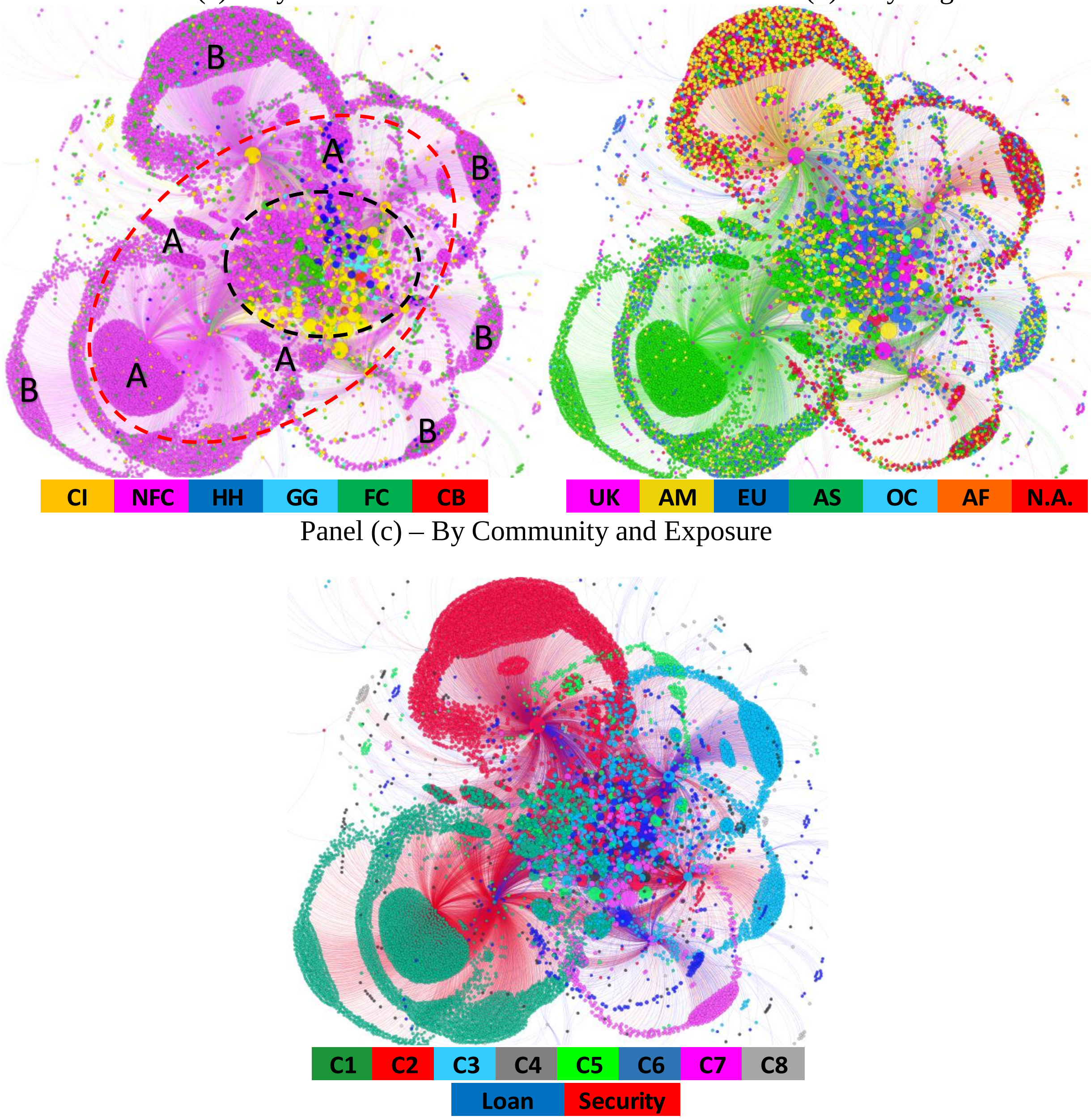
Firstly, we can observe that the UK Global Network shows a core-periphery structure. On the one hand, the core (*dotted black circle*) is composed by those entities mostly connected to the majority of UK banks, and to which UK banks are mostly exposed in terms of gross exposures. Exposures to core entities are those that overlap across banks' portfolios of securities and loans, exhibiting strong dependency. All sectors are well represented in the core, especially non-financial corporates and credit institutions. On top of that, it is possible also to identify three additional sectoral clusters, respectively financial corporates, governments and households. The core is also well diversified in terms of regional clusters, with a strong presence of entities from every key regions, as seen by the presence of European, Asian, American and British entities. Typically, these entities are well-established multinational corporations or key international public organizations which fund themselves globally, and are quoted on stock exchanges. The core is also well diversified in terms of community structure. In fact the core is a combination of entities belonging to the top-7 communities which roughly account for 98% of the total number of relationships. It is important to highlight that communities are composed of entities amongst which dense connections exists. By contrast, sparse connections exist between entities belonging to different communities. In this respect, we can notice that an overlap does not exist between community structure and regional-sectoral composition.

On the other hand, the periphery of the network is composed by multiple sub-sets of entities, which are clustered together around those UK banks that are exposed to the same set of counterparties. The periphery can be divided into two regions - a region made of weak common dependencies and a region made of exclusive relationships, approximated by the area inside and outside the red dotted circle, respectively. Clusters constituted by weak common dependencies are those in which two or few banks are exposed to the same set of counterparties as seen in A-Type clusters in Panel (a)[10]. These clusters are placed closer to the core than B-Type clusters since they are attracted to the centre by the size of their exposures, the number of relationships, and the number of lender banks involved in the relationships.

Figure 1: The Global Network of UK Banks' Exposures

Panel (a) – By Sector

Panel (b) – By Region



Note: The total amount of exposures for Q3-2021 is £ 11 trillion. The network is built by assigning the eigenvector centrality metrics to the size of the nodes, while the colour of the edges is given by the counterparty node's colour. Blue nodes represent the banking sector, red nodes non-financial corporates, purple nodes the government sector, green nodes the financial corporate sector, and finally the light blue nodes the household sector.

[10] If those counterparties were exposed to multiple lenders with relative sizable exposures, they would have been placed by the algorithm in the core of the network.

The entities belonging to the same cluster may share the same regional attribute as seen in the variation of colours for these clusters in Panel (b), highlighting common patterns of regional diversification across banks, but it is not exclusive. Exposures to a B-Type cluster are not shared across banks, and do belong to one single bank, thereby representing a bank's exclusive set of counterparties. This would imply that entity-specific shocks to counterparties belonging to B-Type clusters should not directly reverberate through the network if the lender bank is sufficiently capitalized to absorb the losses. Financial contagion may affect other banks only indirectly like via correlations in asset returns or via common macro shocks. On top of this, we need to acknowledge that by construction of the datasets, we are exploiting a UK-banking centric perspective. As such, entities in B-Type clusters and generally any non-UK bank entity might be also linked to UK banks or other corporates via their asset side exposures, which we do not capture in the Global Network.

Lastly, we can detect that clusters can be also differentiated by the shares of the type of exposures, as seen in the decomposition between securities and loans in Panel (c). Although security exposures cover less than 20% of total gross exposure amounts, they represent roughly 83% of the total number of edges in the network, 2/3 deriving from equity securities and 1/3 from debt securities. This 80%-20% split that we observe is due to the composition of the original datasets. The security datasets capture the entire spectrum of UK banks' security holdings, whereas the loan datasets only cover the subset of largest exposures.

3.4 The Interbank Network

We provide a deep-dive into the topology of the UK interbank network which is constituted on average by 126 reporting banks and 654 counterparty banks of which 611 are non-UK entities. The interbank network covers roughly £1.29 trillion of exposures in Q3-2021, almost 11.7% of the total gross exposure amounts as set out in Table 3. Security exposure amounts are roughly 44% of total interbank exposures, almost three times their share of security exposures to counterparties across all sectors, implying that security relationships tend to be more relevant in the interbank market than in the complete network. Nonetheless, security exposures are still less relevant than loan exposures in terms of sterling amounts. In contrast, 84% of the total number of edges is made of security exposures, of which 55% are equity security exposures and 29% debt security exposures, whereas loan exposures account for 16% of the total number of edges in the interbank market. We emphasize that all interbank exposures are mapped granularly as entity-to-entity relationships, and that on average 71% of exposures are unsecured.

Finally, the average path length coefficient suggests that not all banks are directly connected to each other, with an average of number of steps equal to 2.8. The interbank network is also very sparse, although more dense than the complete network. Among all possible connections, only 0.5% of them are present. Lastly, we see that a small share of interbank exposures accounts for a large share of the total interbank exposure amounts since as is also the case for the complete network, we are dealing with a power-law distribution (alpha coefficient < 2).

Table 3: Interbank Network Characteristics

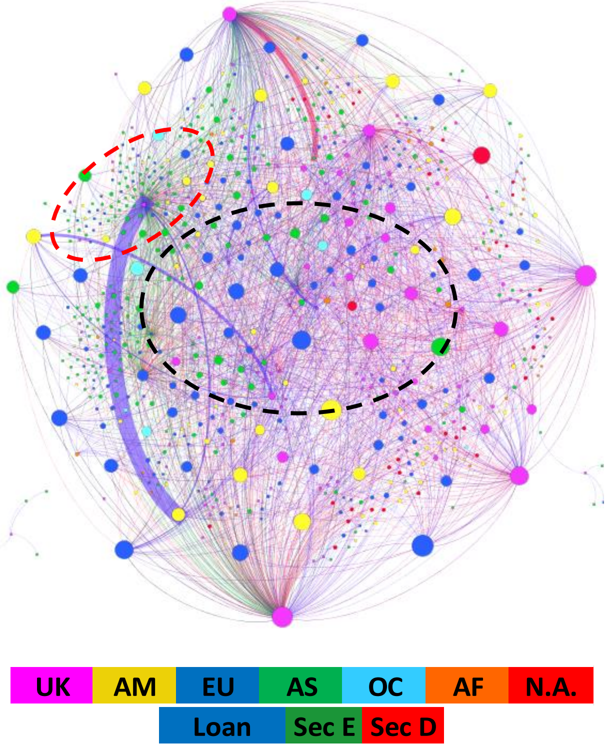
Time	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021	Average
TOT	1278	1165	1153	1160	1192	1195	1208	1162	1240	1188	1166	1163	1187	1189	1293	1196
Unsecured	68%	73%	74%	74%	77%	76%	74%	74%	72%	72%	72%	70%	66%	63%	63%	71%
Gran	1278	1165	1153	1160	1192	1195	1208	1162	1240	1188	1166	1163	1187	1189	1293	1196
Sec	453	452	451	451	492	487	484	474	466	467	462	459	463	469	570	473
Agg	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Edges	3474	3427	3425	3388	3413	3436	3401	3276	3248	3097	3152	3156	3263	3254	3262	3311
Nodes	773	770	769	760	761	769	744	745	706	694	692	695	717	730	736	737
Nodes_L	131	129	129	127	125	129	128	126	129	126	125	125	123	124	120	126
Nodes_B	686	684	683	676	676	679	655	661	623	612	613	614	638	648	659	654
Avg_Edge	0.37	0.34	0.34	0.34	0.35	0.35	0.36	0.35	0.38	0.38	0.37	0.37	0.36	0.37	0.4	0.4
Avg_Node_L	9.8	9.0	8.9	9.1	9.5	9.3	9.4	9.2	9.6	9.4	9.3	9.3	9.7	9.6	10.8	9.5
Avg_Node_B	1.9	1.7	1.7	1.7	1.8	1.8	1.8	1.8	2.0	1.9	1.9	1.9	1.9	1.8	2.0	1.8
avg_path	2.6	2.7	2.7	2.8	2.7	2.8	2.7	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.7	2.8
diameter	233	233	232	232	252	252	252	252	252	252	252	41	41	41	41	190
density	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.5
power_law	1.76	1.72	1.79	1.73	1.74	2.16	1.73	2.20	1.74	1.80	1.88	1.90	1.84	1.83	1.85	1.84

Note: Exposure values are reported in £ billion. Column "TOT" refers to the total original amount of exposures captured, while column "Unsecured" reports the % of Gross Unsecured exposures. Granular exposures (Gran.) refer to the exposure amount mapped with exposure-specific information, securities (Sec.) refer to the exposure amount mapped with ISIN information, while aggregate exposures (Agg.) refer to the exposure amount mapped on aggregate sector-country counterparty basis. AVG_EDGE refers to the average exposure amount per edge, while AVG_NODE reports the average exposure amount per lender bank (L) and per counterparty entity (B).

By looking at the topology of the network depicted in Figure 2, we bring further insights on the UK interbank network structure. In order to highlight these features, we assign the nodes and edges with colours according to their region and type of exposures, respectively. The size of the nodes is proportional to the eigenvector centrality score, whereas the size of exposures is equal to the gross original exposure amount. We notice that the most central institutions captured by their size are not only UK entities, but also European and American banks, corroborating a strong degree of openness and internationalization of the UK banking sector. Moreover, Asian banks tend to be less central overall in the UK interbank network in comparison with their share of exposures in the Global Network. The topology of the interbank network also displays a core-periphery structure, the core highlighted by a black dotted circle. The entities belonging to the core are those that are commonly exposed across all UK banks. UK banks also tend to create their own periphery by building their own communities of interbank relationships highlighted for instance by the red dotted circle. We need to acknowledge that our interbank network graph only highlights relationships from UK banks, whereas many other asset-side relationships may exist from non-UK banks towards UK banks as well as non-UK banks, although they are not displayed given our UK-centric data coverage[11].

Lastly, we highlight the composition of the relationships by exploiting the type of exposure, blue for loans, red for debt securities, and green for equities. We notice that, consistent with what we previously stated, the graphical representation highlights a more relevant presence of security exposures over loan exposures, although loan exposures tend to be more sizeable. In this respect, some banks tend to diversify across type of exposures, while others tend to privilege loan and debt security exposures. Only few banks show remarkable interbank equity exposures.

Figure 2: The UK Interbank Network by Country and Type of Exposure



Note: The total amount of exposures for Q3-2021 is £ 1293 billion. The network is built by assigning the eigenvector centrality metrics to the size of the nodes. The colour of the nodes is attributed by the geographical locations of the entities, while the colour of the edges is given by the type of exposure, respectively blue for loan exposures, green for security equity exposures, and red for debt security exposures.

[11] Community-based relationships are important for mitigating liquidity-funding risks. As found in Allen et al. (2020) banks in a community on average have lower centrality of interbank borrowing as expected, nevertheless being in a community can mitigate the negative effect of lacking trust in obtaining interbank funding.

4. Degree of Concentration Risk and Interconnectedness

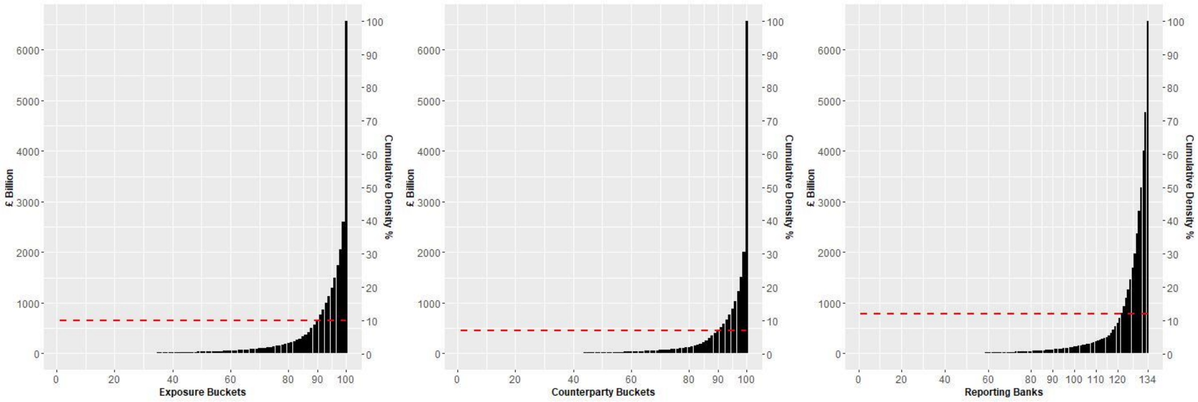
In this section we provide further insights on the degree of concentration risk and interconnectedness of UK banks' granular exposures.

4.1 Concentration Risk

First, we subset the network selecting only those exposures that are granular, thereby omitting aggregate exposures. We are left with roughly £6.65 trillion or 60.3% of the total coverage. Next, we rank exposures by size and we group them into 100 equal buckets, each one constituted by 236 exposures (1% of the total number of exposures). Hence, we construct a cumulative discrete density function. Panel (a) of Figure 3 shows that roughly 60% of the total gross exposure amounts belongs to the 99th percentile, and that the 90th percentile captures roughly 90% of the total coverage. This first result highlights the degree of concentration of UK banks' assets in a small share of large exposures. This is relevant from a modelling perspective since a negative shock to one of these exposures (degree of concentration risk) remarkably affects the stability of the UK banking system. Hence, the distribution of shocks is non-neutral.

Figure 3: Cumulative Density by Exposure, Counterparty and Reporting bank in Q3-2021

Panel (a) –by Exposure　Panel (b) – by Counterparty　Panel (c) –by Reporting Bank



Note: the red line refers to the 90th percentile.

Moving to Panel (b), we provide a discrete cumulative density of total exposure amounts by counterparty constructed in the same way as presented in Panel (a). Each bucket is composed by 121 counterparties. In this respect, this cumulative density is even more right-tailed than the exposure-based one, with the 99th percentile capturing roughly 70% of total gross exposure amounts, and the 90th percentile covering 93% of the total[12]. This result corroborates and complements the previous one, emphasizing more strongly the relevance of modelling granularly the distribution of shocks, also at a counterparty level. The failure or distress of certain counterparty entities may put in jeopardy the UK banking system' financial stability.

[12] Those counterparty entities may be considered as too-big-too fail.

Similarly to Gabaix (2011)'s results, that is, behaviours of large firms (top-100) in the US explain roughly 1/3 of variations in output growth and GDP fluctuations, the very same logic can be applied to banks' assets. Negative idiosyncratic shocks to the top-1% counterparties may endanger the solvency position of UK banks. Also from this counterparty perspective, the distribution of shocks is non-neutral. Lastly, Panel (c) reports the cumulative density by reporting bank. In this case, we do not group them into buckets since the number of reporting banks is much smaller, whereas each bucket now represents one reporting bank. As seen in Panels (a) and (b), the cumulative density in Panel (c) is also strongly right-tailed, with the top-13 banks (1% of the sample) capturing roughly 88% of total UK banking system's assets. From this lending-side perspective, we may say that also the provision of credit jointly with the portfolio holdings of financial assets are in the hands of few large players. Hence, a negative shock to this set of entities therefore may trigger contagion spillovers across the whole interbank and non-interbank network as demonstrated by multiple studies in the network and financial contagion literature (Covi et al. 2021; Cont and Schanning 2017; Kok and Montagna 2013). Overall, this set of stylized facts highlights the importance of modelling the distribution and transmission of shocks on a granular level since there is high level of concentration risk which can only be captured by modelling entity-to-entity relationships.

4.2 Direct and Indirect Interconnectedness

To further shed light on the critical role played by certain entities in the UK Global Network, we provide entity-specific statistics on their degree of concentration risk, direct and indirect connectedness both from the reporting and counterparty side perspectives.

For the reporting side we compute three main metrics (Equation 1a, 1b, 1c), namely: the concentration of a bank's portfolio as the share of top 10% exposures over total exposures by reporting bank i ($Conc_i$), the degree of connectedness of each reporting bank i ($Conn_i$) as the number of times bank i appears on the counterparty side[13], and the degree of overlapping portfolios calculated as the summation of the connectedness coefficients ($Conn_i$) across all counterparties j belonging to the portfolio of bank i (OP_i).

$$Conc_i = \frac{\sum_{90\%}^{K} Exp_{i,k}}{\sum_j Exp_{i,j}} \quad (1a); \qquad Conn_i = \sum_i N_i \quad (1b); \qquad OP_i = \sum_j^J Conn_{i,j} \quad (1c)$$

Next, we rank banks by clustering them into colour buckets according to the weighted average of their standardized metrics, with blue for the tier 1 bucket, with green for the tier 2 bucket, and with white for the tier 3 bucket. Panel (a) of Figure 4 plots these metrics into a

[13] We compute this coefficient only one time for all counterparties, and reporting banks do appear on the counterparty side.

three dimensional graph, in which the X-axis represents concentration risk, the Y-axis Connectedness, and the Z-axis Overlapping Portfolios.

In this respect, focusing on tier 1 banks we identify four entities for illustrative purposes as described in Panel (a) of Table 4. Type-A entities have been placed in the North-Central region (NC), and can be considered the most relevant from a systemic risk monitoring perspective. This set of entities show a very high concentration risk in its portfolio of exposures (its top 10% of exposures represent roughly 90% of its total exposures), meaning it is subject to high idiosyncratic risk. Type-A banks are also very well connected to the other reporting banks (roughly more than 50 banks), meaning that in case of distress, it is likely to trigger direct contagion in the interbank market. Moreover, its portfolio of exposures strongly overlaps with other banks' portfolios, meaning that it may also be subject to the trigger of fire-sales dynamics affecting the whole interbank network indirectly.

By contrast, Type-B entities are located in the North-West region (NW), and can be considered the second most relevant from a systemic risk monitoring perspective. They are prone to a high degree of idiosyncratic risk (high value on the X-axis) and in case of distress they will likely spread risk directly to its interbank peers. However, its portfolio of counterparties is well diversified, and so it will be less susceptible to indirect contagion. Next, Type-C entities in the South-Central region (SC) are the third most relevant in terms of risk-monitoring. In this respect, Type-C entities are subject to a high degree of idiosyncratic risk (X-axis) and indirect risk via overlapping portfolios (Z-axis), nevertheless they won't spread direct contagion in the interbank market (Y-Axis). Lastly, Type-D entities which are located in the South-West region (SW) can be susceptible to idiosyncratic shocks, but show low levels of both direct and indirect contagion spillovers. Finally, it is important to notice that no reporting banks show low levels of concentration risk (X-axis) and at the same time a high degree of both direct and indirect contagion (Y and Z axis).

Table 4: Risk Monitoring Classification

Panel (a)

Reporting Entities	A	B	C	D
Idiosyncratic Risk	H	H	H	H
Direct Contagion	H	H	L	L
Indirect Contagior	H	L	H	L
REGION	NC	NW	SC	SW
SYSTEMIC RISK	H	M	M	L

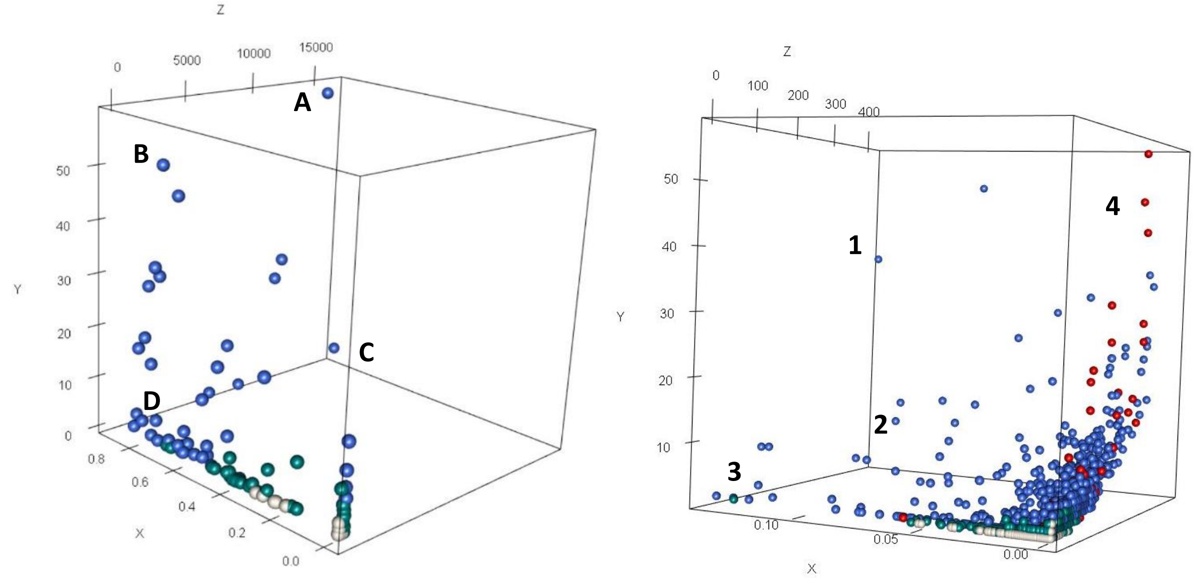
Panel (b)

Counterparty Entities	1	2	3	4
Idiosyncratic Risk	H	H	H	L
Direct Contagion	H	L	L	H
Indirect Contagion	H	H	L	H
REGION	NC	SC	SW	NE
SYSTEMIC RISK	H	M	L	L

Note: "H" stands for high, and "L" for low, and "M" for medium risk. "NC" refers to north-central region, "NW" to north-west, "NE" to north-east, whereas "SC" refers to south-central, and "SW" to south-west.

Figure 4: Concentration, Connectedness, and Overlapping Portfolios

Panel (a) - Reporting Banks Panel (b) – Counterparties



Note: For panel (a) X-axis refers to Concentration, Y-axis refers to Connectedness, and Z-axis refers to Overlapping Portfolio. For panel (b) X-axis refers to Concentration risk measured as the average size of exposures in % of total exposure amounts in the system, Y-axis refers to Connectedness that is number of banks connected to the entity, and Z-axis refers to Indirect Contagion, first and second layers of connected entities. Red dots highlight reporting banks.

By moving to the analysis of the counterparty side, that is Panel (b) of Figure 4, we compute three main metrics which slightly differ from those previously reported (Equation 2a, 2b, 2c)[14]. Hence, we compute first the concentration risk of a counterparty as the share of gross exposures of counterparty j over total gross exposure amounts ($Conc_j$) divided by $Conn_j$ thereby capturing the average size of exposures. We then compute the degree of connectedness of each counterparty entity j ($Conn_j$)[15], and finally the level of indirect contagion approximated by the summation of the connectedness coefficients ($Conn_j$) across all reporting banks connected to the counterparty j. The colour bucketing is classified as discussed previously with the addition of red dots which identify the UK banks which appear as counterparties.

$$Conc_j = \frac{\frac{\sum_j Exp_{i,j}}{\sum_i Exp_{i,j}}}{Conn_j} \quad (2a); \qquad Conn_j = \sum_j N_j \quad (2b); \qquad IC_j = \sum_i^I Conn_{j,i} \quad (2c)$$

In this respect, focusing on tier 1 counterparties, we identify four types of entities for illustrative purposes as described in Panel (b) of Table 4. These entities are the most relevant from a systemic risk monitoring perspective since they are located in the North-Central region (NC), thereby representing a high degree of idiosyncratic risk (X-axis) for multiple reporting banks (Y-axis), which in turn are very well connected to other banks in the interbank network

[14] We eliminate few outliers on the X-axis for the graphical representation.

[15] This metric is the same as the one computed for the reporting side, that is, the number of reporting banks (i) counterparty j is connected to.

(Z-axis). Type-2 entities which are located in the South-Central region (SC), represent a high degree of idiosyncratic risk (X-axis), but a low level of connectedness since they are connected to only a small fraction of UK banks (Y-axis), though these banks are central in the interbank market (Z-axis). These entities can be considered as medium-risk providers for the system. Next, in the South-West region we find Type-3 entities which are low-risk providers for the system. These entities exhibit a high degree of idiosyncratic risk for their reporting banks (X-axis), but at the same time they are connected to only a very small set of banks (Y-axis) that are not very central in the interbank network (Z-axis). Finally, Type-4 entities are located in the North-East region (NE) and represents a low-risk for the system. This group of counterparties mostly comprises banks (red dots) which represent a low level of idiosyncratic risk for their bank peers. Nevertheless, they are connected with many peers (Y-axis), which in turn are very well connected within the interbank market (Z-axis).

Overall, we can state that degree of concentration risk in the UK banking system both from a reporting and counterparty perspective is high. This characteristic makes the UK banking sector vulnerable to idiosyncratic shocks which via direct and indirect connectedness may spread risk across the global interbank network (Figure 2), within and outside the UK banking system. These stylized facts are informative for the modelling approach we should adopt in order to capture the role played by concentration risk in the determination of the level of systemic risk.

5. Capital at Risk

In this section we move a step-forward in the assessment of the UK banking system's degree of financial stability. Hence, we aim at quantifying potential losses of the UK banking system and disentangle their composition. To achieve that, we exploit complementary data on PD and LGD parameters by counterparty sector and country as detailed in Appendix A (section 1.5).

In this respect, two main exercises are provided. First, we compute expected one-year ahead loss estimates, also defined as Capital at Risk estimates (CaR). Second, in order to incorporate the degree of concentration risk and interconnectedness into our loss estimates we move away from an expected loss calculation methodology and we compute Conditional Capital at Risk Estimates (CCaR) by means of stochastic simulations. Hence we compute conditional loss estimates according to the 90^{th}, 97.5^{th} and 99^{th} percentile of the loss distribution and we thus estimate the severity and probability of the "initial shock". The stochastic approach allows us to model scenario uncertainty, assess the severity of severe stress scenarios and the trigger event in probabilistic terms. In the end, we decompose the results to shed light on the sources of tail risk for the UK banking sector.

5.1 Measuring Capital at Risk

We compute 1-year ahead expected losses using sector and country-specific LGD and PD parameters provided by each reporting bank. Expected losses are computed using the complete set of exposure - both granular and aggregate - and exposure-based information on the share of unsecured exposure amounts[16]. In this respect, we use a standardized approach to loss calculation and we treat loan and security exposures equally, thereby applying the same LGD and PD parameters to both types of exposures[17]. Hence, we sum for each reporting bank i expected losses computed on a counterparty basis j and we aggregate them across all reporting banks to achieve a measure of Capital at Risk for the UK banking sector (Equation 3).

$$Capital\ at\ Risk \equiv \sum_{i}^{I} \sum_{j}^{J} Exp_{i,j} * LGD_{i,j} * PD_j \qquad (3)$$

$$where\text{: } i\ refers\ to\ the\ reporting\ bank\ and\ j\ to\ counterparty$$

Figure 5 reports the estimated expected loss amounts decomposed by sector and region of the counterparty. We want to emphasize that loss estimates are for one-year ahead since we use 1-year expected probabilities of default parameters estimated by the reporting banks using the internal ratings-based approach (IRB)[18].

In terms of Capital at Risk (CaR), the UK banking system's loss estimate in Q3-2021 is close to £51.8 billion (0.5% of total exposure amounts), up by 24% (£41.7 billion) relative to the pre-crisis period approximated by estimates for Q4-2019. Importantly the time-series is quite stable over time, ranging between £41.7 and £45 billion till Q1-2020, and then when the Pandemic starts, the time-series closely tracks the build-up of counterparty risks. The increase is mostly due to an increase in banks' PD estimates between Q1-2020 and Q1-2021 as the result of the COVID-19 crisis[19]. In Q1-2021, at the peak of the Covid-19 Crisis, total expected losses amounted to £ 56.7 billion, up by 36% from pre-crisis levels[20].

Looking at the expected loss estimates by sector reported in Panel (b), most of the losses stem from exposures towards non-financial corporates (NFC), almost £24.7 billion (47.7%), followed by the non-bank financial corporate sector (FC) with £15.9 billion (30.7%), and

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[16] Hence, we estimate losses only using the amount of unsecured exposures ($Exp_{i,j}$), thereby deducting on an exposure basis the secured exposure amount from the gross exposure amount.

[17] Security exposures concern debt and equity holdings. We do not compute market-risk losses using security-specific parameters such as haircuts and price impacts functions.

[18] For more details on the methodology see BIS (2001). https://www.bis.org/publ/bcbsca05.pdf

[19] Changes in LGD parameters contribute less to the increase in estimated losses. A slight increase take place in Q4-2020 and Q1-2021. See Appendix A section 1.5.

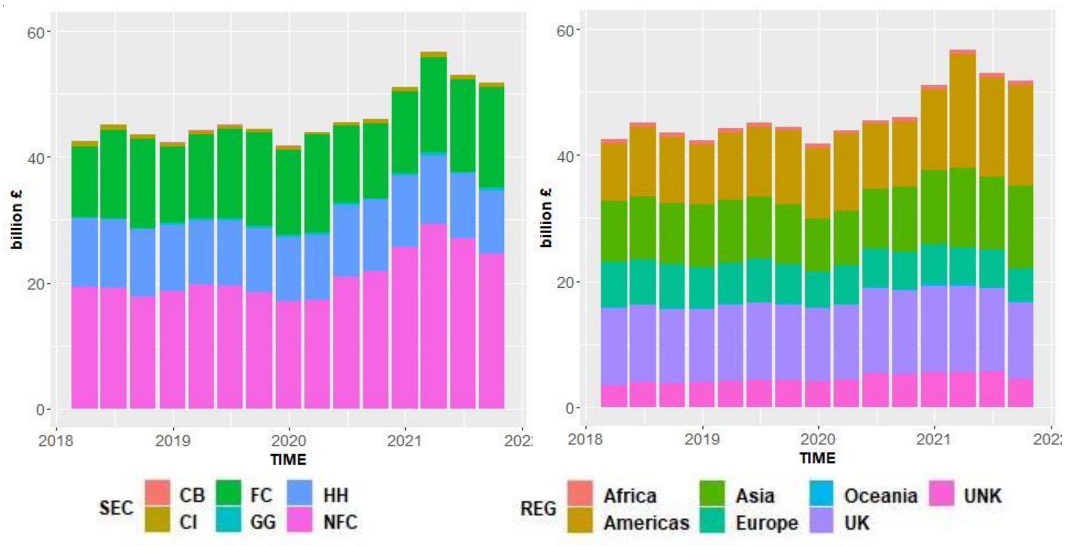
[20] Almost £31.2 billion losses (55%) are estimated using granular exposures, while £25.5 billion stems from aggregated exposures.

finally by the household sector (HH) £9.9 billion (19.1%). Not surprisingly expected loss estimates vis-à-vis governments (GG) and central banks (CB) account for less than 1% (£0.55 billion), the smallest component, although gross exposures towards Governments account for roughly 18% of the total coverage.

Similarly, expected losses towards credit institutions account for only 1.5% of the total (£0.8 billion), although their gross exposure amounts account for almost 12% of the total. This result is due to a very low average probability of default applied to CI counterparty sector, below 0.2% or 20 basis points, that is, a bank defaulting every 500 years. This result emphasizes the relevance of modelling contagion and amplification effects within the interbank market using microstructural models in order to quantify and factor systemic risk and network risk factors into CI's PD calculations.

Figure 5: UK Banks' Expected Losses (1-Year Ahead)

Panel (a) – by Sector Panel (b) – by Geographical Region



Overall, the most important component is clearly expected losses stemming from exposures towards the non-financial sector, capturing roughly 47.7% of the total (£24.7 billion). This is why, in the credit risk and stress testing literature, most of the estimation effort is spent in accurately estimating losses from counterparties belonging to the corporate sector[21].

Looking at Panel (b) providing the geographical decomposition, loss estimates are similarly spread across major regions, respectively £16 billion from Americas (31%), £13.2 billion from Asian countries (25.6%) and £12.1 billion from within the UK (23.3%). Finally, expected losses from European countries accounts for £5.1 billion (9.8%), the only region that actually

[21] In this respect, PD and LGD parameters are estimated using the IRB approach for each counterparty sector and country, exploiting also granular information on type of exposures, for instance differentiating between non-SMEs and SME exposures, and focusing on wholesale credit exposures. Retail exposures and related LGD and PD parameters do not enter into this calculation.

experienced a decrease since the start of the pandemic, down by 10% from £5.6 billion in Q4-2019. Moreover, the loss share from unknown locations is non-negligible, roughly 8.7% of the total expected losses in Q3-2021[22]. The geographical loss decomposition corroborates the global nature of UK banks' risk exposure. UK banks tend to import shocks more from abroad than from within the United Kingdom, making the UK financial cycle's much more synchronized with the global economic cycle than with the UK economic cycle[23].

5.1.1 Benchmarking

Expected losses increase during the Covid-crisis precisely due to an increase in counterparty risk in the non-financial corporate sector. In Q1-2021 expected losses vis-à-vis non-financial corporations increase up to £29.4 billion or by 71% between Q4-2019 and Q1-2021. In this respect, the average PD parameter[24] for the NFC sector in the same time period increased remarkably up to 2.2% from an average of 1.8% (by 22%), whereas LGD parameter increased up to 58.9% from 51.7% (by 13%). Hence, LGD parameters remained relatively more stable during the Covid-19 crisis, while PD were subject to revisions by reporting banks.

This set of results emphasizes the severity of the Covid-19 crisis, but necessitates some benchmarking in order to assess their accuracy. Unfortunately, our data availability is limited. The Global Network only starts in Q1-2018, thereby not allowing us to compare our results with historical estimates for the 2008 Great Financial Crisis. Nevertheless, we may attempt to compare our estimates with those of other studies, although we should bear in mind that it is difficult to find up-to-date studies with credit loss estimates for UK banks, especially using granular exposure data. In this respect, the BIS Quarterly Review of March 2021 provides credit loss estimates and projections due to the Covid-19 crisis for G7 countries' banking systems using Hardy and Schmieder (2013)' s methodology. This methodology estimates the impact of output on credit loss rates as a non-linear function of both the depth of the recession and its cumulative severity[25]. The report thus provides estimates specifically for the UK, whose

[22] This is due to the fact that PD parameters where not available for unidentified locations, and we approximate them according to the average of the sample by sector of the counterparty.
[23] Appendix B provides a breakdown of the CaR estimate by NACE classification of economic activities.
[24] Average across reporting banks and counterparty countries. See Appendix A, section 1.5.
[25] The BIS report calculates the change in credit losses by multiplying the projections of the change in credit loss rates by sectoral credit exposures. In addition to the sectoral credit loss rates, the authors of the report calculate aggregate credit loss rates for each economy based on the aggregate output projections to put the sectoral data into perspective. Based on this approach, the report concludes as follows: "based on our sectoral GDP projections, in a plausible central scenario we find that corporate credit losses during 2020–22 could be equivalent to about three times the pre-crisis level on average across the G7, China and Australia. The additional credit losses emerging from the crisis during the three-year period would cumulate to slightly above 2% of annual GDP or $1 trillion" (BIS, 2021 pp. 68).

increase in cumulative corporate credit losses over the 2020–22 period due to the pandemic amounts to 5.1% of annual GDP (as of 2019), the G7 country most severely affected. This estimate can be translated into roughly £110 billion of credit losses over three years. By calculating our cumulative expected losses over the same period, our estimates lead to an average cumulative loss of £73 billion[26], thereby an increase of 30% (£17 billion) relative to pre-crisis levels estimated using as benchmark the 2018-2019 sample period.

Although the methodologies differ substantially, the BIS report takes a top-down sectoral approach, while ours is a bottom-up granular assessment, results do not remarkably differ. In this respect, our estimates use more up to date data, snapshot ending in Q3-2021 instead of Q4-2020 as in the BIS exercise, thereby incorporating via PD and LGD parameters more up-to-date expectations on the future state of the UK economy.

5.2 Measuring Conditional Capital at Risk

In this section we move away from the analysis of expected loss estimates, which may be informative on the UK banking sector's average probability of default, and focus on measuring the likelihood and severity of tail events factoring-in the degree of concentration risk and interconnectedness of the UK banking system's network of exposures. Hence, we try to size the impact of those initial shocks that can be considered sizeable as discussed in Acemoglu et al. (2015). In this context, we do not compute amplification and contagion effects stemming from interbank financial exposures as the financial network literature does, but instead we treat interbank exposures alike any other counterparty exposure vis-a-vis the other sectors.

From a policy maker perspective this complementary assessment is essential for sizing the sources of potential extreme vulnerabilities. It provides a probabilistic assessment of tail-events so as to contextualize the likelihood of their realization at every point in time[27]. Hence, we try to model scenario uncertainty using a stochastic approach to scenario design following Montagna et al. (2021) and Sydow et al. (2021). In this respect, we compute Conditional Capital at Risk estimates (CCaR), that is, UK banks' median losses conditional to the 90th, 97.5th and 99th percentile of the loss distribution.

[26] We take the quarterly average loss estimates in 2020 (£ 21.5 billion), in 2021 (£ 27 billion) and we use Q3-2021 estimates (£ 24.5 billion) as an average projection for 2022.

[27] Top-down stress test exercises are benchmarked on historical macro estimates of extreme events, and so they lose the forward-looking dimension, thereby not providing an estimate for the likelihood of adverse stress scenarios. Using microstructural bottom-up approaches compared to top-down macro models results become a function of exposure and counterparty-specific parameters and ultimately network-specific characteristics.

5.2.1 Tail Events Scenario Design

We split the sample of exposures between granular exposures towards specific counterparty and aggregated exposures towards countries and sectors. For aggregated exposures we still compute losses in expectation as the average component, while for granular exposures we compute a distribution of losses, that is, the stochastic component[28]. So the computation of the stochastic component is based on a network of 31,415 edges and 14,069 counterparties which are potentially defaulting entities, covering roughly £5.96 trillion of gross granular exposure amounts (60% of the total coverage)[29]. The stochastic component hence will factor-in the degree of concentration risk and interconnectedness of the UK banking system's network of exposures. The expected loss component instead is calculated upon £4.1 trillion of gross aggregated exposures[30].

Since counterparty specific PD parameters are not available, we assign to each counterparty the PD parameter by sector and country averaged across all reporting banks' estimates. This approach resembles a pool-IRB approach of counterparty default rates since we use information reported by all UK reporting banks for each counterparty sector and country. This approach ensures robustness since it is an average estimate across several IRB models[31].

Next in order to model the level of interdependency in the intersectoral input-output firms' linkages - network origins - as in Acemoglu et al. (2016), we estimate a correlation structure of counterparty defaults (based on reported counterparty PD) by country and sector exploiting a panel dataset covering 134 countries and 4 sectors (NFC, FC, CI, GG) ranging between Q1-2018 and Q3-2021. This leads to an average correlation across countries and sectors for the full sample of 0.045 as reported in Figure 6[32]. Nevertheless there is lot of heterogeneity across sectors and countries, with negative correlation coefficients for some pairs. Hence, we should acknowledge that depending on the time period of the sample we use, the correlation structure does change. The correlation matrix based on counterparty PD by country and sector have been

[28] We don't model stochastically losses vis-à-vis aggregate exposures since it would imply that an entire sector for a country would default, and so all exposures vis-à-vis that sector. Hence we measure losses in expectations for the share of exposures that we can't map granularly. The only exception is the sector central banks (CB) whose losses are model in expectation.

[29] We exclude granular exposures towards central banks from this calculation.

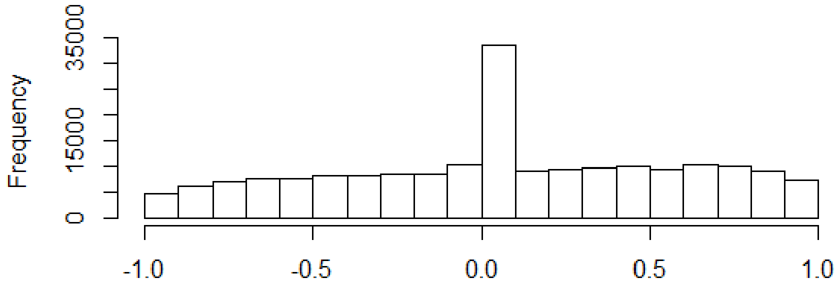
[30] Alike the expected loss exercise we use only the unsecured exposure amounts for calculating loss estimates for both the stochastic and average loss components. .

[31] The ECB in 2019 has approved the use of pool-IRB approaches in order to better measure PD and LGD parameters. This approach is used especially to estimate counterparty default rates for those type of counterparties whose historical default rates are very low and thus difficult to estimate such as for wholesale exposures (See ECB, 2019).

[32] In this exercise the correlation is time-invariant. We use the average across all reported quarters. The peak of the distribution coincides with the average correlation coefficient since we fill NAs with the average correlation coefficient.

estimated over 15 quarters during which the Covid-19 crisis took place, leading to a strengthening of correlation across countries and sectors. The average correlation across countries and sectors for the subsample Q1-2018 till Q4-2019 (pre Covid-19) is close to 0.03, whereas for the sub-sample covering the Covid-19 crisis the average correlation coefficient was higher, close to 0.08.

Figure 6: Distribution of Correlation Coefficients between Q1-2018 and Q3-2021



Note: Average across all correlation parameters by country-sector pairs equal to 0.045, thereby approximating median stress events as estimated in Hardy and Schmieder (2013).

As we can see correlation coefficients do change over the business cycle and are affected by macroeconomic and financial conditions. For instance, Hardy and Schmieder (2013) relies on the empirical estimates of Duellmann et al. (2008) who provide estimates on fluctuations of asset correlations under macroeconomic stress for a sample of large Western European corporates between 1997–2003. Conditional to their data sample, asset correlations fluctuated strongly, ranging from 0.04 to 0.16, with a mean at 0.1. Overall, our estimates are lower than Duellmann et al. (2008) due to differences in the sectoral coverage, since the estimates given here are an average across sectors, and also include financial corporates and governments which experience much lower historical probability of defaults. Hence, by sub-setting our sample to only non-financial corporates (NFC), we find that the average correlation coefficients for the corporate sector across countries is close to 0.1, and respectively 0.07 before the Covid-19 crisis (Q1-2018 to Q4-2019), and 0.13 during the Covid-19 crisis (Q1-2020 to Q3-2021). Hence, our estimates are aligned with and corroborates Duellmann et al. (2008)'s estimates for the pre-crisis period for the corporate sector.

Moreover, Hardy and Schmieder (2013)'s estimates for asset correlation differ conditional to the degree of stress scenario. For instance, during normal conditions (median), medium stress (90th percentile) and severe stress conditions (97.5th percentile) asset correlation increases respectively from 0.1, to 0.22 and 0.3. In this respect, our average correlation estimates for the corporate sector during the Covid-19 period (0.13) can be classified in between normal and medium stress conditions.[33]. This is due to the type of stress that the Covid-19 crisis has produced, that is, a heterogeneous stress across countries and sectors. Moreover, we should stress that also the timing was different, since not all the countries have been hit simultaneously. This heterogeneous shock which is reflected in change in counterparty PDs may increase the positive correlation for certain country-sector pairs or decrease it for other country-sector pairs. This is consistent with the BIS (2019)'s results on credit loss estimates for the G7 countries' banking systems, since they conclude that the Covid-19 crisis seems not to be as severe as the GFC[34] and closer to a medium stress event[35]. Overall, we can state that our correlation matrix of counterparty default probabilities averaged over the full sample period can be considered a reliable proxy for medium-low stress events, thereby quite conservative[36]. In Section 5.3 we will test our results to this assumption.

We then finally produce 10,000 Montecarlo simulations of Bernulli vectors of corporate defaults for 14,069 counterparties by modelling a multivariate normal distribution with uniform marginals and a Gaussian copula with a covariance matrix characterized by the correlation structure above estimated (Montagna et al. 2021). Each entry of the Bernulli vector take value 1 if the counterparty defaulted or value 0 if it did not. Hence, for each simulation/scenario, we compute the stochastic loss component for each reporting bank by multiplying exposures at default by 1 or 0 depending on whether the counterparty in that scenario defaulted or not. We then sum the stochastic component and the expected loss component by bank to obtain total loss estimates for each reporting bank, and for the whole UK banking system by summing across banks.

5.2.2 Severity and Likelihood of Tail Events

We provide distributions of total loss estimates (CCaR estimates) for the UK banking system for all quarters (Table 5), decomposing them by the expected loss component and the stochastic loss component. Starting from a visual inspection of Figure 7 which reports the loss distribution for Q4-2019 (pre-crisis period) total losses differ remarkably between the left tail (low severity scenarios) and the right tail (high severity scenarios) of the distribution, respectively £23 billion (min) and £343 billion (max). As we move closer to the right tail, we can see that the share of

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[33] We need to emphasize that the Covid-19 crisis has affected sectors and countries heterogeneously, for this reason the average correlation coefficient did not increase remarkably.

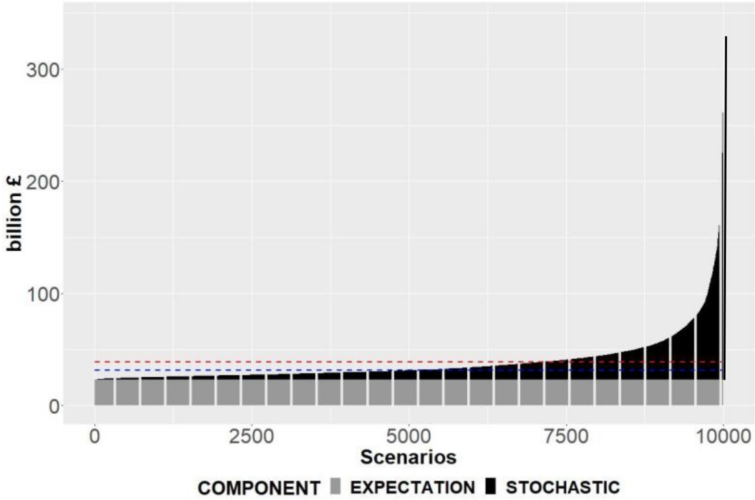
[34] These results are based on the parameters and elasticities provided in Hardy and Schmieder (2013).

[35] In this respect, the study used parameters and elasticities for credit loss estimates calculation that were an average between medium and severe stress events.

[36] We could have calculate a correlation structure for different sub-periods, but this would create problems in comparing stochastic loss estimates across quarters. Hence, we prioritize comparability of results across time. Moreover, as emphasized by Schmieder et al. (2011) fixed IRB correlations based on low PDs can be used as benchmark estimate for supervisory purposes. See also Lopez (2004).

stochastic losses increases over the share of expected losses. Out of £343 billion, the contribution of the stochastic component amounts up to £320 billion, roughly to 93% of total loss contribution for that scenario. This evidence shows a high dispersion even in "normal times", with the most extreme scenario being 15 times worse than the least severe and, 8.8 times more severe than an average scenario (£39 billion). The median losses in the 97.5th percentile scenarios classified as "severe stress" amount up to £132 billion, roughly 3.4 times more than an average scenario[37]. Hence, modelling and analysing scenario uncertainty is very important to shed light upon the *severity* of extreme events.

Figure 7: UK Banks' Stochastic Distribution of Losses in Normal Times (Q4-2019)



Note: grey bars refer to the expected loss component and they are equal by construction across all scenarios. Black bars refer to the stochastic loss component and they are ranked from left to right by severity. Red line refers to the average loss, while the blue line to the median loss.

Nevertheless, we need also to assess this value in probabilistic terms. In this respect, the likelihood of experiencing an extreme event of £132 billion losses or above the median loss of the 97.5th percentile, which can be considered a severe distress event based on the above definition of Hardy and Schmieder (2013), is low, that is, 125 scenarios over 10,000 simulations, hence a probability of 1.25% (once every 80 years). However, if we benchmark the probability against experiencing a medium stress event (median loss of the 90th percentile), that is, above £76 billion, the probability increases up to 5% (once every 20 years). In the end, if we benchmark the probability against experiencing an extreme stress event (median loss of the 99th percentile), that is, above £173 billion, the probability decreases to 0.5% (once every 200 years). In this respect, if we look at the cumulative losses experienced in the 90th percentile of the distribution, it accounts for roughly 23.4%, 9.4% in the 97.5th percentile, and 4.8% in

[37] In this respect, the BOE's 2019 stress testing exercise estimates roughly £180 billion of losses from credit and traded risks over a five year period given an adverse scenario which resembles macroeconomic and financial conditions experienced during the GFC.

the 99th percentile. These empirical findings emphasize that a large share of total losses takes place given the realization of tail events.

Table 5: UK Banks' Stochastic Distribution of Losses – Benchmark Case

STATISTICS	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
Avg_tot	38	42	40	38	41	42	40	39	42	42	42	47	54	47	47
Avg_st	16	17	16	16	17	18	16	16	16	18	18	22	28	22	23
Avg_ex	22	25	23	23	24	24	24	23	26	24	24	25	26	24	25
Median_tot	31	34	33	31	33	34	33	31	33	33	33	35	38	37	37
Median_99	195	197	193	194	192	178	178	173	213	212	219	258	302	232	222
Median_97.5	149	150	133	149	143	137	134	132	151	156	165	206	240	177	171
Median_90	72	79	73	72	78	80	78	76	85	89	92	111	152	103	109
Median_st	9	9	10	8	10	10	9	8	8	9	9	10	13	12	12
Share_99	5.6	5.1	5.3	5.8	5.3	4.8	4.8	4.8	5.5	5.6	5.5	6.1	6.1	5.4	5.1
Share_97.5	10.4	9.8	9.7	10.7	10	9.4	9.3	9.4	10.4	10.6	10.7	12.1	12.2	10.5	10
Share_90	23.9	23.4	22.7	24.3	23.7	23.1	23.1	23.4	24.7	25.7	26	28.8	30.7	26.2	26
Max_tot	548	506	435	726	397	483	374	343	524	621	461	721	588	433	383
Max_st	526	481	411	703	373	459	350	320	498	597	437	697	562	409	358
Prob_99	0.6%	0.6%	0.5%	0.6%	0.5%	0.4%	0.4%	0.3%	0.7%	0.8%	0.9%	1.6%	2.8%	1.1%	0.9%
Prob_97.5	1.4%	1.5%	1.1%	1.4%	1.3%	1.1%	1.1%	1.0%	1.5%	1.7%	1.9%	3.5%	5.4%	2.2%	2.3%
Prob_90	4.4%	5.3%	4.5%	4.5%	5.3%	5.5%	5.3%	5.1%	6.2%	7.0%	7.5%	9.2%	13.2%	10.6%	10.2%

Note: "Avg_tot" refers to average banks' losses, "Avg_st" refers to the stochastic loss component, "Avg_ex" refers to the expected loss component, "Median_tot" refers to the median losses, "Median_99", "Median_97.5", "Median_90" refers respectively to the median loss for the 99th, 97.5th and 90th percentile of the loss distribution representing medium, severe and extreme stress events. Similarly "Share" represents the share of total losses cumulated across scenarios for the 99th, 97.5th and 90th percentile of the loss distribution. "Max_tot" refers to the most extreme scenario of the loss distribution, while "Max_st" refers to the stochastic component of the most extreme scenario. In the end, "Prob_99", "Prob_97.5" and "Prob_90" refer to the probability of medium, severe and extreme stress events, respectively with losses higher than £76 billion, £ 132 billion and £173 billion benchmarked on Q4-2019 estimates.

However, macroeconomic and financial conditions may change over the business cycle and given unexpected shocks such as the Covid-19 Pandemic. In this respect, Figure 8 provides the stochastic distribution of banks' losses calculated in Q1-2021, that is, at the Peak of the Covid-19 crisis[38]. First of all, the mass in the right tail of the distribution remarkably increased, scenarios above the 90th percentile captures roughly 30.7% of total losses, compared to 23.4% in Q4-2019. Median Losses for scenarios in the 97.5th percentile now stands to £240 billion, almost 82% higher compared to Q4-2019. What is noticeable is how the stochastic component increases its relevance relative to the expected loss component, thereby increasing the overall severity of extreme events. Furthermore the most extreme event now reaches a level of £588 billion, a quarter on quarter increase of 71%. Overall, the severity of extreme events increased remarkably during the Covid-19 crisis, that is, given a worsening of financial and macroeconomic conditions which are reflected in higher levels of counterparty PD and LGD parameters[39].

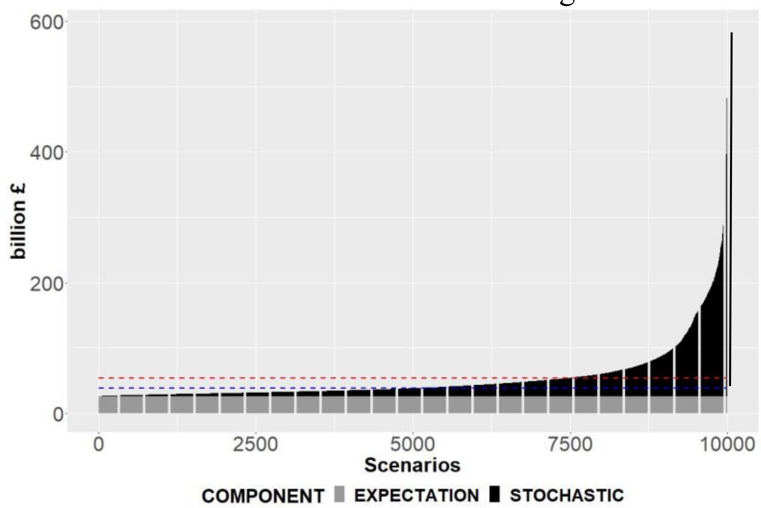
However, not only did the severity increase, but also the likelihood of experiencing extreme events. In order to properly benchmark the likelihood with the results presented for Q4-2019,

[38] We need to emphasize that the key difference between Q4-2019 and Q1-2021, apart from the underlying network of exposures, is the increased levels of PD and LGD parameters estimated by the banks for each counterparty country and sector. The network structure changes over time, but it is slow-moving, and as we have seen in section 3, it hasn't experienced remarkable changes between Q4-2019 and Q3-2021.

[39] The correlation matrix is fixed across quarters.

we keep the threshold to identify severe distress events constant at £132 billion of losses, that is, the median loss of the 97.5th percentile in Q4-2019. Hence, we try to answer the following question: "what is the probability of experiencing in Q1-2021 - at the peak of the Covid-19 crisis - the same type of 'severe distress events' as classified during the pre-crisis period?". The answer is 5.4%, as 539 scenarios (over 10000 simulations) show total losses higher than £132 billion in Q1-2021. In Q4-2019 it was 1%, moving from 1 severe distress scenario every 100 years, to 1 severe distress scenario every 16.6 years. However, if we benchmark the probability against experiencing a "medium stress" event (median loss of the 90th percentile of £ 76 billion in Q4-2019), the probability is close to 13.2%, that is, 1320 scenarios over 10000 simulations (once every 7.5 years). The cumulative losses experienced in the 90th percentile of the distribution account for roughly 30.7% of the total, 12.2% for scenarios in the 97.5th percentile, and 6.1% in the 99th percentile scenarios. Overall, we have seen how both the severity and probability of severe distress events increased remarkably during the pandemic given the change in macro and financial conditions.

Figure 8: UK Banks' Stochastic Distribution of Losses during the Covid-19 Crisis (Q1-2021)



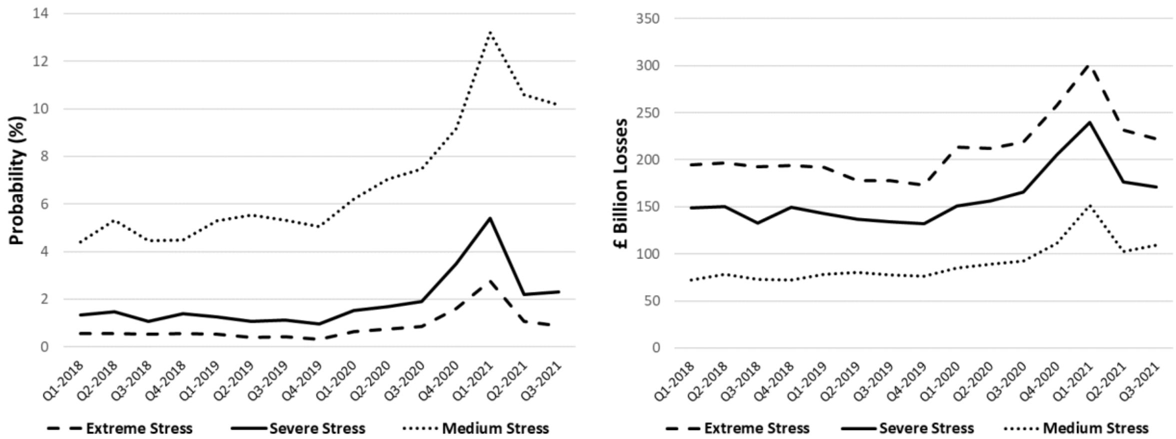
Note: grey bars refer to the expected loss component and they are equal by construction across all scenarios. Black bars refer to the stochastic loss component and they are ranked from left to right by severity. Red line refers to the average loss, while the blue line to the median loss.

In the end for monitoring purposes we provide a time-series evolution of probabilities and severity of Tail Events - Figure 9. In this respect, we compute the probabilities and severity for medium, severe and extreme stress events following the classification of Hardy and Schmieder (2013). Hence, we condition the set of scenarios to those with losses above the median losses for the 90th, 97.5th and 99th percentile averaged between Q1- 2018 and Q4-2019, that is, in pre-crisis times, respectively £ 76 billion for the 90th percentile, 132 billion for the 97.5th percentile, and 189 billion for the 99th percentile. The build-up of systemic risk in the UK banking sector approximated by the probability - Panel (a) - and severity - Panel (b) - of severe distress events

(97.5th percentile) by the start of the Covid-19 pandemic is very clear. Moreover, although both systemic risk measures decline after reaching the peak in Q1-2021, in Q3-2021 they still remain higher than pre-crisis levels. This is even more evident for medium stress events (dotted lines).

Figure 9: Probabilities and Severity of Extreme Events for the UK banking Sector

Panel (a) - Probability Panel (b) – Severity (CCaR)



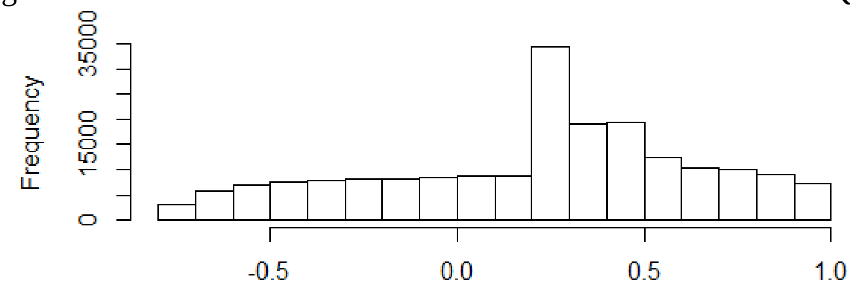
Note: Medium Stress refers to scenarios above the 90th percentile, Severe Stress refers to scenarios above the 97.5th percentile, and Extreme Stress refers to scenarios in the 99th percentile. Classification based on Hardy and Schmieder (2013). Probabilities of tail events are calculated conditional to the average median losses for each percentile over Q1-2018 and Q4-2019, respectively £ 76 billion for the 90th percentile, 132 billion for the 97.5th percentile, and 173 billion for the 99th percentile. Severity is approximated by the conditional capital at risk measure (CCaR). The number of simulations equal to 10,000.

5.3 The Role of Asset Correlation

Asset correlations—as emphasized by Hardy and Schmieder (2013) and by Duellmann et al. (2008)—are key to modelling correlated default probabilities in solvency stress test exercises. Usually in standard solvency stress test exercises, the focus is placed upon the estimation of losses in expectation conditional to an adverse scenario, for which the role of correlated shocks and correlated defaults is neglected. As we can see from the results in the previous section, average loss estimates are not affected by the correlation structure and size. However, when we study tail events like severe stress scenarios, correlations play a key role in determining their severity and likelihood. Hence, overcoming scenario uncertainty implies also testing results to variations in the correlation structure of shocks, in our case correlated counterparty defaults. In previous exercises we were using a correlation matrix based on IRB based PD estimates by country and sector over the period Q1-2018 and Q3-2021. The average correlation parameter across all countries and sectors is 0.045, and 0.1 for specifically the corporate sector. This was a conservative assumption, since during crisis times, asset correlations tend to strengthen, respectively close to 0.22 for medium stress events and close to 0.3 for severe stress events.

Hence, in this exercise we want to test the sensitivity of our results to an increase in the correlation structure of shocks. To achieve that, first we estimate the correlation matrix over the crisis period Q1-2020 to Q4-2021 in order to maintain the correlation structure between country-sector pairs as it was during the Covid-19 crisis. This leads us to an average correlation coefficient close to 0.08, still too low compared to Hardy and Schmieder (2013)'s estimate for medium stress events. Hence, we reduce negative correlation coefficients and increase positive correlation coefficients by a constant equal to 0.2. This ad-hoc constant is added to all correlation coefficients smaller than 0.3 in order make the distribution shift to the right. As we can notice in Figure 10, now the mean and peak of the distribution coincides with an average correlation coefficient of 0.22 as estimated by Hardy and Schmieder (2013).

Figure 10: Distribution of Stress Correlation Coefficients between Q1-2018 and Q3-2021

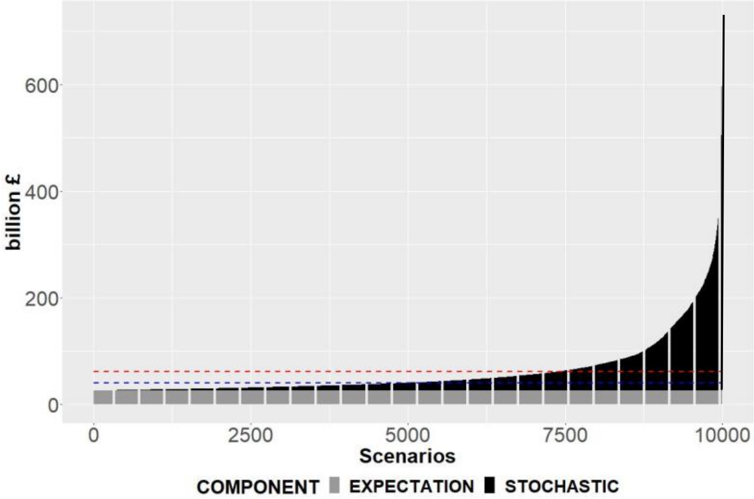


Note: Average across all correlation parameters by country-sector pairs equal to 0.22, thereby approximating medium stress events as estimated in Hardy and Schmieder (2013).

By inspecting Figure 11 and Table 6, we notice that the severity of extreme events further increase relative to the previous baseline case. The right tail of the distribution gets fatter and taller. The most extreme scenario now leads to 721 billion of losses, an increase of 22.5% relative to the £588 billion previously estimated in the baseline case. Now the 90th percentile scenarios account for 34% of total cumulated losses (30.1% in the previous exercise), emphasizing that extreme events tend to account for an even larger share of total cumulated losses given a higher degree of correlated defaults. Hence severity of medium, severe and extreme stress events approximated by CCaR estimates increase as correlation in firms' PDs increases.

To compare the estimated likelihood of extreme events with the previous exercise, we condition the set of stress scenarios to those scenarios with an average median loss above or equal £ 76 billion for the 90th percentile (medium), 132 billion for the 97.5th percentile (severe), and 173 billion for the 99th percentile (extreme). Given this stress correlation structure, the probability of experiencing severe distress events (97.5th percentile) in Q1-2021 increase to 8.3% from 5.4%, that is, we estimate 825 scenarios with total losses larger than 132 billion (over 10000 simulations). For medium stress events, the probability is 19.1%, that is, 1914 scenarios over 10000 simulations with losses above £76 billion. In the end also the probability of extreme stress events increases to 4.9% from 2.8% in the baseline estimates.

Figure 11: UK Banks' Stochastic Distribution of Losses during the Covid-19 Crisis (Q1-2021) conditional to a Stress Correlation Structure in Counterparty Defaults



Note: grey bars refer to the expected loss component and they are equal by construction across all scenarios. Black bars refer to the stochastic loss component and they are ranked from left to right by severity. Red line refers to the average loss, while the blue line to the median loss.

Table 6: UK Banks' Stochastic Distribution of Losses based on a correlation structure based on GVA by NACE Sectors

STATISTICS	Medium-Stress Correlation Structure							Baseline Correlation Structure						
	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
Avg_tot	47	47	48	55	62	53	54	42	42	42	47	54	47	47
Avg_st	22	23	24	30	36	29	30	16	18	18	22	28	22	23
Avg_ex	26	24	24	25	26	24	25	26	24	24	25	26	24	25
Median_tot	35	34	34	37	41	39	39	33	33	33	35	38	37	37
Median_99	259	271	265	335	383	295	292	213	212	219	258	302	232	222
Median_97.5	202	204	203	264	293	234	228	151	156	165	206	240	177	171
Median_90	113	116	116	157	187	131	135	85	89	92	111	152	103	109
Median_st	10	10	10	12	15	14	15	8	9	9	10	13	12	12
Share_99	6.1	6	6.1	6.8	6.7	6.2	6	5.5	5.6	5.5	6.1	6.1	5.4	5.1
Share_97.5	11.8	12	11.8	13.4	13	12.1	11.7	10.4	10.6	10.7	12.1	12.2	10.5	10
Share_90	28.3	29.2	29	32.7	34	29.8	29.4	24.7	25.7	26	28.8	30.7	26.2	26
Max_tot	529	563	559	780	721	681	672	524	621	461	721	588	433	383
Max_st	503	538	535	755	696	656	647	498	597	437	697	562	409	358
Prob_99	1.5%	1.6%	1.5%	3.3%	4.9%	2.2%	2.3%	0.7%	0.8%	0.9%	1.6%	2.8%	1.1%	0.9%
Prob_97.5	3.1%	3.5%	3.1%	6.0%	8.3%	4.3%	4.5%	1.5%	1.7%	1.9%	3.5%	5.4%	2.2%	2.3%
Prob_90	9.6%	11.1%	11.4%	14.6%	19.1%	16.4%	15.6%	6.2%	7.0%	7.5%	9.2%	13.2%	10.6%	10.2%

Note: "Avg_tot" refers to average banks' losses, "Avg_st" refers to the stochastic loss component, "Avg_ex" refers to the expected loss component, "Median_tot" refers to the median losses, "Median_99", "Median_97.5", "Median_90" refers respectively to the median loss for the 99th, 97.5th and 90th percentile of the loss distribution representing medium, severe and extreme stress events. Similarly "Share" represents the share of total losses cumulated across scenarios for the 99th, 97.5th and 90th percentile of the loss distribution. "Max_tot" refers to the most extreme scenario of the loss distribution, while "Max_st" refers to the stochastic component of the most extreme scenario. In the end, "Prob_99", "Prob_97.5" and "Prob_90" refer to the probability of medium, severe and extreme stress events, respectively with losses higher than £76 billion, £ 132 billion and £173 billion benchmarked on Q4-2019 estimates.

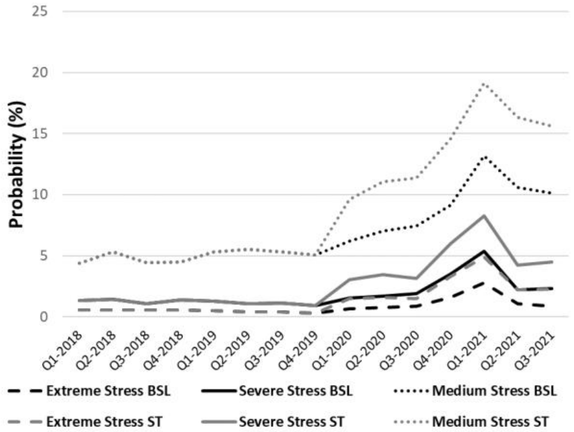
In the end, Figure 12 reports the probability and severity of medium, severe and extreme stress events over time according to a stress and a baseline correlation structure (black versus grey lines). We can note from the visual inspection that the probability and severity of stress events in each percentile of the distribution shifted up starting in Q1-2020[40]. In Q3-2021 both probability and severity of stress events (ST) still remain well above the pre-crisis levels, even more if counterparty defaults are highly correlated. We want to emphasize that these estimates

[40] The stress correlation structure (ST) has been used only for the estimation between Q1-2020 and Q3-2021.

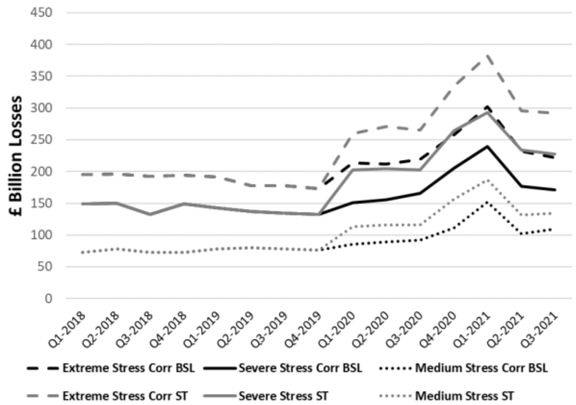
are some kind conservative since we use a stress correlation structure that equal a medium stress scenario (not a severe stress) as classified by Hardy and Schmieder (2013). Furthermore we want to emphasize that expected losses do not change at all, since correlation does not matters in expectation, but only affects the shape of the loss distribution. To conclude, we want to emphasize that PD and LGD parameters in this exercise remain equal to those in the baseline case.

Figure 12: Comparison of Probability and Severity of Extreme Events for the UK Banking Sector conditional to a Stress and Baseline Correlation Structure

Panel (a) - Probability



Panel (b) – Severity (CCaR)



Note: ST refers to results estimated conditional to a stress correlation structure (average equal to 0.22) approximating medium stress events. Whereas BS refers to baseline results. Medium Stress refers to scenarios above the 90th percentile, Severe Stress refers to scenarios above the 97.5th percentile, and Extreme Stress refers to scenarios in the 99th percentile. Classification based on Hardy and Schmieder (2013). Stress estimates have been calculated only for the last part of the sample capturing the Covid-19 crisis period, starting in Q1-2020 and ending in Q3-2021. Probabilities of tail events are calculated conditional to the average median losses for each percentile over Q1-2018 and Q4-2019, respectively £ 76 billion for the 90th percentile (medium), 142 billion for the 97.5th percentile (severe), and 173 billion for the 99th percentile (extreme). Severity is approximated by the conditional capital at risk measure (CCaR). The number of simulations equal to 10,000.

5.4 Conditional Capital at Risk Decomposition

In this section, we decompose UK banks' CCaR estimates into their sector and regional decomposition in order to identify the sources of tail events. We focus the analysis on severe distress scenarios, that is, those scenarios in the 97.5th percentile of the distribution. Results are provided for Q1-2021 in order to capture the peak of the Covid-19 crisis, although Appendix C provides the decomposition over the entire sample period. Table 7 provides a breakdown of average losses for severe distress scenarios by sector. The decomposition is provided only for the stochastic component, since in the tail of the distribution stochastic losses capture roughly 90% of total losses. The most important sector is non-financial corporates (NFC) with a contribution of 94.6% to total average loss in severe stress scenarios. Importantly the NFC sector also shows a loss ratio of 9% as share of NFC granular gross exposures. This estimate approximates the share of NFC exposures that potentially is subject to default conditional to a severe stress scenario. Then there follows financial corporates (FC) which account for only

2.6% of total average losses and credit institutions (CI) with 1.9%. As we can see the financial sector (CI+FI) is a small contributor to total average losses in severe stress scenarios, although their total granular exposures combined account for 31% of total granular exposures. This is due to multiple reasons. First probabilities of defaults for counterparty sector CI are very low, ranging between 0.1% and 0.3% across developed regions. Moreover, the correlation structure across countries is three time stronger for the NFC sector rather than the CI and FC sectors. This implies that especially in the 97.5th percentile of scenarios - the severe ones - clusters of counterparty defaults will take place within the sector with the higher correlation structure such as NFC sector and with higher PDs. In the end, we need to emphasize that our methodology does not capture amplification and contagion effects taking place within the financial system. Contagion and amplification mechanisms such as asset fire-sales will definitely strengthen correlated defaults within and among FC and CI sectors as well as their loss contribution to severe stress events as shown in Montagna et al. (2021). This methodological extension goes beyond the scope of this paper, and is discussed in the Conclusion.

Finally, governments (GG) contributes only by 0.9%, although it is the sector that shows the second highest amount of gross granular exposures. We should emphasize that the contribution of FC could potentially be much higher since we capture only 27.5% of total FC exposures with granular information[41]. Overall, the total loss ratio across all sectors for severe distress scenarios is equal to 3.8% of total granular exposures and the loss share across sectors is stable across the entire sample period as reported in Appendix C.

Table 7: Sectoral Decomposition of CCaR Estimates (Q1-2021)

Sectors	NFC	FC	CI	GG	Total
Exposures (£bn)	2487	688	1256	1861	6292
AVG Loss (£bn)	224	6	4	2	237
Loss Ratio (%)	9.0%	0.9%	0.4%	0.1%	3.8%
Loss Share (%)	94.6%	2.6%	1.9%	0.9%	/

Next, Table 8 provides a breakdown of average losses for severe distress scenarios by geographical location. The highest contributor at the peak of the Covid-19 crisis is Americas with a share of 39.5% and a loss ratio of 7.3%. In this respect, the Americas' loss ratio is the highest among all geographical regions followed by "unknown territories" (UNK) with a value of 4.6% and by Asian countries with 3.9%. Whereas, in terms of loss share, Asian countries are the second highest contributor, more than unknown territories, respectively 29.2% instead of 19.8%. In the end we can see that UK and Europe matters for a small share of total tail

[41] The household sector is missing since we don't have granular exposures for this sector.

losses, respectively 5.8% and 5%. Although the UK have a similar share of granular gross exposures to the Americas, the loss ratio is six times higher in the Americas than in the UK. However, this was not the case pre-Covid crisis. In fact, results in Appendix C show that Americas accounted for only 8% of total loss contribution over Q1-2018 and Q4-2019, whereas Asian countries were the highest with roughly 38% and the UK contributed to roughly 10% instead of 5.8% in Q1-2021. The dramatic increase in the contribution by Americas countries is due to a drastic increase in their loss ratio jumping from 1.1% pre Covid-19 crisis to 7.3% at the peak of the crisis, and not for a quantity effect due to a larger share of granular exposures towards Americas. This result highlights how the Pandemic has heterogeneous economic consequences across sectors but also across regions and countries. The Covid-19 crisis has reshaped the sources of systemic risk, shifting the focus from Asian countries to American ones. Overall, we can state that tail events affecting the UK banking sector are more likely to stem from regions outside the UK, corroborating the fact that the UK banking sector is clearly more exposed internationally than domestically as a small open economy suggests, and the global role played by UK banks in supporting liquidity conditions and real economic investments across sectors and countries.

Table 8: Regional Decomposition of CCaR estimates (Q1-2021)

Regions	Asia	Americas	UK	Europe	UNK	Africa	Oceania	Total
Exposures (£bn)	1790	1291	1194	933	1023	31	31	6293
AVG Loss (£bn)	69.2	93.9	13.7	11.9	47.0	1.2	0.3	237
Loss Ratio (%)	3.9%	7.3%	1.2%	1.3%	4.6%	3.9%	0.9%	3.8%
Loss Share (%)	29.2%	39.6%	5.8%	5.0%	19.8%	0.5%	0.1%	/

6. Sizing Exposures to Climate-Related Transition Risks

In this last section before concluding, we provide evidence on future potential sources of financial stability risks for the UK banking sector such as financial risks related to the climate transition. This literature is still at an early stage of development, especially on the empirical side, since only recently have central banks and policy institutions started to collect and analyse financial institutions' exposure data from the climate angle. Among others, the European Banking Authority (EBA, 2021), in its Financial Risk Assessment of the Banking System of December 2020, has analysed the impact of transition risk for a universe of 2.4 trillion euros of loans of EU banks. The European Central Bank (Giuzio et al. 2019) was the first to publish an exercise to size EA sectoral security exposures towards climate policy-relevant sectors, and more recently has performed a stress test exercise to size climate-related transition and physical risks (granular loan and security holdings) for 1,600 consolidated banking groups in the euro area (Alogoskoufis et al. 2021 and Alessi et al. 2021). Also, the Central Bank of Austria studied

(Battistion et al. 2020) outstanding credits and bonds held by Austrian banks (EUR 946 billion at year-end 2019) towards climate transition risks. This type of analysis has been also performed on non-bank financial entities such as the European Insurance and Occupational Pensions Authority (EIOPA, 2018) which performed a climate risk assessment on insurances' security portfolio holdings covering roughly €7.7 trillion of assets. Lastly, Roncoroni et al. (2021) assesses with a microstructural network model Mexican banks and investment funds' risks stemming from exposures towards climate policy-relevant sectors covering roughly $627 billion of security and 214 billion of loans. As far as our case study of the UK banking system is concerned, the Bank of England (2021) has published its Climate Biannual Stress Test Scenarios (CBES) to size risks stemming from climate-related transition and physical risks for UK banks and insurances. Our study is complementary to the CBES exercise since it covers banks' security exposures on top of loan exposures and it applies the same methodology used in the above mentioned studies so as to facilitate comparison of results across jurisdiction. In this respect, the common feature across all these studies is the methodology used to size exposures towards climate policy-relevant sectors (CPRS), which is based on Battiston et al. (2017), and the taxonomy alignment coefficients (TAC approach) used to assess the approximate degree of greenness for a given NACE class based on Alessi et al. (2019). We highlight that this analysis is explorative and represents a first attempt to sizing the degree of transition risk and greenness of the UK banking sector exploiting granular information on UK banks' loan and security exposures.

6.1 Sizing UK Banks' Exposures towards climate policy-relevant sectors

We follow Battiston et al. (2017) in classifying economic activities into climate policy-relevant sectors. This analysis allows to assess the economic and financial risk that firms may experience given a climate transition, that is, an economy reaching net-zero emissions by 2050 as specified in the Paris Agreement. CPRSs have been classified by using three main criteria: (i) their direct and indirect contribution to GHG emissions; (ii) their relevance for climate policy implementation; (iii) their role in the energy value chain. The starting point for this classification is the 4-digit NACE classification of economic activities, which is mapped into six main climate-policy relevant sectors, that is, fossil fuels, utilities, energy-intensive, buildings, transportation, agriculture[42]. The rationale for the CPRS classification is that the NACE classification does not offer a sufficiently granular breakdown to distinguish between

[42] For a detailed info on the MAP between 4-digit NACE codes and CPRS see Roncoroni et al. (2021) or access the following webpage which is constantly updated: https://www.finexus.uzh.ch/en/projects/EU-Taxonomy-Alignement.html.

those activities based on fossil fuels versus renewable energy, that is, the energy technology used in their production function, which is key element to assess in a climate-transition scenario[43]. This is the reason why the CPRS classification is regarded as a reference for climate financial risk assessment[44]. In terms of CPRS classification, we have to acknowledge that not all the NACE codes enters into this classification. The most relevant exceptions are “K” financial and insurance activities and “O” public administration and defence and compulsory social security activities which combined account for 67% of total granular gross exposures. Hence, CPRSs focus mostly on the real economic sectors, (NFC exposures) and are mapped from 4-digit NACE codes retrieved from 11 macro (1-digit) NACE activities[45]. The coverage of these 11 NACE activities account for £591 billion or 9% of total granular exposures in Q3-2021. Among these, we are able to map £392 billion into the CPRS classification, roughly 13% of granular corporate exposures (NFC) or 3.6% relative to UK Banks' Total Exposures[46] (as reported in Panel (a) of Figure 13 and Table 9).

This is an important finding since the majority of UK banks' assets fall into sectors in which transition risk is expected to be low. Nevertheless, we need to emphasize that this result covers only the granular part of UK banks' exposures since the aggregate part can't be mapped with NACE codes. In this respect, among the £4374 billion of aggregate exposures, £537 billion are vis-à-vis the non-financial corporate sector (NFC). By assuming that the distribution of NFC aggregate loan exposures towards CPRSs remains unchanged (13% of NFC granular exposures falling into CPRSs)[47], we estimate that potentially an additional £70 billion may be added to CPRS exposures. This leads to £463 billion or 4.2% of UK banks' total exposures subject to

[43] Overall, the advantage of the CPRS approach is that it allows a climate-relevant assessment to be made of a large part of financial assets (equity holdings, corporate bonds, loans) that can be applied in a comparable way across portfolios and jurisdictions, is actionable on standard data and that covers both low- and high-carbon sectors (thus complementing the EU Taxonomy). This allows a picture to be obtained of the level of environmental sustainability of banks' positions with currently available information.

[44] Another widely used approach to quantify transition risk consists of using carbon footprints and mapping GHG emissions to individual borrowers or to their sectors. This approach can be applied at different levels of granularity (i.e. borrowers or sector) and it usually requires the usage of data from external providers. Under this approach, which is run at obligor level, banks' total original exposures are allocated to six buckets of GHG emission intensity. The source of the GHG emission intensity is Trucost (S&P Global) https://www.trucost.com

[45] Respectively A, B, C, D, F, G, H, I, L, M, N. We have to acknowledge that not all 4-digit NACE codes belonging of these 1-digit NACE activities are used for the CPRS classification. In this respect, we do not capture any exposure from “M7110” Architectural and engineering activities and related technical consultancy, the only NACE-CPRS class missing from our sample

[46] Corporate exposures identified as counterparty sector “NFC” amount up to £2961 billion, out of which £2424 billion are granular exposures (see section 3.2).

[47] We use 13% since the remaining aggregate exposures from NFC only refers to loan exposures. Security exposures are fully captured by granular data.

climate policy relevant sectors classification[48]. It is important to note that this figure might still understate the total potential risks to UK banks from climate-related transition risks, since roughly 35 % of the UK banks' total exposures are held vis-à-vis financial entities (K) which falls outside the CPRS classification. Moreover, the household sector which accounts for 16.7% of UK banks' total exposures falls outside the scope of the CPRS classification[49].

Figure 13: CPRS Exposures Coverage

Panel (a) – Gross Exposures Panel (b) – Breakdown by NACE 1-digit code

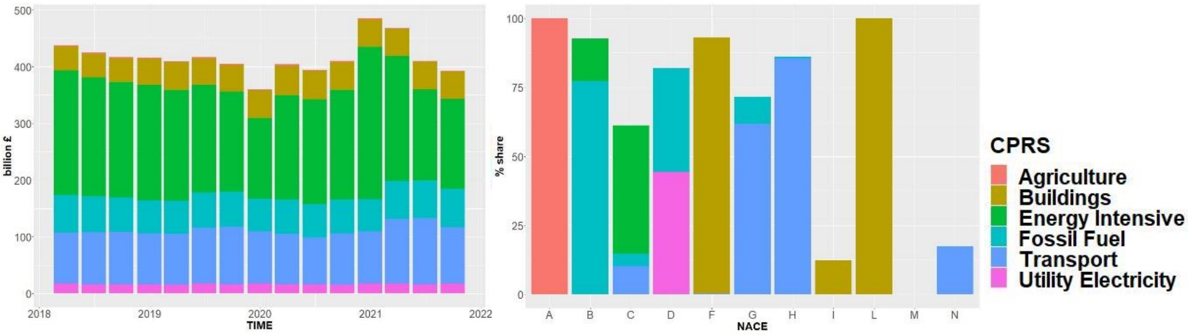


Table 10 provides a comparison with other comparable studies in the literature, i.e. EU banking system, EU insurance corporations, and Austrian banking system. In order to compare the results with the EU banking system, we collect evidence from EBA (2021) exercise on EU banks' loan exposures and from Alessi et al. 2019 for EU banks' security exposures. The coverage of the two data samples is not identical. EBA (2021) exercise covers all EU-27 countries plus Norway and the United Kingdom, but focuses only on a subsample of banks which account for 50% of EU banks' exposures. In this respect, we rescale all estimates provided by EBA (2021) by a factor of 2, thereby assuming that the share of CPRS exposures remains constant as estimated for the UK banks on aggregate exposure amounts. Contrary, Alessi et al. 2019's exercise excludes security exposures from UK banks. In this respect, we augment their estimates with our CPRS estimates on UK banks' security exposures.

Overall, the UK banking sector's share of total assets subject to climate-related transition risk is close to 4.2%, while the EU banking sector is relatively higher, close to 8.9%. Looking more closely at the contribution of loan exposures to CPRS exposures, we can see that the loan book accounts for 2.5% in the UK (0.6% estimated plus 1.9% calculated), compared to 6.3%

[48] Potentially a share of NFC aggregate exposures (£537 billion) may be allocated to the NACE activity "O - Public administration and defence; compulsory social security" which is outside the scope of CPRS classification.

[49] We acknowledge that the introduction of stricter energy efficiency standards could significantly affect the value of real estate portfolios, in particular for residential real estate, given that housing accounts for a significant portion of energy consumption and carbon emissions. Higher carbon prices could therefore significantly affect the energy costs of housing and, in turn decrease the credit worthiness of borrowers and the value of the collateral pledged (recovery rate) on housing mortgages. Commercial real estate may be affected too.

in the EU. Similarly, the trading book account for 1.6% in the UK and 2.5% in the EU. Overall, in both jurisdictions banks' exposures towards CPRSs are diversified similarly across loan and security exposures, the former accounting for two-thirds and the latter for one-third. As far as the composition of security portfolios is concerned, we can see that the equity share is in both jurisdictions over-weighted compared to the debt security share, 86% in the UK and 91% in the EU. Overall, this comparison highlights that UK and EU banks tend to be exposed to climate policy relevant sectors similarly across asset classes, although the EU banking is more exposed overall. Other studies focusing on the EU insurance corporations (EIOPA 2018) and on the Austria banking system Battiston et al. (2020) show higher estimates, respectively 13% and 26%.

Table 9: Comparison of CPRS UK banks' CPRS exposures

Sector	Derivation	Type	CPRS Exp. % TA	CPRS Exp. % NFC Exp.	Total NFC Exp. (bn)	CPRS Exp. (bn)	SOURCE
UK Banks	Estimated	Loan & Security	4.2%	15.6%	2961	463	Own Calculations
		Loan	0.6%	13.0%	537	70	
	Calculated	Loan & Security	3.6%	16.2%	2424	393	
		Loan	1.9%	13.0%	1633	213	
		Security	1.6%	22.8%	791	180	
		Equity	1.5%	25.8%	633	163	
		Debt	0.2%	10.8%	158	17	
EU Banks	Calculated and Estimated	Loans & Security	8.9%	50.4%	7568	3816	Own Calculations
		Loans	6.3%	58%	4600	2720	EBA 2021
		Security	2.5%	37%	2968	1096	Alessi et al. 2019
		Equity Security	2.2%	36%	2591	943	
		Debt Security	0.4%	41%	378	153	
EU Insurances	Calculated	Security	13%		7692	1000	EIOPA 2018
OeNB	Calculated	Loan & Security	20%	26%	864	228	Battistion et al. 2020

Note: EBA 2021 and Alessi et al. 2019 size assets, respectively loans and securities, towards the counterparty sector non-financial corporations (NFCs, according to the ESA2010 classification) resident in the EU. The EU composition in Alessi et al. 2019 excludes Croatia, Sweden and the UK, while EBA 2021 includes the 27-EU countries, plus Norway and the United Kingdom. Moreover EBA 2021 estimates cover roughly 50% of the EU banking sector's total assets. Given this, and to make the sample comparable, CPRS estimates for EU banks' security exposures are augmented with UK banks' estimates, whereas EU banks' loan exposures are rescaled by a factor of 2 to reflect a complete balance-sheet perspective. EU Banks' total assets amounted in the end of 2019 to € 43 trillion (Source ECB Statistical Data Warehouse). EU banks' exposures are reported in billion Euros.

Finally, looking at the composition of CPRS sectors, the "Energy Intensive" sector is the most relevant CPRS component, accounting for 40.5% (£159 billion) of total CPRS granular exposures. The second most relevant CPRS sector is "Transport" with 25% (£99 billion), followed by "Fossil Fuels" with 17% (£68 billion) and "Buildings" with 12% (£48 billion),. The remaining CPRS classes are the "Utility Electricity" with 4.6% (£18 billion) and Agriculture with 0.3% (£1.4 billion). By comparing UK banks' CPRS decomposition with the one provided in Alessi et al. (2019) for the EU macro sectors, we can state that they are aligned[50]. The only exception is the "Buildings" component whose contribution is higher for the UK banking sector relative to the EU banks.

6.2 Degree of "Greenness" of UK banks' portfolios – TAC Approach

The classification approach applied in the previous section aimed at quantifying and categorising the share of banks' exposures that could be relevant from a climate perspective, focusing on those sectors that are more likely to experience an impact from climate transition policies, thereby sizing "brown" exposures. Our focus in this section, in contrast, is on the quantification of the green share of banks' exposures. These metrics provides a complementary perspective to the CPRS approach highlighting how firms contribute to and cope with a climate-friendly transition. This indicator, the green asset ratio, was proposed by the EBA's "Advice to the European Commission on key performance indicators" for consideration in the banks' disclosures of the alignment of their activities with the EU Taxonomy[51].

In this respect, we compute the green asset ratio using the taxonomy alignment coefficient approach (TAC), which is based on Alessi et al. (2019). Not all the NACE classes are covered by this taxonomy, only those that matching the EU taxonomy as of 2020. The TAC approach provides sector-specific standardised coefficients for a subset of NACE sectors in order to approximate the sectoral alignment based on the features of the relevant technical screening criteria and relevant characteristics of the sector as a whole. The TAC represents the approximate degree of greenness for a given NACE class (1 to 4 digit codes) in percentage points ranging from 0 to 100[52]. Hence we multiply each TAC NACE-specific factors for the exposure amounts falling into each NACE class. Overall, across all TAC-related NACE classes, we capture £607 billion of exposures, out of which £22.8 billion can be classified as "green" assets, roughly 3.8% of NACE-TAC relevant exposures - Figure 14 and Table 11. If we compare this estimates with the one provided by EBA 2021 exercise on EU banks' loan

[50] This comparison is made only with the share of CPRS exposures for security exposures, since the EBA 2021 exercises covering the loan book of EU banks does not provide a CPRS decomposition.

[51] The EU taxonomy is currently limited to defining green activities considered as environmentally sustainable and technical screening criteria have been so far developed for two environmental objectives, climate change mitigation and climate change adaptation. Applying the taxonomy at NACE section level means identifying the share of exposures, to a specific NACE section (e.g. NACE classes), that is related to taxonomy compliant activities ('green') or not.

[52] The NACE class that are currently considered as of 2020 are: "A" Agriculture, forestry and fishery, "C" Manufacturing, "D" Electricity, Gas, Steam and air conditioning supply, "E" water supply, sewerage, waste management and remediation activities, "F" construction, "G" Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles, "H" transportation and storage, "J" Real estate activities, "L" Real Estate Activities, and "N" administrative and support service activities. TAC coefficient are reported here: https://publications.jrc.ec.europa.eu/repository/bitstream/JRC118663/jrc118663-uzh_taxonomy-alignment-tool-2020.xlsx

exposures, they size roughly 162 billion of green exposures, or 22.7% of total exposures amount covered by EU taxonomy. The result for UK banks is much lower compared to the EU banks on average. We have to acknowledge that the EU sample focuses only on loan exposures. In this respect, we subset our sample according to loan and security exposures, and we compute TAC estimates for both portfolios. We see that the loan portfolio has a much higher green asset ratio, almost 6.4%, whereas security exposures are only 1% of the total. Hence, UK banks' loan exposures tend to show a higher green ratio compared to the security portfolio.

Figure 14: Breakdown of TAC exposures by NACE 1-digit classification

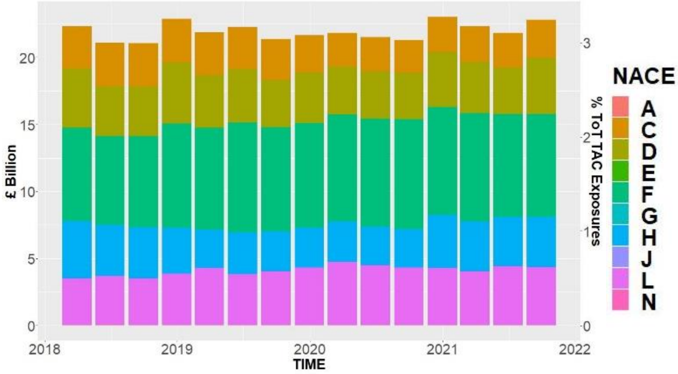


Table 10: UK banks' TAC Estimates by loan and security portfolios

NACE	Total Exposures				Loan Exposures			Security Exposures		
	TAC (Bn)	TOT (Bn)	NACE Ratio %	TAC Share	TAC (Bn)	TOT (Bn)	TAC Share	TAC (Bn)	TOT (Bn)	TAC Share
F	7.7	21	37%	1.3%	5.9	15.9	1.9%	1.8	4.6	0.6%
L	4.3	29	15%	0.7%	4.0	26.5	1.3%	0.3	2.3	0.1%
D	4.2	40	11%	0.7%	3.7	32.7	1.2%	0.5	7	0.2%
H	3.7	31	12%	0.6%	3.3	16.1	1.1%	0.4	14.6	0.1%
C	2.8	327	0.9%	0.5%	2.7	113.0	0.9%	0.1	214	0.0%
N	0.1	16	0.3%	0.0%	0.1	14.2	0.0%	0.0	2.3	0.0%
G	0.0	59	0.0%	0.0%	0.0	39.2	0.0%	0.0	20	0.0%
A	0.0	1.4	0.0%	0.0%	0.0	1.3	0.0%	0.0	0.0	0.0%
E	0.0	18.1	0.0%	0.0%	0.0	17.1	0.0%	0.0	1.0	0.0%
J	0.0	66	0.0%	0.0%	0.0	30.9	0.0%	0.0	35	0.0%
TOT	22.8	608	/	3.8%	19.7	307	6.4%	3.1	301	1.0%

7. Discussions and Conclusion

Concentration risk and interconnectedness are systemic risk dimensions that only through network analysis can be unfold, and granular data are the key to this quest. Achieving the former, implies a consistent and shared approach to the latter. Shocks to large non-financial corporates - the granular origins of aggregate fluctuations - determine fluctuations in output (GDP) as shown in Gabaix (2011), as well as a high level of interdependency in the intersectoral input-output linkages - network origins - may drive aggregate fluctuations in outputs as shown in Acemoglu et al. (2016). The same rationale applies to the microstructure of the financial system, which in turn determines fluctuations in Systemic Risk as shown in

Acemoglu et al. (2015). The degree of concentration risk as well as of interconnectedness both in the economic system and in the financial system have strong implications for the system's functioning and its propensity to (in)stability. In this regard, we have provided in Section 3 key insights on the distribution of UK banks' exposures across sectors, regions, and type of assets as well as on the degree of direct and indirect interconnectedness of UK banks. We have also documented the degree of concentration risk across three levels, respectively on an exposure, counterparty and reporting bank basis. All these risk dimensions provide indicative evidence that the microstructure of the UK banking sector is potentially conducive to instability given a high degree of concentration risk.

According to the aforementioned studies, in this set-up idiosyncratic shocks to specific UK banks' counterparties have implications for fluctuations in the aggregate level of systemic risk, as well as idiosyncratic shocks to specific banks may have implications for fluctuations in economic activity. Our work did focus on the former stream, though we didn't perform a solvency stress test exercise which requires us to relate an individual bank's loss estimate to the bank's capital base. Instead we assess systemic risk from a system-perspective as a function of the actual network structure of UK banks' exposures and of variations in financial conditions proxied by changes in PD and LGD parameters of banks' counterparties. We so computed UK banks' expected losses also defined as Capital at Risk (CaR) from both credit and market risk exposures.[53] In this respect, we quantify that the UK banking system's quarterly loss estimate in Q3-2021 was close to £51.8 billion (0.5% of total exposure amounts). We also quantify the impact of the Covid-19 crisis in terms of CaR, which increased in Q1-2021 relative to Q4-2019 by 36%, passing from £ 41.7 billion to £ 56.7 billion. Moreover, the CaR analysis has shown that the UK banking system is more prone to import shocks from abroad (3/4) rather than face them domestically (1/4). From a sectoral perspective, we also assess that 2/3 of the CaR is due to risks in the real economic sector (NFC + HH), and 1/3 to non-bank financial exposures (FC).

However, CaR estimates are not a function of the network structure, do not take into consideration the distributional features of the network, and whether we use granular or aggregate exposures the analysis would lead to very similar conclusions. Nonetheless, the concept of Capital at Risk is intuitive and may convey clear information on the average level of risk in the system, but it is not a good proxy for systemic risk or tail-event analysis.

[53] We don't perform a solvency stress test exercise, we only quantify risks to the UK banking sector by calculating credit and market risk losses stemming respectively from loan and security exposures.

Concentration risk and interconnectedness, risk features identifying the network structure, are not taken into consideration in this expected loss calculation.

For this reason, we modelled scenario uncertainty as a function of the realized network structure. Losses materialize not in expectations, but precisely because of the specific realisation of a counterparty default or of a set of counterparty defaults. Hence, the degree of exposure heterogeneity in the network structure captured by the degree of concentration risk and interconnectedness matters for the aggregate level of systemic risk[54]. And the level of systemic risk that materializes is a function of the set of counterparties that actually default - the size of the initial shock - as emphasized by Acemoglu et al. (2015). In our framework, the size of the initial shock is a function of the average default probability assigned by the reporting banks to each counterparty by sector and country for each quarter, and also of the average loss given default parameters. More precisely, the size of the initial shock is a function of the number and of the distribution of counterparty defaults. In this paper, we don't focus on testing our results by increasing/decreasing PD parameters (stressed PDs) which are given, but we try to assess how results may change given a different realization of the same probabilistic scenario.[55] Hence, what matters is the modelling of interdependency in the input-output linkages of banks' counterparties, that is, modelling the correlation in asset returns of banks' counterparties as emphasized by Acemoglu et al. (2016). We achieve this by computing a time invariant correlation structure for counterparty defaults by country and sector using variations in banks' counterparty PD parameters by country and sector over the period Q1-2018 to Q3-2021. By means of Montecarlo simulations thus we compute banks' loss distribution for 10.000 realizations of the same probabilistic scenario, which is a function of the set of counterparty PDs and the estimated correlation structure for counterparty defaults. This probabilistic approach allows us to measure (in £) the potential current severity of tail events captured by our Conditional Capital at Risk measure (CCaR). The CCaR measure is derived for a set of medium, severe, and extreme stress events, respectively conditioning the loss estimates to the 90^{th}, 97.5^{th} and 99^{th} percentile of the loss distribution. Furthermore this approach also allows us to quantify the likelihood of the realization of such stress events by computing conditional probability estimates to the severity of the stress event we target. In this respect, we estimate that the probability of experiencing a severe stress event in the UK of more than £ 132 billion losses has increased up to 5.4% in Q1-2021 from 1.25% in Q4-2019. Whereas the severity of

[54] We don't test our results to variations in the network structure since in our set-up the network structure is given, is not uncertain, and represents our starting point.
[55] Probability of defaults are exogenously given by banks and track financial and economic developments.

a severe distress event in Q1-2021 increased up to £ 240 billion of median losses, almost up by 82% since Q4-2019. Most of the increase is due to an exogenous increase in counterparty PDs - size of the shocks - instead of a change in the underlying network structure (distribution of shocks) which is slow-moving[56]. The loss distribution is then very dispersed across realizations of the same probabilistic scenario, and capturing this dispersion allows us to assess the severity and likelihood of potential tail events.

In the end, we shed lights upon the sensitivity of our results to a variation in the degree of correlation of counterparty defaults. Hence we assume that there is a strengthening in the interdependency of input-output relationships of banks' counterparties. For instance this may be due to a stronger synchronization of counterparties' revenues across sectors and economic activities (supply chain relationships like just-in-time manufacturing) or due to a synchronization of business cycles across countries. More in general common sectoral shocks like the Covid-19 Pandemic or like climate-related transition risks may generate a strengthening in asset correlations as well as counterparty defaults across sectors and countries. Hence, we keep unchanged everything else except the size of the correlation parameters of counterparty defaults. In fact the structure of the correlation matrix remains the same in relative terms, though in absolute terms the average correlation across all sector-country pairs increases from 0.08 to 0.22. Given this stressed correlation structure, the probability of experiencing severe distress events (97.5th percentile) in Q1-2021 increase to 8.3% from 5.4%. For medium stress events and severe stress events, the probability is close to 19.1% and 4.9%, respectively. The intuition behind this result is that the strengthening of the correlation in counterparty defaults leads to a higher likelihood of experiencing clusters of defaults by country and sector thereby increasing the severity of tail events and so their conditional likelihood[57].

Overall, expected loss estimates are completely silent about the increase in the level of systemic risk approximated by the increase in the probability of experiencing a severe stress event. Capital at Risk estimates are not a function of the structure and degree of correlation in counterparties' defaults. Correlations do not play any role in expectation. It is the analysis of the loss distribution, thereby overcoming scenario uncertainty, that is very informative on the severity and likelihood of banking and economic crises as already emphasized by Adrian et al. (2019), among others. We conclude by investigating the sources of tail-events by decomposing

[56] Counterparty PD parameters change given the change in banks' expectation on counterparty risk by sector and country. Contrary, LGD parameters only experienced small variations.

[57] By changing the correlation structure, that is, varying the interdependency across country-sector pairs (average correlation is unchanged), may lead to both a decrease or increase in the likelihood and severity of stress events depending on the underlying network of UK banks' exposures.

Conditional Capital at Risk by its various contributions in terms of sector, region and economic activity. This is important for policy makers since allow to identify and so monitor the build-up of tail risks. The CCaR decomposition strengthens further the conclusion derived from the CaR decomposition, that is the sources of average risk (CaR) and especially systemic risk (CCaR) for the UK banking sector are mostly due to exposures outside the UK jurisdiction and vis-à-vis the non-financial corporate sector, respectively 94.2% and 94.6% of median loss estimates for severe stress scenarios.

In the end, we want to emphasize that our network approach to stress testing the UK banking system' asset side have also some limitations, which in turn have implications for our CaR and CCaR estimates, with potential revisions both upwards and downwards. First of all, we only model losses from direct exposures, and we don't model amplification effects or second-round losses arising from interbank or intra financial sector's exposures via contagion or fire-sales spillovers. In this respect, our approach is closer to a standard stress test methodology rather than a financial network stress testing methodology as developed by Montagna et al. (2021), Sydow et al (2021), and Roncoroni et al. (2021), among others. As we have seen CaR and CCaR estimates capture a little amount of losses stemming from credit institutions and financial corporations, accounting for less than 5% of losses in severe stress events. Hence, our estimates tend to underestimate systemic risk spillovers stemming from these sectors. Future extensions of this work should tackle this methodological gap, and directly model financial amplification mechanisms. This is even more important since losses stemming from security exposures are modelled similarly to credit risk exposures, and are not derived with an ad-hoc price impact function as for instance in Coen et al. (2019). Our estimates are conservative in this respect, since fire-sales mechanisms via overlapping portfolios of exposures may also negatively affect the price of securities of those counterparties which actually did not default in tail scenarios. Hence, banks' conditional capital at risk estimates should be a function of correlations in the real economic sector as well as in the financial sector since the price of securities is actually a function of financial institutions' management strategies. Hence, modelling financial amplification mechanisms would benefit from extending the coverage of the Global Network beyond the banking sector, for instance to the UK insurance and pension fund sectors as well as to the investment fund sector. In this regard, we should also acknowledge that the Global Network does not capture derivative exposures. We leave these dimensions to future research.

Another limitation of the current work is that it relies on PD parameters that are not counterparty-specific. Our risk parameters are homogeneous across counterparties belonging to the same sector and country. This assumption which is due to the limitation in terms of granular coverage of our supervisory data source may lead to an over estimation of CaR and CCaR estimates. The rationale is the following. Given that the distribution of exposures follow a power-law distribution, that is, large corporates capture 90% of total UK banks' exposures, and given that small corporates are likely to experience on average higher probability of defaults than large corporates, we tend to assign higher PDs to the set of largest exposures. In this respect, the current work would benefit from using Moody's Riskcalc database which provides counterparty specific PD parameters at least for a set of large quoted corporates so as to increase the degree of heterogeneity in counterparty risk. Related to this, we have to emphasize that our data source for risk factors exploits banks' own assessment of their specific counterparty risk. This subjective assessment may present both pros and cons. On the one hand, banks may have superior knowledge on their counterparty risk compared to external data sources, thereby contributing to enhance our loss estimates. Moreover, banks' counterparty risk factors reflect banks' short to medium term expectations on financial and economic developments (1-year ahead). Hence, our CaR and CCaR estimates incorporate banks' expectations about the future state of the world economy, thereby working as potential early warning indicators for a banking system's loss of confidence (or overconfidence). This type of signals may inform policy makers on the timing of releasing (tightening) capital buffer requirements in order to sustain funding to the real corporate sector. This is crucial since a deterioration of confidence vis-à-vis the non-financial corporate sector may directly exacerbate liquidity conditions of non-financial corporates, and in turn increase the likelihood of corporate defaults, which in the end worsen banks' solvency position. On the other hand, using subjective estimates of risk factors may lead to potential bias, since banks may under or overestimate counterparty risk. In this respect, we tackle this source of estimation bias by averaging PD and LGD parameters by country and sector across reporting banks, thereby implementing a pool approach to counterparty risk. Nevertheless, for policy analysis and policy applications it would be relevant to test our results to homogenous and heterogeneous variations in risk parameters so as to overcome parameter uncertainty, as we did for scenario uncertainty. However, CaR estimates are a linear function of both PD and LGD parameters, hence a homogeneous increase in risk factors would lead to a homogenous increase in expected losses. This is not true for tail losses approximated by CCaR estimates since an increase in PD parameters would affect also the correlation structure of corporate defaults. Further work is needed to shed light upon the relationship between risk parameters and tail events, in terms of both severity and likelihood. By contrast, we test our results to a variation in the correlation structure and number of Montecarlo simulations.

In the end, we want to highlight few other concerns and potential extensions of our work. Our results are not affected by the number of Montecarlo simulations. We perform sensitivity analysis using 20.000 simulations, and CCaR estimates do not change. Furthermore, we should also acknowledge that the country coverage should be improved since 12.8% of total exposures could not be mapped with a country code. Finally, the granular coverage of the Global Network, although quite comprehensive, still requires further improvement. Roughly 40% of total exposure amounts were captured with aggregated exposures by country and sector, thereby not entering into the calculation of the stochastic loss component for the Conditional Capital at Risk measure. Instead they enter the calculation of the CCaR as expected loss component, thereby leading to an under-estimation of the severity and likelihood of tail events. This is especially relevant for exposures vis-a-vis the household sector which accounts for 16.7% of total exposures.

To conclude, the incipit of this paper highlighted the challenging journey the research and policy community undertook to shed light upon the role played by modern financial systems in the unfolding of events such as the Great Financial Crisis. By adopting a network perspective, empirical works in this vein started investigating the microstructure of the financial system across countries and sectors focusing on those features - concentration and interconnectedness - that may contribute to the financial system's functioning and its propensity to (in)stability. In this paper, we have highlighted the role of those features in strengthening the severity and likelihood of tail events for the UK banking sector. Hence, a highly interconnected and concentrated financial system as well as economic system may provide clear efficiency benefits during tranquil times, but at the same time the very same features also increase the system's level of instability once the tranquil times come to an end.

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Technical Appendix (A)

1. A Roadmap to Construct a Granular Data Infrastructure

The Basel Committee on Banking Supervision (BCBS, 2014) set out a global regulatory framework called "large exposures" to monitor and measure concentration risk arising from a counterparty failure. This was the first and crucial step in raising global awareness among financial market participants (public and private) about the need for more granular and up-to-date sources of exposure information. This need is now even more compelling in light of the sudden and fast-moving Covid-19 Pandemic that has affected counterparties across sectors and countries in remarkable different ways and with different timings.

A successful implementation of a comprehensive data collection on exposures at the firm-counterparty level has been hard to achieve, and is yet to be fully accomplished. While the regulation in theory requires firms to precisely identify counterparties via their name and legal entity identifier (LEI code), in practice the consistency of reporting has varied significantly across regulated firms. This counterparty identification problem via LEI code and firms' names is not exclusive for the UK jurisdiction, but is shared across jurisdictions as highlighted for the Euro Area (EA) in Covi et al. (2021). Counterparty legal names differ across reporting institutions even within the same jurisdiction, and LEI codes are often difficult to retrieve and associate to counterparty names. In general, the LEI adoption across jurisdictions has been unbalanced and is low outside securities and OTC derivatives markets (FSB, 2019: 25), making it difficult for credit institutions and financial firms to associate LEI codes to counterparties especially from the banking book. Hence, LEI coverage still remains too low to encourage further regulatory uses or to reach a potential tipping point where voluntary take-up by market participants would suffice to propel further adoption (FSB, 2019: 25). In addition, there is a lack of know-how amongst firms about how to handle and map big granular exposure datasets, making the challenge of implementing the regulatory reporting requirements an operational issue from the firms' perspective as well.

These data challenges haven't held back the implementation of the large exposures regulation or the collection of other granular exposure datasets, such as security or derivative portfolio holdings, though they have slowed down and complicated the exploitation of this exposure-type datasets for prudential supervision. For central bankers, supervisors, and regulators to maximise the potential of using these datasets for monitoring financial stability risks and supervisory purposes, the first and foremost pre-requisite is a high-quality mapping of counterparties to legal entity names and LEI codes in a consistent manner across firms and time, which is not yet the case in current granular regulatory data collections.

In 2012, the Financial Stability Board - conscious of the challenges and costs for the private sector as well as the wide range of benefits[58] this data transition and improvement in underlying data quality may provide in the medium-long run to all market participants - was endorsed by G-20 countries to promote a "global adoption of the LEI framework to support authorities and market participants in identifying and managing financial risks". As part of this initiative, the FSB in 2014 kick-started the construction of the Global Legal Entity Identifier Foundation (GLEIF) database as the operational arm of the system that federates local LEI issuers under the oversight of the LEI Regulatory Oversight Committee (ROC)[59]. This presents a fundamental step in disseminating reference and group structure information as a public good and in pushing forward and supporting a global-scale adoption of LEI codes for the identification of financial and non-financial firms. As emphasized by the ESRB (Laurent et al. 2021), LEI codes have the potential to become the identifier of the global economy. Moreover, in order to support LEI adoption by financial market participants, the EU Regulation No 600/2014 (also defined as MiFIR) has limited the access entities can have to financial markets in the European Union without an associated LEI code. As documented by the ESRB, the adoption in Q1-2017 of this LEI reference standard which was applied to various collections of granular data sources[60] led to a remarkable increase in LEI issuance per month, that is, in counterparty LEI-based identification. Overall these regulatory and data initiatives represent a key milestone in terms of supporting a global scale adoption of LEI codes as firm-specific identifiers.

Nevertheless, a common and consistent adoption of LEI codes across firms on a global scale still requires a full integration of the LEI identification approach into data management systems, both in the private sector as well as in the public sector. Why is this integration process not straightforward? The current data management systems are based upon using unique internal identifiers (*not* LEI-based) to classify each counterparty (client), and those internal IDs

[58] In terms of i) monitoring financial risks; ii) exposure aggregation in data reporting; iii) statistical analysis; iv) understanding the structures of multinational companies, market structure and trading networks; v) and facilitating market surveillance and compliance assessments (FSB, 2019: 25).

[59] The ROC is composed by 65 financial markets regulators and other public authorities and 19 observers from more than 50 countries. It promotes the broad public interest by improving the quality of data used in financial data reporting, improving the ability to monitor financial risk, and lowering regulatory reporting costs through the harmonization of these standards across jurisdictions. Access at: https://www.leiroc.org/

[60] The European Market Infrastructure Regulation (EMIR), the Markets in Financial Instruments Directive (MiFID II), MiFIR, Solvency II and the Central Securities Depositories Regulation (CSDR). See Laurent et al. (2021) for an overview of these regulations and impact.

differ across reporting banks, even within the same jurisdiction. In order to bridge this data gap, the GLEIF database represents an excellent master data reference source for mapping counterparty entities with LEI codes by exploiting the legal name and/or the security identifier (ISIN code) stored in the GLEIF database[61].

Capitalising on this master data reference source, the first contribution of the paper is to provide a data infrastructure framework for cleaning, mapping, and merging firms' counterparty information and for reconstructing balance sheet based granular financial network exploiting multiple supervisory data sources. As part of this framework, we apply a mapping-searching algorithm across 8 million entities collected from the entire spectrum of global counterparties in the UK banks' portfolios of loan and security exposures. We thus document a roadmap to build a granular automatic and scalable data infrastructure. This is our first contribution in the paper, and necessary step for then studying and analysing the network of UK banks' exposures on a global scale exploiting counterparty-specific information. In this respect, we follow the works of Covi et al. (2021) in mapping bank-specific information using LEI identifiers and Montagna et al. (2021) who extend the approach to a global map of counterparties in order to merge different granular supervisory datasets for the Euro Area (EA) banking sector. The datasets we use share the standard structure of granular datasets collected both for supervisory and non-supervisory purposes. They also share the standard structure for both security ISIN-based datasets as well as for LEI-based datasets, making this data infrastructure framework applicable to any data management system. The data infrastructure's value-add is therefore twofold, respectively enabling i) the mapping of counterparties via LEI and ISIN codes and so producing a consistently mapped network of exposures, and ii) the linking of qualitative and quantitative counterparty-specific information via LEI codes using multiple private and public data sources. Overall, the data infrastructure and mapping algorithm increase the coverage of counterparty LEI codes from 55% to 91% for the large exposures dataset (LE) and up to 97% and 87% for the security ISIN-based datasets from respectively 0% and 66%.

1.1 Network Data Sources

In this section we describe the datasets we use to construct the UK banks' global network. In order to achieve a comprehensive coverage of the UK banks' asset side we need to draw from various data sources of different levels of granularity. First, we introduce two *entity-based*

[61] As explained before, for security and derivative instruments, a full map of ISIN codes to LEI codes is provided by the GLEIF website. So for this type of assets, the LEI mapping process is easier to implement.

datasets (LE and C67) capturing entity to entity relationships, where the reporting and counterparty sides are identified via Legal Entity Identifiers (LEI codes). Next, we present two *security-based* datasets covering entity to security relationships, where the reporting side is still identified via a LEI code, as in the entity-based datasets, but the counterparty side is now identified via ISIN codes tracking the security issued. The level of granularity of the security-based datasets is higher than the entity-based datasets since multiple ISIN codes belong to one single entity. In the end, since the coverage of these granular datasets is not exhaustive, we collect one *aggregate-based* dataset, for which the reporting side is identified with a LEI code, whereas the counterparty side is aggregated by sector and country of origin.

1.1.1 Granular Entity-Based Datasets

Large Exposures Dataset (LE)

The large exposures (LE) framework serves as a backstop to the capital framework by ensuring that the maximum loss a bank would face in the event of a sudden default of individual counterparty or a group of connected clients that are linked by economic dependence or control would not endanger the bank's solvency.[62] All exposures captured under the risk-based capital framework are also subject to the LE framework, including both on- and off-balance sheet exposures included in the banking and trading book without applying risk weights or degrees of risk. As per LE rules, banks are required to limit their exposures to an individual client or group of connected clients to 25% of eligible capital after applying any credit provisions, accounting valuation adjustments and eligible credit risk mitigation techniques used to hedge or reduce credit risk as well as applying relevant exemptions.

The supervisory data collection on exposures in scope of the LE framework started in 2014 as part of Common Reporting Framework (COREP) regime with a quarterly frequency. Specifically, COREP templates C.27, C.28, C.29, C.30 are submitted by UK banks at the solo entity level, UK consolidated group level as well as at the level of any prudential sub-consolidations which may apply (ring-fenced bank sub-consolidations for example). The LE dataset captures only those exposures that meet the definition of a large exposure i.e. that are larger than 10% of a bank's/consolidation group's eligible capital or are above €300

[62] Supervisory framework for measuring and controlling large exposures (bis.org)

million[63,64]. The LE dataset is so constructed with an entity to entity relationship, and the counterparty side is identified with the legal name or group name and where possible with a Legal Entity Identifier (LEI code). Additional counterparty information is provided such as the SECTOR, COUNTRY and NACE classification of the entity. Moreover, the LE dataset also provides a rich set of exposure attributes, which allow us to distinguish debt, equity, derivate and off-balance sheet exposures. Moreover, the dataset also provides information on the amount of exposure which is subject to exemptions from LE limits and on the amount of exposure that is secured by credit risk mitigation instruments[65]. For our scope, we will focus on two main variables of interests: gross original exposure amount and the gross original exposures amount after having deducted the credit risk mitigation instruments so as to classify the exposure amounts into secured and unsecured exposure amounts. In the end, the LE dataset provides information on the maturity breakdown of the top 10 largest exposures vis a vis regulated and unregulated entities (template C.30).

The LE dataset given its reporting threshold is quite comprehensive covering a large share of banks' exposures towards credit institutions (CI), governments (GG) and central banks (CB). The dataset captures a smaller share of exposures towards non-financial corporations (NFC) and non-bank financial corporations (FC). This difference in the sectoral coverage is due to the size of the exposures, which especially for exposures towards small-medium size entities are smaller than the reporting threshold. Looking at the interbank network specifically, exposures from large reporting banks towards small-size banks also tend to be under-populated. No exposures vis-à-vis the household sector (HH) is provided as part the LE dataset. The dataset is a global dataset, capturing all UK banks' exposures classified as large exposures vis-à-vis any entity located worldwide. The dataset is a UK-centric, meaning that on the reporting side, only UK firms, subsidiaries of international banking groups domiciled in the UK or UK consolidation groups are present. This feature is common across all data sources.

Although the LE dataset is very rich, constructing a consistent network of bilateral relationships is not immediate. Consistent identification of counterparty entities is complex and

[63] From 2014 to 2017, transitional provisions outlined in CRR Article 494 allowed firms to include decreasing amounts of Tier 1 capital in the definition of eligible capital as it applied to large exposures. In 2014, the applicable amount of Tier 2 capital was a 100% of Tier 1 capital. During 2015 and 2016, the applicable amount of Tier 2 capital was capped at 75% and 50% of the value of Tier 1 capital respectively to allow firms. From 1 January 2017, the applicable amount of Tier 2 capital settled at a third as set out in CRR Art 4 (71)(b). From 1 Jan 2022, eligible capital will be defined as Tier 1 capital only as per the Basel Standard on large exposures.

[64] From 1 Jan 2022, this threshold will be set at £260 million.

[65] Exemptions are mostly applied to exposures vis-à-vis certain general governments and central banks based on their assigned risk weights as per relevant regulatory requirements as well as to certain entities in bank's wider group based on prior approval from the PRA.

challenging. Reporting banks may classify the very same counterparty with a slightly different legal name, or report the legal name of the subsidiaries instead of the group name. Moreover, the LEI dimension is not always available because firms may not have a LEI code (especially for small firms or subsidiaries) or because the reporting bank does not provide the LEI code against the counterparty (indicated as “not available/NA”). Moreover, when the entity on the counterparty side is classified as a group of connected clients, the reporting firm is obliged to report only the name of the head of group but not the related LEI code. There may also be variation in LEI codes and legal names reported against the same counterparty by the same reporting bank across time. This identification gap on the counterparty side is the main challenge we need to overcome in order to construct a consistent network of bilateral relationships. Similar problems arise for the COUNTRY, SECTOR and NACE dimensions which are often missing. These data identification issues are common to all granular data sources since the collection of these datasets started only relatively recently and reporting infrastructure is still being refined. In this respect, one of the main contribution of this paper is to develop and present a procedure to overcome these challenges and fully exploit these extremely rich and unique data sources. This data source covers over time roughly as unbalance panel 425 reporting banks, 6592 counterparties for a total of 213.428 exposure data up to Q3-2021.

Liability Dataset (C.67)

The Liability Dataset (C67) provides information on the 10 largest funding sources of the UK banks on a monthly frequency where the funding obtained from each counterparty or group of connected clients exceeds a threshold of 1% of total liabilities as at the reporting date. Its collection aims at monitoring concentration risk on the liability side and allows regulatory authorities to monitor a bank’s liquidity risk that falls outside the scope of the reports on liquidity coverage and stable funding. This dataset is useful to reconstruct a part of the asset side of non-UK bank exposures, and to complement to certain extent exposures from large-size UK banks towards small-size UK banks which are not captured in the LE dataset due to the reporting threshold. The dataset also captures exposures from governments and central banks towards UK banks.

The dataset presents a similar structure, although simplified, to the LE dataset. Exposure amounts are reported in gross terms, and exposures are classified by type of instruments, which allows us to disentangle between secured and unsecured funding exposures[66]. A maturity

[66] Information on the Large Exposures data can be retrieved from the Financial Conduct Authority Website.

breakdown is also provided, with a variable defining the average weighted maturity of the exposure in days. The funding provider is also identified with their legal name and the related LEI code. The COUNTRY and SECTOR dimensions are also reported, but not the NACE classification. This dataset presents the same data identification issues previously described thereby also requiring a consistent mapping of the counterparty entities. In this respect, this data source covers over time roughly 241 reporting banks, 2201 counterparties and 84506 data points up to Q3-2021.

1.1.2 Granular Security-Based Datasets

In order to monitor and model market risk and increase the coverage of the UK banks' Global Network, we aim to collect UK banks' security holdings. To achieve that, we exploit two main and complementary data sources, respectively the SHS and AS datasets. The former is collected on an annual basis by the BoE's Stress Test Division to exclusively monitor seven major UK banks (ACS banks) on a consolidated basis for the annual cyclical scenario[67], whereas the latter is collected on a quarterly frequency by the BoE's Data and Statistics Division to monitor a larger sample of UK banks on an unconsolidated basis. Both datasets have a common data structure. Reporting banks are identified with their legal names and LEI codes, whereas the counterparty side is mapped with an ISIN code for each security held, an LEI code of the issuer, and a legal name as well as the country and sector of the counterparty. For each security, the datasets also report the maturity date of the contract, splitting between equity and debt securities, and the currency in which the security has been issued. In the end, for each security exposure, amounts are reported at nominal and market values. These datasets are big granular datasets. The SHS and AS datasets covers over time respectively 13 and 33 reporting banks; 28,033 and 41,197 counterparties; 69,938 and 115732 ISIN-based security instruments; and 199,501 and 1,360,809 security exposures up to Q3-2021.

Just as with the entity-based datasets presented in the previous sub-section, these security datasets also present some data issues. For instance, ISIN codes might be wrongly typed and LEI codes identifying the issuer of the security may be missing as well as the country and sectoral tags. Moreover, counterparty names are also reported differently across reporting firms. Hence, in order to construct a multilayer network of granular exposures in which reporting and counterparty entities are consistently and uniquely identified across reporting

[67] ACS banks are those banks that are subject to the annual cyclical scenario, and there are seven of them: HSBC, Barclays, Standard Chartered, Lloyds, Nationwide, Santander, and Royal Bank of Scotland.

firms and time, these data issues need to be tackled and solved via a cleaning a mapping procedure which will be presented in section 2.2.

1.1.3 Aggregate Sector-Country Exposures

With the LE, C67, SHS and AS datasets we are able to map entity to entity relationships. They represent the granular information of our global network. However, the coverage of UK banks' total assets is not complete if we limit our analysis to this collection. For the objective of performing a stress test exercise and computing accurate and reliable financial stability metrics from a supervisory and policy perspective, we should aim to increase the coverage of the asset side to the largest extent possible even though we may lose some degree of granularity in doing so. In this respect, we collect data from FINREP supervisory template F.20.04, which contains information on the geographical and sectoral breakdown of UK banks' assets. That is, for each country in which the reporting bank is exposed and for each asset class (derivatives, equity instruments, debt securities, and loans and advances) and for each sector as applicable (credit institutions - CI, other financial corporations - FC, non-financial corporations - NFC, central banks - CB, general governments - GG, and households - HH), the firm is required to report its exposures as gross carrying amounts. These three dimensions, COUNTRY, SECTOR and type of INSTRUMENT are consistent with the dimensions previously described in the granular template thereby not requiring us an additional matching effort across datasets. Our wrangled F.20.04 dataset, also defined as aggregate exposure dataset, has 166,436 observations on 11 attributes, starting in Q1 2018 and (for our purposes here) ending in Q3 2021.

This dataset is important for the reconstruction of the Global Network especially for filling up three main counterparty sectors: HH, NFC, and FC. On the one hand, the household sector is missing from the granular datasets previously reported. This sector is crucial for modelling risk stemming from domestic exposures since a large share of exposures to households are within the UK. On the other hand, UK banks' large exposures vis-à-vis non-financial corporates and non-bank financial corporates may miss a significant portion of exposures towards small-medium enterprises and funds due to the reporting threshold of the large exposure regulation. By contrast, large exposures towards CIs, GGs and CBs tend to be sizeable enough to be captured in the LE dataset. Therefore, the aggregate exposure dataset helps to extend the coverage of these remaining sectors. Moreover, this dataset is also useful for benchmarking purposes so as to quantify the share of granular exposures captured by country and sector.

After having collected the F.20.04 dataset, we need to proceed with the data manipulation procedure since the granular datasets and the aggregate exposure dataset cannot be directly merged as they stand. Both the exposure-datasets and the aggregate-exposure dataset need to be first cleaned, mapped and subset before they are merged since these datasets have exposures in common. This is an important step to avoid double-counting issues. In the next section, we are going to describe the procedure for cleaning and mapping the granular exposure-datasets, whereas in section 2.4 we provide a description of the merging procedure.

1.2 Cleaning and Mapping Algorithm

1.2.1 Cleaning Procedure

In order to construct the UK banks' network of granular exposures, we need to identify reporting banks and counterparty entities uniquely across three main dimensions: time, dataset, and reporting firm. In the LE and C67 datasets we have two main identifiers, respectively the NAME and LEI of the counterparty. However, the very same counterparty may be reported with a slightly different name even by the same reporting bank across datasets and time. The name of the counterparty may also differ across reporting banks within the same dataset and reporting period. In order to homogenise the name, we create an additional variable, defined as CLEAN_NAME, which is the original name cleaned of special characters, white spaces, and digits. Next, we move to the LEI identifier, which is a unique code of 20 characters. However, also in this case, the LEI code may be missing or wrongly typed. In this respect, we remove all illicit LEI codes which are longer or shorter than 20 characters and those that include characters which are not letters or digits. This procedure is also applied to the SHS and AS security datasets. Nevertheless, these latter two datasets also have an ISIN dimension, which links multiple ISIN codes to the LEI code of the issuer. For the ISIN codes, as is the case for the LEI codes, they may be wrongly typed. In this respect, we remove all ISIN codes which are longer or shorter than their permitted length of 12 characters and those that include characters which are not letters or numbers. For those data entries in which the ISIN code is missing, we remove those entries from the datasets since it won't be possible to fill the missing ISIN during the mapping procedure even if we might have the related LEI code of the counterparty because multiple matches exist between ISIN codes to a single LEI. By contrast, we do keep those data entries with a missing LEI since only one unique match exists between an ISIN code and LEI code and between a NAME and LEI code.

1.2.2 Mapping Procedure

The key challenge of working with granular data is the unique identification of entities across reporting firms, datasets and time. The main objective of the mapping algorithm is to assign to each entity an identifier (ID number) which is unique across time. In order to achieve this outcome, we exploit the information reported by the firms regarding their exposures namely, the original counterparty NAME, the CLEAN_NAME we created, the LEI code and an ISIN code when it is a security exposure dataset (SHS and AS datasets). Moreover, in order to increase further the coverage of NAME, LEI codes and ISIN codes beyond those values already present in the exposure-datasets, we also retrieve two additional datasets from an open source website called GLEI[68]. The GLEI dataset has several dimensions and data tables. The GLEI_1 dataset provides a map of LEI to NAME of roughly 1.9 million entities[69]. The GLEI_2 dataset provides a map of ISIN to LEI of roughly 5.9 million securities[70]. These datasets are the most comprehensive map of legal classified entities around the world, and they are updated daily.

As first step of the procedure, we create a data table by combining all unique entities identified from each exposure-dataset. A unique entity is defined as one entity that has at least one field among the fields NAME, CLEANED NAME, LEI and ISIN which differs from another entity. If one field is missing (such as the ISIN field for non-security exposures), we exploit information only from the remaining fields. The same applies when one field is not available (NA), for instance because a reporting firm did not provide information about the LEI code of the counterparty entity. In this respect, we exploit information only by using the NAME and the CLEANED NAME variables. This initial data table is composed by roughly 8.6 million unique entities.

As a second step, we apply the mapping algorithm to the initial data table we created. The algorithm consists of a searching procedure which identifies sequentially all entities which display the same exact CLEAN_NAME across all entries, then the same LEI code and finally the same ISIN code and assigns to them a unique ID number. Hence, the algorithm looks for matches between pairs of fields: CLEAN_NAME to NAME, LEI to NAME, and ISIN to LEI. The rationale for the searching algorithm is as follows. One reporting firm may report the NAME of a given counterparty but not the related LEI code, while at the same time another

[68] Online Source: https://www.gleif.org/it/

[69] The data source is LEI-CDF v2.1 Golden Copy retrieved from: https://www.gleif.org/it/lei-data/gleif-golden-copy/download-the-golden-copy#/. Moreover, the GLEI golden source dataset also provides information on firms' attributes, such as geolocation, headquarter etc.

[70] The ISIN-LEI data source was retrieved from: https://www.gleif.org/it/lei-data/lei-mapping/download-isin-to-lei-relationship-files#

reporting entity may report the NAME of the same counterparty along with the LEI code. The same logic applies to the other fields. Given this intuition, we are able to assign the same ID to the same entity by exploiting common information across pairs and across reporting firms, datasets and time periods. For the CLEAN_NAME to NAME matching pair, we use an exact string match rather than a fuzzy match since we want to avoid the risk of matching the wrong entity. We have to avoid introducing any matching error during the searching procedure because the error will propagate across matching pairs throughout the mapping procedure.

As a third step, once we have identified each entity with a unique ID, we create our final entity table by selecting one exemplar entity for each unique ID based on a statistical approach. Specifically, fields such as NAME and LEI codes for each unique ID will be then filled respectively with the NAME and LEI code that appear the most times for the same ID, that is, the most common entry NAME and LEI code. We do this, since sometimes firms report the wrong LEI code for the same NAME field. For this reason, during the searching procedure we give priority in assigning ID by NAME over LEI codes. In fact the searching procedure starts by assigning ID by NAME_CLEAN to NAME and after by LEI to NAME. The resulting Master Entity Table (Table 1) displays 2 million entries, roughly one fourth of the size of the initial data table.

Next, we add three additional columns to the table, respectively the COUNTRY, SECTOR and NACE fields of the entity, again by keeping the most common entry that appears in the data table for each variable. These dimensions provide relevant complementary information about the counterparty entity, which are important for modelling purposes—for instance to compute geographical or sectoral risk metrics (such as for stress testing exercises and for benchmarking aggregate exposures by country and sector).

Finally, we add to the entity table two additional columns referring to the consolidation status of the counterparty entity. This dimension is relevant since it gives us the flexibility to choose to model risk (depending on the scope of the exercise) at the highest level of consolidation or on an unconsolidated basis. By exploiting the GLEI_3 dataset, which provides a LEI relationship between each LEI code of the GLEI_1 dataset and its direct and ultimate parent company's LEI code, we construct two consolidation variables, respectively the ultimate parent ID within the UK jurisdiction (UP_ID_UK) and the ultimate parent ID worldwide (UP_ID_WW)[71]. To achieve that, we search across all LEI codes of the entity table, and once

[71] The data sources is RR-CDF v.1.1 Golden Copy that can be retrieved from: https://www.gleif.org/it/lei-data/gleif-golden-copy/download-the-golden-copy#/

we find a match between the LEI code in the entity table and the GLEI_3 dataset, we assign the ID previously created matching the ultimate parent's LEI code reported in the GLEI_3 dataset. If the ultimate parent's LEI code in the GLEI-3 dataset matches the LEI code in the entity table, that entity is the ultimate parent and therefore the ID and the ultimate parent ID are the same. The distinction between ultimate parent ID within the UK and the ultimate parent ID worldwide is achieved by applying the same procedure but differentiating by the COUNTRY dimension of the entity. The mapping algorithm is computationally efficient, and it takes roughly ~20 minutes to run. Moreover, the algorithm is scalable, that is, the addition of more information to the initial data table always improves its accuracy. Therefore by adding new granular data sources with the same dimensions and by increasing the time coverage of the datasets, the accuracy of the mapping function increases as long as the computational time. This is an important property of the function since the resulting data infrastructure can be automatically updated on a quarterly basis, and as a result, the mapping accuracy will improve endogenously and over time. To further improve the mapping accuracy, an ex-post manual cleaning exercise can be applied. The strategy is to select the top 100 exposures (in terms of amounts) not mapped after the first run of the algorithm and to construct a dataset with the same pair of fields and then manually fill in the LEI codes retrieved from the GLEI dataset. This dataset will be then introduced as an additional mapping source on top of the GLEI datasets into the mapping process. Thus, the information manually imputed will be automatically retrieved in following runs of the algorithm. The accuracy will improve non-linearly since the searching and mapping procedure will amplify the matching process via matching pairs. In this respect, Table 1 reports an example of the final output of the Master Entity Table. In particular, this example neatly shows how, through our mapping algorithm, we are able to successfully match an entity with its ultimate parent. We should emphasize that by having the LEI code dimension for each counterparty we can potentially add qualitative and quantitative variables to each counterparty by making matches with and exploiting other complementary data sources. Section 2.5 will provide additional information on the collection of complementary information for analytical and modelling purposes.

Table 1: Master Entity Table

NAME	LEI	ID	LEI UP	ID_UP	CTY	SEC	NACE 4 DIGIT	NACE
BP international limited	G1KG0OQD10NOMCMLDZ35	2469	213800LH1BZH3DI6G760	557	UK	NFC	4671	G
BP plc	213800LH1BZH3DI6G760	557	/	557	UK	NFC	1920	C

1.3 Efficiency of the Mapping Procedure

Using the Master Entity Data Table, we are able to assign our unique ID identifier to each counterparty in the original data source and to each reporting bank. Once we have implemented this step, we can refill the qualitative fields in the original datasets such as NAME, LEI, COUNTRY, SECTOR, and NACE classification with the cleaned information. This allows us to compute the efficiency of the mapping algorithm. In this respect, Table 2 provides a coverage of the LEI, COUNTRY, SECTOR and NACE dimensions before and after the mapping procedure. We want to emphasize that with our mapping approach we reach an LEI coverage above 87% across all granular data sources. This allows us to obtain a complete sectoral coverage and a very high country coverage above 93% of total exposure amounts. The sectoral classification by NACE economic activities is less accurate ranging between 62% and 92% of total coverage across data sources. This emphasizes the difficulties in aggregating information at a granular levels via counterparty-specific legal entity identifiers.

Table 2: Efficiency of the Mapping Algorithm by Data Source and Counterparty Dimension as share of total exposure coverage

Coverage				
LEI	LE	C67	SHS	AS
Raw Data	55%	95%	0%	66%
Clean Data	91%	97%	97%	87%
COUNTRY	LE	C67	SHS	AS
Raw Data	35%	91%	0	100%
Clean Data	93.00%	100%	98%	100%
SECTOR	LE	C67	SHS	AS
Raw Data	35%	91%	0	0
Clean Data	100%	100%	100%	100%
NACE	LE	C67	SHS	AS
Raw Data	22%	0	0	0
Clean Data	85%	90%	92%	62%

1.4 Data Infrastructure

We construct a data infrastructure in order to automatize the mapping procedure and make the dataset easily updatable so as to extend the horizon of the Global Network on a quarterly basis, and in doing so regularly improve its efficiency. The data infrastructure has been developed in R and consists of three main blocks. The first block concerns the automatic download and preparation of the original data sources in a standardized format, that is, by selecting only the dimensions/columns previously described. Since we are working with big granular datasets, reducing the dimension of the data frames is crucial to minimize the computational time of the whole process. Next, we apply the cleaning and mapping algorithm in order to consistently identify entities with unique IDs. This block is fundamental to be able to uniquely identify exposures across datasets between the same reporting firm and counterparty entities, and in doing so, also be able to subset the datasets consistently thereby avoiding double-counting of exposures across datasets during the merging procedure. Therefore, the higher the accuracy of the mapping algorithm, the higher is the accuracy of the merging procedure. Finally, the third block aims at constructing the Global Network which will be used for policy and research purposes and is divided into the three following steps.

1.4.1 Step 1 - Consolidate Reporting Side

The first step involves the selection of reporting firms. To avoid double counting of exposures between subsidiaries and the head of group, we select only those UK reporting banks that report at the highest consolidation level. In this respect, we select a subset of firms, respectively consolidated banking groups and solo entities which do not belong to any other consolidated banking group. In this subset, two types of firms will appear, UK banks and non-UK bank subsidiaries domiciled in the UK. For those datasets which only report exposures at a subsidiary level such as the AS security dataset, by exploiting the information collected on the GROUP structure, we will consolidate the reporting side by merging security exposures of multiple subsidiaries belonging to the same banking group into a single entity. This would allow us to display on the reporting side the same banking groups and solo entities across datasets. The objective of the manipulation is threefold: i) homogenize the reporting side; ii) further reduce the size of the datasets; iii) avoid double counting of reported exposures.

1.4.2 Step 2 - Exposure Cleaning and Refilling

Since firms sometimes make mistakes on the original reported amount of the exposures, we run some quality control checks. We remove all exposures that, as gross original amounts, are larger than 20% of a firm’s total assets from the LE and C67 datasets and those security exposures (ISIN based) that are larger than 6% of a firm’s total assets. The selection of these thresholds is an ad-hoc selection based on our specific-reported sample. Second, to reduce further the size of the datasets we set a floor cap to the size of the exposure. We keep all exposures that are larger than £1 million for the LE and the C67 datasets. As far as the security datasets are concerned, since they also report *short* exposures which are reported as negative values, we keep all exposures that are larger than £1 million in absolute value, i.e. > £1 million and < –£1 million. In the end, once we have prepared the reporting side and cleaned exposure amounts that are considered as outliers, we proceed to refill the security datasets from missing quarters so as to achieve a homogeneous quarterly frequency across data sources.

The LE dataset is reported with a quarterly frequency, and the sample starts in Q1-2015. The C67 dataset is reported with a monthly frequency, and to align the two datasets, we select exposures reported on the months that match the end of each reporting quarter. These two datasets are our core data sources and they do not require any further data manipulation in this respect. By contrast, the SHS dataset has an annual frequency with a snapshot date based in Q4, starting from 2018. Whereas, the AS dataset has a quarterly frequency, but the collection started only in Q1-2019. Hence, we exploit an interesting characteristic of these granular exposure datasets. Overall, we notice that exposures among a reporting firm and a counterparty entity tend to be constant over time, with only small variations in terms of exposure amounts across quarters. For instance exposure amounts at T-2 and T+2 are relatively similar. This shows that the largest exposures in our datasets are slow-moving, and the larger is the exposure amount, the higher is the likelihood of this feature being valid. This characteristic is evident in both exposure-based and security-based datasets. We exploit this property of our data and we fill the missing quarters of the SHS datasets (Q1-Q2-Q3) by back-filling the values provided for the Q4 snapshot. For those security contracts which are debt contracts, we also have to adjust the maturity and issuance date, which is recalculated proportionally to the time shift. The same filling strategy is applied to the AS dataset thereby bringing backwards the Q1-2019 snapshot to fill the missing snapshots in Q4, Q3, Q2, and Q1 of 2018. We do this mainly to extend the time coverage of the datasets in the past to the largest extent possible.

Finally, before merging exposures consistently across datasets and creating the Global Network of Granular Exposures, we implement a final step in which we create a common data-column structure across datasets and fill in values for entries in rows and columns which present NAs. Every dataset should have nine columns set out as follows. Column (1) for the reporting bank ID (also defined as LENDER), column (2) for the counterparty entity ID (also defined as BORROWER), column (3) identifying the REPORTED_PERIOD, column (4) identifying the type of exposures called SEC_TAG, column (5) reporting the original exposure amount (also defined ORIGINAL_EXP), column (6) reporting the short-term exposure amount (also defined ORIGINAL_EXP_ST), column (7) reporting the equity exposure amount (also defined EQUITY), column (8) reporting the net exposure amount (also defined NET_EXP), and column (9) reporting the source of the dataset (also defined SOURCE)[72].

The LE dataset represents our core dataset and the column-structure described above resembles the one already present in the LE dataset. The columns that show exposure amounts are columns (5) to (9). Column (5), which shows gross exposure amounts, is completely filled with values in every dataset. However, we have missing values for column (6), that is, short-term exposures for the LE dataset, since the maturity structure of exposures is provided only for the top-20 exposures in the LE dataset. Hence, we fill short-term exposure amounts for these rows using the average short-term exposure amount calculated over time for each lender against all relevant borrowers. If NAs are still present, we use the average short-term exposure amount by counterparty borrower, or otherwise the average by country and counterparty sector. Using this approach, we are able to fill all short-term exposure amounts for rows corresponding to the LE dataset. Another column that exhibits NAs is column (8) “net exposure amounts” capturing unsecured exposures in the C67 dataset, as that column is missing from the original data source. In this case, we exploit information on the type of instrument, which is provided in the C67 dataset. Hence, we insert 0 when an instrument is a collateralized instrument[73]. Otherwise, we insert the average percentage by reporting and counterparty entity calculated from the LE dataset. The same procedure is applied to the AS and SHS security datasets for which column (8) is also missing. Finally, column (7) is missing from the C67 dataset. However, in this case we directly insert 0 for these rows against this column since in the C67 datasets there are no equity instruments.

1.4.3 Step 3 - Merging Strategy

The final step consists in two consolidation procedures: i) aggregation of exposures by counterparty entity; and ii) merging of exposures consistently across datasets. The former aims at aggregating exposures of one reporting firm within the same time period vis-à-vis multiple counterparty entities belonging to the same group of entities, whether they are credit institutions, financial corporations or non-financial corporations. Since we have reconstructed the group structure for each counterparty entity, we can use the variable UK_UP_ID to sum exposure amounts across counterparty entities belonging to the same ultimate parent within the

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[72] Some datasets have some empty columns which are fill with 0. For instance, the C67 dataset has no equity exposures, thereby column (7) will be filled with zeros. Contrary the security datasets do not have non-security exposures by constructions, and also it will be filled with zeros.

[73] The set of instruments is the following: funding obtained from intragroup counterparties (IGCP), funding obtained from repurchase agreements (SFT), other secured wholesale funding (OSWF), and other funding products (OFP). Info about the instruments can be found here: eba.europa

UK jurisdiction for rows corresponding to the LE and C67 datasets. The fields we sum are the gross exposure amounts, the short-term exposure amounts, the net exposure amounts, and the equity exposure amounts. Similarly, we implement the same procedure for the security datasets by summing all amounts by ISIN codes for the same counterparty entity although differentiating between equity and debt security exposures. We then aggregate exposures by UK_UP_ID of the counterparty as we had done in the case of the LE and C67 datasets. Therefore we may have two security exposures between a reporting firm and the same counterparty entity within the same time period, respectively one for equity and one for debt instruments. Hence, the security datasets will lose the ISIN dimension, and they become exposure-based datasets, that is, displaying an entity to entity relationship identified by a LEI code. Nevertheless, the ISIN-related information won't be lost since we keep a column for short-term exposure amounts, which are calculated by summing exposure amounts across debt security contracts with maturity date below 30 days. Moreover we keep a clear distinction between equity and debt exposures. Once we have consolidated the exposures and security exposures by UK_UP_ID, we have four datasets with the very same column and row structure.

The second step of the procedure consists of merging exposures across datasets. We first construct the network of LE and C67 exposures, also defined as edges_LE_C67. To do this, we add to the LE dataset all exposures from the C67 dataset that are not already present in the LE dataset. Secondly, when an exposure between the same reporting firm and counterparty entity appears in both LE and C67, we keep the exposure reported in the LE dataset. Next, we implement the same procedure with the security datasets SHS and AS. We derive the network of securities (edges_AS_SHS) by adding to the AS dataset all exposures from the SHS dataset that are not already present in in the AS dataset. Hence, we give priority to the AS dataset over the SHS dataset since the AS dataset has a quarterly frequency, as we have already noted. Finally, we merge the two newly created networks, that is, edges_LE_C67 and the edges_AS_SHS. Before doing so, we split the edges_LE_C67 exposures into two sets. We subtract the equity exposures from the gross original exposure amounts and we add the equity exposures as new rows into the dataset and we distinguish these rows in the SOURCE column by tagging them as "SLE". These exposures are equity security exposures stemming from the LE dataset. Hence, the edges_LE_C67 network is divided into debt exposures (loan + security) and equity security exposures. Next, we aim to separate loan exposures in the edges_LE_C67 network from those exposures that instead are debt security exposures. To achieve that, we match debt security exposures among the same reporting firm and counterparty entity among the two network datasets edges_LE_C67 and edges_AS_SHS for each reported period. Then we remove from the edges_LE_C67 network the gross exposure amount that appears in the edges_AS_SHS security network. Hence, the remaining amount of debt exposures tagged as "LE" and "C67" in the SOURCE column are now only loan exposures. In this respect, in the SEC_TAG column we now classified those debt exposures as loan exposures "L". Then we add those exposures from the edges_AS_SHS network to the edges_LE_C67 dataset as new rows. As was the case for exposure values derived from the LE dataset, the SOURCE column will also identify the original data sources from which those rows come from, such as AS or SHS datasets. We then carry out the same procedure for those matched equity security exposures that match exposures in the LE dataset and we keep those that are stemming from the LE dataset[74]. If the matched equity exposure from the edges_AS_SHS dataset is larger than the exposure from the edges_LE_C67 dataset, we add an additional row with an amount that is equal to the difference in the two amounts. In contrast, all exposures that appear in the edges_AS_SHS network and do not appear in the edges_LE_C67 network (unique exposures) are directly added as new rows. We thus arrive at the completion of the Global Network of Granular Exposures which is made of i) loan exposures, ii) debt security exposures, and iii) equity security exposures. Nevertheless, the sum across all exposures for each reporting bank may not still match the total assets of each bank for two main reasons: i) loan exposures to the household sector, and ii) loan exposures towards small-medium size enterprises which are not captured by the LE dataset since they are smaller than LE reporting threshold. In this respect, in order to complete the asset side coverage we exploit the supervisory template F.20.04 reporting aggregate exposures by country and sector of counterparty. First we assign a unique ID to each country-sector pair starting from the last sequential ID number previously defined in the entity table and we add them to the entity table as new counterparty entities. The name assigned to these rows will be defined as the combination of the country and sectoral codes, for instance UK-HH for the UK household sector. Then, we aggregate granular exposures from the Global Network by reporting firm and reported period and by sector and country pair. We then match for each reporting firm the total aggregate exposures by country and sector retrieved from the supervisory template F.20.04 with the aggregated granular exposures by country and sector computed from the Global Network. Hence, for each reporting firm and reported period and country and sector pair we take the difference in the two exposure amounts (aggregate exposures – aggregated granular exposures) and we add it as new rows. These new rows are then identified under the SOURCE column with the tag "FIN" from FINREP data source and

[74] The amount of equity exposures here matched is a small share of the total equity exposure amounts.

we classify them as loan exposures “L” in the column SEC_TAG. The Global Network of Granular Exposures is thus augmented with aggregate exposures to each country-sector pair. Table 3 reports the number of reporting banks we cover for each single data source after these procedures have been applied. We have in total 17 banks that have a complete coverage across all loan, security and aggregated exposures, whereas the rest of the sample is covered only partially. However, we can notice that for a large set of reporting banks we are able to retrieve information on their large exposures (LE) which capture a large share of a bank’s total gross exposure amounts. In Section 3 we provide a detailed description of the Global Network in order to assess the contribution of each single dataset to the total asset coverage as well as a quantitative analysis of the exposure variables we derived so as to subset the datasets across different risk dimensions.

Table 3: Coverage of Reporting Banks by Dataset

Reporting Banks	LE	C67	GRAN	SHS	SAS	SEC	FINREP	COMPLETE
125	120	13	121	8	20	23	33	17

1.5 Complementary Data Sources

We now provide additional information on other complementary data sources we use for modelling and stress testing purposes. First of all, we collect solvency information on banks’ capital base (CET1), risk weighted assets (RWAs), and total assets (TA), respectively from COREP supervisory templates C.01 and C.02 as well as FINREP supervisory template F.01. Then we complement exposure and counterparty information by retrieving loss given default (LGD) and probability of default (PD) parameters from COREP supervisory templates C.09.02 and approximating these values to apply by country and sector of the counterparty[75]. This template is submitted by firms who have received prior approval from the PRA to use the internal-ratings based (IRB) approach to determine capital requirements for certain exposures and whose non-domestic exposures are greater than 10% of total exposures. Under the IRB approach, firms are allowed to rely on their own estimates of risk components such as PD and/or LGD rather than using supervisory estimates for most asset classes in scope. In general, in order to arrive at these estimates, banks need to build a model that meaningfully differentiates risk by defining grades and assigning obligors or exposures to each grade or pool.

The COREP supervisory templates C.09.02 provides a detailed breakdown of each reporting bank’ LGDs and PDs parameters by country and sector of the counterparty. Firms provide these estimates for 5 major obligor sectors such as corporate, sovereign, bank, retail

[75] The structure of the COREP templates can be retrieved here: eba.europa

and equity[76]. PD parameters are calibrated to the long-run average PD of one-year default rates based on exposures on the banking book. While PDs are based at the obligor level, LGDs are based at the facility level. Overall, the PD and LGD datasets covers on a quarterly basis roughly 17 reporting banks at the highest level of consolidation, 247 countries, and obligors in 16 sub-sectors, for a total of 485.834 data points from Q1-2018 up to Q3-2021. In this respect, as an illustrative example, Panel A and Panel B of Table 4 reports the development over time of the average PD and LGD parameters for the non-financial corporate sector (NFC) by regional location of the counterparty[77]. These estimates are the result of a pool-estimation approach since we compute an exposure-weighted average across all reporting banks in the sample. We want to stress the fact that these parameters are an average across countries, and strong heterogeneity exists among countries belonging to the same region. We also note that while these estimates are based on a supervisory templates submitted by a limited sub-set of reporting banks, this dataset provides useful insights into firms' internal estimates of risk by country and sector albeit at an aggregate level. In theory, the optimal approach would be to map each entity with one ad-hoc counterparty-specific PD parameter. However, datasets like Moodys Riskcalc, though they provide quarterly time series of PD and LGD parameters by firm identified with an LEI code, these datasets cover only a sub-set of large corporates[78].

[76] The corporate asset class can be also split between exposures towards SMEs and non-SMEs and other sub-classes. A similar splitting is applied to retail exposures. For an overview of the sector and asset classes covered see: CRE30 - IRB approach: overview and asset class definitions (bis.org)

[77] Table I and II in the appendix reports average value for each counterparty sector, respectively governments (GG) and central banks (CB), credit institutions (CI), financial corporates (FC), and households (HH).

[78] Information on Riskcalc can be retrieved at the following website.

Table 4 – Panel A: Average Corporate Sector PD by Region

Region-Sector	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
Africa_CB	0.8%	0.9%	1.0%	1.0%	0.9%	0.8%	0.8%	0.8%	1.0%	1.0%	1.1%	1.2%	1.3%	1.2%	1.3%
Americas_CB	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.5%	0.5%	0.7%	0.8%	0.8%	0.6%	0.8%	0.1%
Asia_CB	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Europe_CB	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Oceania_CB	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
UK_CB	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%
Africa_CI	1.0%	0.8%	1.3%	0.7%	0.8%	0.7%	0.6%	1.9%	0.9%	1.9%	1.7%	1.8%	1.9%	1.9%	1.8%
Americas_CI	0.1%	0.2%	0.1%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%
Asia_CI	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.2%	0.2%	0.3%	0.3%	0.3%	0.3%
Europe_CI	0.3%	0.3%	0.3%	0.3%	0.2%	0.3%	0.2%	0.3%	0.2%	0.2%	0.2%	0.2%	0.1%	0.2%	0.1%
Oceania_CI	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
UK_CI	0.4%	0.4%	0.3%	0.3%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.2%	0.1%	0.1%	0.1%
Africa_FC	9.6%	1.2%	4.6%	4.4%	4.7%	4.0%	5.6%	5.3%	5.0%	5.8%	6.2%	5.3%	4.7%	5.8%	6.7%
Americas_FC	2.9%	3.0%	2.9%	3.0%	2.9%	2.8%	2.7%	2.7%	2.7%	2.7%	2.6%	2.5%	2.4%	2.3%	2.2%
Asia_FC	1.2%	1.2%	1.1%	1.1%	1.2%	1.1%	1.1%	1.1%	1.2%	1.1%	1.1%	1.1%	1.1%	1.1%	1.1%
Europe_FC	8.3%	8.3%	8.1%	6.7%	7.7%	7.0%	6.7%	6.4%	5.7%	5.4%	4.9%	4.4%	4.3%	3.9%	3.7%
Oceania_FC	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	0.9%	1.0%	1.7%	3.2%	3.0%	2.7%	2.6%	2.3%
UK_FC	2.5%	2.4%	2.4%	2.5%	2.4%	2.4%	2.4%	2.3%	2.3%	2.5%	2.4%	2.3%	2.3%	2.1%	2.1%
Africa_GG	0.8%	0.9%	1.0%	1.0%	0.9%	0.8%	0.8%	0.8%	1.0%	1.0%	1.1%	1.2%	1.3%	1.2%	1.3%
Americas_GG	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.5%	0.5%	0.7%	0.8%	0.8%	0.6%	0.8%	0.1%
Asia_GG	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
Europe_GG	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Oceania_GG	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
UK_GG	0.0%	0.0%	0.0%	0.1%	0.1%	0.1%	0.1%	0.0%	0.1%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%
Africa_HH	2.3%	3.6%	3.4%	2.9%	2.8%	2.8%	2.6%	3.1%	2.9%	3.3%	3.4%	3.8%	3.7%	4.4%	4.1%
Americas_HH	0.8%	0.8%	0.7%	0.7%	0.7%	0.7%	0.8%	0.9%	0.9%	1.1%	1.2%	1.2%	1.6%	1.6%	1.3%
Asia_HH	0.8%	1.2%	1.2%	1.2%	1.2%	1.1%	1.1%	1.1%	1.2%	1.3%	1.3%	1.3%	1.3%	1.2%	1.2%
Europe_HH	2.0%	1.8%	1.8%	1.6%	1.8%	1.8%	1.7%	1.6%	1.5%	1.8%	1.5%	1.4%	1.3%	1.3%	1.2%
Oceania_HH	0.5%	0.5%	0.5%	0.5%	0.4%	0.4%	0.4%	0.4%	0.4%	0.7%	1.1%	1.0%	1.0%	0.9%	0.9%
UK_HH	2.4%	2.4%	2.3%	2.3%	2.3%	2.3%	2.3%	2.2%	2.3%	2.5%	2.5%	2.4%	2.4%	2.2%	2.2%
Africa_NFC	8.0%	9.4%	8.5%	7.0%	7.2%	7.2%	7.0%	7.1%	6.8%	8.1%	8.6%	10.4%	9.2%	11.1%	10.8%
Americas_NFC	1.3%	1.2%	1.1%	1.0%	1.1%	1.2%	1.2%	1.2%	1.3%	1.7%	1.7%	1.7%	3.0%	3.0%	2.8%
Asia_NFC	2.3%	2.3%	2.4%	2.3%	2.3%	2.1%	2.0%	2.1%	2.2%	2.5%	2.6%	2.8%	2.6%	2.5%	2.4%
Europe_NFC	1.7%	1.6%	1.6%	1.7%	1.7%	1.8%	1.8%	1.6%	1.6%	2.1%	2.1%	2.3%	2.1%	2.1%	1.9%
Oceania_NFC	0.9%	0.9%	0.9%	0.8%	0.7%	0.7%	0.7%	0.7%	0.7%	1.2%	1.2%	1.0%	1.0%	1.0%	1.1%
UK_NFC	2.7%	2.6%	2.4%	2.5%	2.6%	2.7%	2.6%	2.6%	2.6%	3.1%	3.2%	3.3%	3.2%	3.0%	2.9%

Table 4 – Panel B: Average Corporate Sector PD by Region

Region-Sector	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
Africa_CB	46%	47%	47%	45%	45%	45%	45%	44%	45%	45%	45%	45%	45%	44%	44%
Americas_CB	42%	42%	42%	41%	42%	41%	41%	41%	41%	42%	42%	42%	43%	43%	43%
Asia_CB	44%	44%	45%	44%	44%	44%	43%	44%	44%	44%	45%	45%	45%	45%	44%
Europe_CB	55%	56%	46%	47%	46%	46%	46%	46%	46%	46%	46%	46%	46%	46%	46%
Oceania_CB	42%	42%	41%	42%	41%	41%	41%	42%	40%	39%	42%	46%	46%	45%	45%
UK_CB	56%	61%	48%	49%	47%	47%	46%	48%	48%	49%	48%	49%	49%	48%	48%
Africa_CI	39%	43%	39%	40%	34%	35%	36%	40%	36%	36%	37%	36%	33%	34%	41%
Americas_CI	49%	49%	45%	47%	47%	46%	46%	47%	46%	45%	42%	43%	43%	43%	43%
Asia_CI	45%	45%	44%	41%	40%	41%	41%	42%	41%	40%	39%	41%	41%	39%	39%
Europe_CI	47%	48%	45%	48%	48%	47%	46%	47%	47%	48%	25%	32%	25%	27%	25%
Oceania_CI	45%	40%	47%	45%	47%	46%	46%	46%	45%	43%	42%	41%	40%	41%	40%
UK_CI	41%	43%	39%	37%	38%	37%	37%	35%	36%	38%	35%	37%	35%	33%	32%
Africa_FC	27%	22%	23%	24%	11%	11%	12%	15%	14%	15%	17%	16%	15%	19%	17%
Americas_FC	40%	40%	39%	40%	40%	39%	39%	38%	39%	38%	37%	37%	36%	35%	35%
Asia_FC	34%	34%	34%	34%	34%	34%	33%	32%	32%	31%	31%	31%	31%	30%	30%
Europe_FC	26%	25%	24%	24%	25%	25%	25%	24%	25%	24%	24%	24%	23%	23%	23%
Oceania_FC	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%	11%
UK_FC	24%	24%	24%	24%	23%	23%	23%	23%	23%	22%	22%	22%	21%	21%	21%
Africa_GG	46%	47%	47%	45%	45%	45%	45%	44%	45%	45%	45%	45%	45%	44%	44%
Americas_GG	42%	42%	42%	41%	42%	41%	41%	41%	41%	42%	42%	42%	43%	43%	43%
Asia_GG	44%	44%	45%	44%	44%	44%	43%	44%	44%	44%	45%	45%	45%	45%	44%
Europe_GG	55%	56%	46%	47%	46%	46%	46%	46%	46%	46%	46%	46%	46%	46%	46%
Oceania_GG	42%	42%	41%	42%	41%	41%	41%	42%	40%	39%	42%	46%	46%	45%	45%
UK_GG	56%	61%	48%	49%	47%	47%	46%	48%	48%	49%	48%	49%	49%	48%	48%
Africa_HH	42%	45%	44%	42%	42%	42%	42%	43%	43%	43%	42%	42%	42%	42%	43%
Americas_HH	42%	42%	42%	41%	41%	41%	40%	40%	41%	41%	39%	39%	40%	40%	40%
Asia_HH	44%	41%	41%	40%	41%	41%	41%	37%	40%	40%	39%	40%	40%	40%	39%
Europe_HH	45%	44%	41%	42%	42%	41%	41%	41%	42%	42%	35%	37%	34%	36%	36%
Oceania_HH	39%	37%	37%	37%	37%	37%	37%	36%	36%	36%	36%	36%	36%	36%	36%
UK_HH	29%	29%	29%	28%	28%	28%	27%	27%	27%	27%	26%	26%	26%	26%	25%
Africa_NFC	40%	41%	41%	40%	40%	41%	40%	42%	42%	42%	40%	41%	42%	43%	43%
Americas_NFC	40%	40%	40%	40%	39%	39%	38%	38%	39%	39%	36%	36%	37%	37%	38%
Asia_NFC	42%	42%	42%	42%	42%	43%	42%	42%	42%	42%	40%	40%	41%	41%	41%
Europe_NFC	43%	42%	41%	42%	42%	42%	42%	41%	43%	42%	40%	39%	40%	40%	41%
Oceania_NFC	46%	45%	45%	45%	45%	45%	44%	43%	44%	44%	43%	43%	43%	44%	45%
UK_NFC	39%	39%	38%	38%	38%	38%	37%	37%	37%	37%	35%	35%	35%	37%	35%

1.6 Multilayer Network Statistics

The Global Network of UK banks' exposures is composed by six data sources divided into three loan exposure datasets (C67, LE, FINREP) and three security exposures datasets (SHS, SAS, SLE). There are three key variables of interest, namely, gross original exposure amounts, unsecured exposure amounts, and the short-term exposure amounts.

Figure 1 presents the coverage over time of the Global Network by data source and by type of exposure. Panel (a) compares the total amount of UK banks' gross exposures with the UK banking sector's total assets (red dotted line) at each point in time. The Global Network captures £11 trillion of exposures out of £12.1 trillion of total assets in Q3-2021, roughly 91% of the UK banking system' asset side. The exposure coverage relative to total assets is stable over time, although at the beginning of the period, the fitting is better than in the last part of the sample period. This is potentially due to a slight over-filling of exposures in the past since the security datasets were not available in that part of the sample period[79]. Next, we note that the time series does not experience notable jumps. The average quarter-on-quarter variation is equal to 3 percentage points, with a maximum variation of 9% in Q1-2020 relative to Q4-2019 consistent with a similar expansion of the UK banking sector's balance sheet. This feature also holds for the contribution of each dataset to the total coverage, which is stable over time. The aggregated exposures dataset by country and sector (derived from FINREP) contributes to 39.7% of the total coverage, whereas all granular exposure datasets combined make 60.3%[80]. On the one hand, security exposure datasets capture 16% of the total, respectively 7.8% (SHS), 7.7% (SAS), and 0.3% (SLE). On the other hand, loan exposure datasets capture 44.3% of the total, respectively 44.3% (LE) and 0.1% (C67)[81].

We now move to Panel (b), where we split the gross exposure amounts into the share of unsecured exposures by data sources. The unsecured exposure amount measures the part of exposures which is not collateralized or subject to credit risk mitigation techniques. Overall, unsecured exposures capture roughly 52% of the total gross exposure amounts in Q3-2021. Like the coverage of gross amounts, the unsecured exposure amounts are also quite stable over time, experiencing an average of 2 percentage points quarter-on-quarter variation. This also applies to the specific contribution of each dataset to the total. Nevertheless, we can see that

[79] Another potential reason is that for some banks we do not have a full coverage of all datasets.

[80] Sydow et al. (2021) provides estimate for the share of EA banks' granular loans to individual firms, which represents roughly 21% of banks' total assets. Moreover, they highlight that information on granular securities holdings in banks' balance sheets covers only 7% of total assets.

[81] This dataset is relevant for mapping exposures from non-UK entities vis-à-vis UK banks, which are not directly captured in the granular raw data collections.

the contribution of unsecured exposure amounts to the total is not proportional to the contribution of gross exposure amounts by dataset. For instance, we can notice that the contribution of FINREP unsecured exposures to the total tends to be higher (48.5% vs 39.7%) relative to the contribution to gross exposures. This observation is by construction of the dataset, since the FINREP dataset does not provide information on the unsecured exposure amounts. Thus we treat exposures to the household sector for which we don't have information from the LE dataset as fully unsecured. By contrast, the LE dataset's unsecured exposures contribution (30% vs 44.3%) tends to be smaller than the gross exposure contribution. The remaining datasets do not show remarkable differences.

On the far right of the figure, Panel (c) reports the share of gross exposures maturing before 30 days. As we can see, roughly 10.2% of exposures can be classified as short-term exposures. The bulk of short-term exposures come from the LE dataset, roughly 92.7%, whereas the remaining part comes from the security datasets, almost 7.3%.

Figure 1 thus highlights the rationale and value-add of combining and exploiting the various data sources described in section 1. The outcome is a good and stable coverage of the UK banking sector's asset side. Having detailed the contribution of each data sources to the composition of the Global Network, we now move to the presentation of the decomposition by counterparty sector and country of origin of UK banks' exposures.

Figure 1: Time-Series Decomposition of total coverage by data source

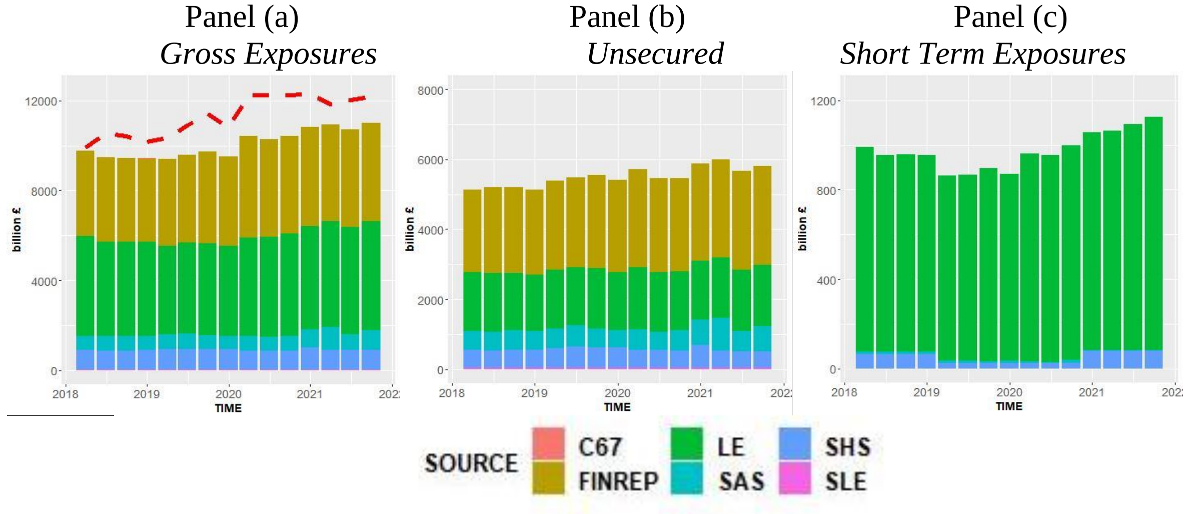


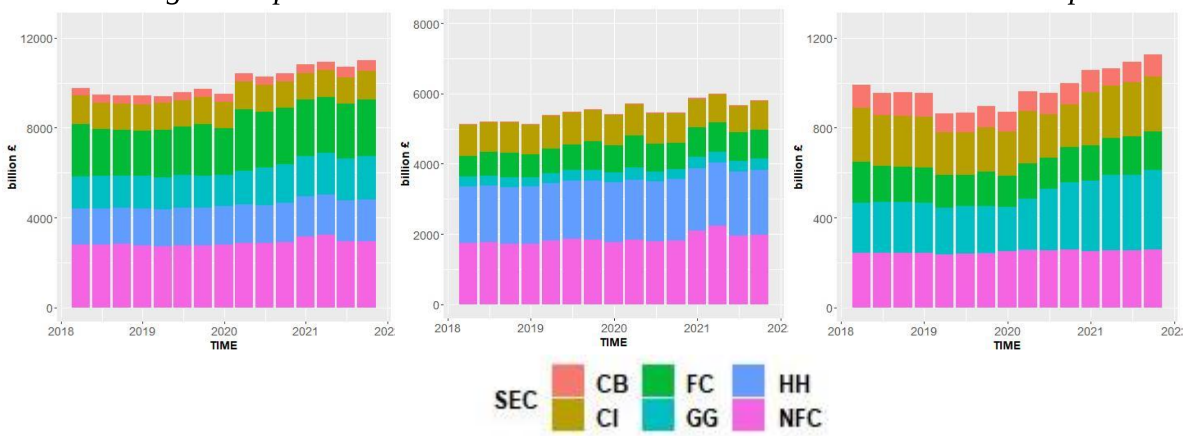
Figure 2 shows the contribution by sector to total exposures over time. In Q3-2021, the most relevant counterparty sector is non-financial corporations (NFC) capturing 26.9% of total gross exposure amounts. Then follow exposures to financial corporations (FC) with 22.8%, and, after that, exposures to general governments (GG) with 17.7%, to the household sectors (HH) with 16.7%, to credit institutions (CI) with 11.7%, and finally to central banks (CB) with 4.2%.

Moving to unsecured exposures (Panel b), we see that the contributions by sector differ from the contributions of the same sectors to total gross exposures. In fact, the share of gross exposures towards certain sectors tends to be more secured than vis-à-vis other sectors, which aligns with what we would expect based on the nature of the financial transactions reporting banks enter into with entities in these sectors. For instance, the contribution of GG's unsecured exposures accounts for 5.8% of the total instead of 21.9% in gross terms, with an unsecured gross exposure ratio of 17.2% (defined as unsecured exposures/gross exposures). Another sector showing a similar feature is CB, with an unsecured gross exposure ratio of 6.8%. In contrast, unsecured exposures towards both the financial sectors (FC and CI) and the real economic sectors (NFC and HH) show a remarkable higher ratio, respectively 33%, 63%, 67% and 100%[82].

Panel (c) presents the sectoral decomposition of short-term exposures. Almost 31.4% stems from exposures to GG, followed by exposures towards NFC (22.9%), then to CI (21.5%), to FC (15.3%), and to CB (8.9%).

Figure 2: Time-Series Decomposition of total coverage by counterparty sector

Panel (a)	Panel (b)	Panel (c)
Original Exposures	*Unsecured*	*Short Term Exposures*



Finally, Figure 3 shows the contribution over time by geographical region. (We do not provide the breakdown by country for graphical purposes.) Panel (a) highlights that in Q3-2021, UK banks were mostly exposed domestically for roughly 31.6% of total gross exposures. This is followed by exposures to Asian countries with 24.8%, Americas with 19.7%, Europe with 13%, Oceania with 1% and Africa with 0.5%. We have also 9.3% of gross exposures which couldn't be mapped to their country of origin. By looking at Panel (b) we can assess the contribution of each region to the total amount of unsecured exposures. Overall the

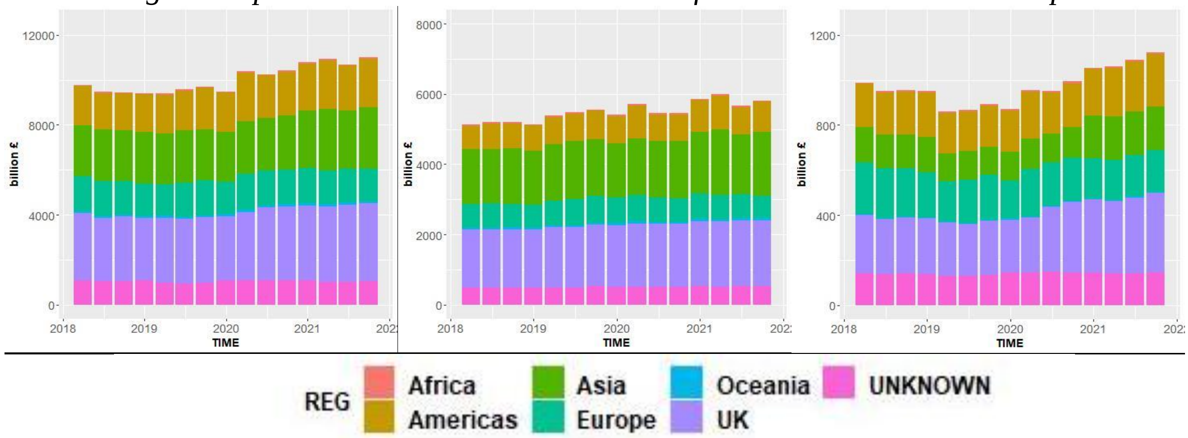
[82] As we discussed by construction the household sector presents an equal amount of gross and unsecured exposures since we do not have data in the regard.

decomposition of unsecured exposures is similar to the share of gross exposure amounts. Few exceptions are exposures to the Asian region which increases up to 31% from 24.8%. As a consequence, the share of unsecured exposures towards Americas slightly decreases to 14.8% from 19.7%, as well as to Europe, down by 2%.

We also provide a regional break-down of short-term exposures in Panel (c). Roughly 31.4% of the total comes from exposures to counterparties within the UK, while 20.5% from counterparties located in the Americas, 17.5% from Asian countries, 16.4% from Europe, and 12.8% of the total could not be mapped to a country (unknown source). Significantly smaller shares of exposures come from African countries (0.5%) and from Oceania (0.4%).

Figure 3: Time-Series Decomposition of total coverage by counterparty region

Panel (a)	Panel (b)	Panel (c)
Original Exposures	*Loss Given Default*	*Short Term Exposures*



Appendix B - Capital at Risk

1. Decomposition By NACE Classification of Economic Activities

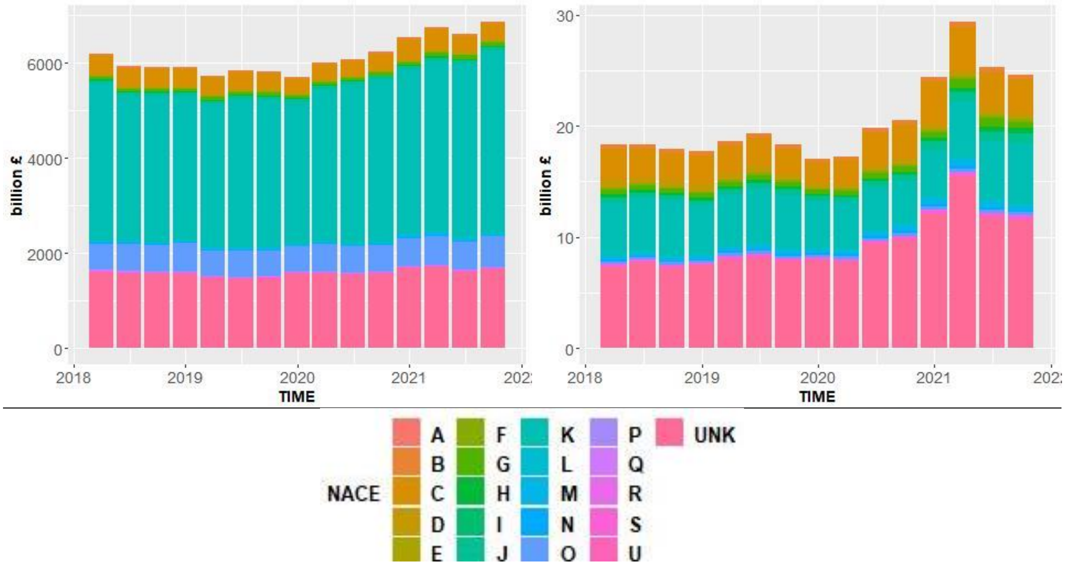
In this section, we limit the UK banks' Global Network to only the subset of granular exposures, thereby eliminating aggregate exposures. We do this because NACE classification of economic activity can be associated to counterparty entities only via LEI codes which are entity-specific. The NACE taxonomy is divided into 1 to 4-digit codes depending on the degree of precision to be chosen for the identification of economic activities. The 1-digit code classification refers to the macro sectoral classification, which is divided into 21 economic activities. In contrast, the 4-digit code classification refers to a micro sectoral classification splitting economic activities into roughly 1000 classes. Out of 2 million entities, we are able to map 0.65 million entities with a 4-digit NACE code, roughly 34% of the sample. This finding highlights the complexity and challenges researchers and private corporations face to work with granular entity-specific information. This finding also emphasizes the importance of further developing a common and shared LEI-based approach to counterparty identification as suggested by François et al. (2021) in order to enable an easy and accurate matching of qualitative and quantitative firm-specific attributes.

We start by plotting over time the coverage of gross exposures by 1-digit NACE codes in order to define the frame of the macro sectors as reported in Panel (a) of Figure 4. The granular sample captures roughly £6646 billion of exposures in Q3-2021, roughly 60.3% of the total exposure coverage. Although the 4-digit code coverage is only 34%, we see that in terms of exposure amounts, the unmapped share of granular exposures is only 24%. This is due to the fact that the share of mapped entities that we capture is constituted mostly by large corporations and global institutions which are the main receivers of UK banks' exposures. According to this classification we can map exposures towards 20 economic activities, although the majority of gross exposure amounts are concentrated into three major categories.

Looking at Table 5 reporting the decomposition for the snapshot date Q3-2021, "K" financial and insurance activities accounted for £3851 billion (56%), "O" public administration and defence and compulsory social security for £634 billion (9.5%), and "C" manufacturing for £327 billion (4.9%). All the remaining economic activities account for the remaining £245 billion, roughly 3.6% of total granular exposure amounts. This decomposition emphasizes the degree of financialization of UK banks' exposures. Nevertheless the K category covers a wide range of financial institutions which substantially differ from one another for their type of business, such as credit institutions, central banks, insurances, pension funds, broker companies, etc. Overall, the coverage and decomposition across NACE codes is quite stable over time, with only small quarter on quarter variations. This implies that the allocation of UK banks' exposures tent to be slow-moving, adjusting with a frequency greater than the time coverage of our sample. The only exception is the counterparty sector K financial and insurance activities. In fact in Q3-2021 relative to the start of the COVID-19 crisis dated as Q4-2019, gross exposure amounts towards K category grew by 29%. Both empirical evidences i) share and ii) frequency at which exposures to the K sector adjust highlight the importance of further decomposing exposures into more granular buckets (2-digit NACE codes) in order to possibly identify specific sectoral trends.

Figure 4: UK Banks' Expected Losses by NACE 1-digit classification

Panel (b) - Expected Loss



Note: A - Agriculture, forestry and fishing; B - Mining and quarrying; C - Manufacturing; D - Electricity, gas, steam and air conditioning supply; E - Water supply; sewerage; waste management and remediation activities; F - Construction; G - Wholesale and retail trade; repair of motor vehicles and motorcycles; H - Transporting and storage; I - Accommodation and food service activities; J - Information and communication; K - Financial and insurance activities; L - Real estate activities; M - Professional, scientific and technical activities; N - Administrative and support service activities; O - Public administration and defence; compulsory social security; P – Education; Q - Human health and social work activities; R - Arts, entertainment and recreation; S - Other services activities; T - Activities of households as employers; U - Activities of extraterritorial organisations and bodies.

Before doing that, we dig deeper into the loss decomposition by economic activity over time as presented in Figure 4 and for a single snapshot in Table 5. From the visual inspection of Panel (b) we see that expected losses stemming from granular exposures increased by 43% between Q4-2019 and Q3-2021, passing from £17.2 billion to £24.5 billion respectively. The largest increase (£5 billion) took place in Q1-2021 relative to Q4-2020. Two-thirds of this increase (roughly £10 billion) is due to an increase in expected losses vis-à-vis unmapped NACE categories, which account for the largest share of expected losses in Q3-2021, approximately 46% or £11.5 billion. This is due to a price effect rather than a quantity effect. In fact gross exposure amounts towards unmapped entities did not increase accordingly, implying that PD instead did. Next, we can see that roughly 22% of expected losses stems from the K set of financial activities, although the same set represents 56% of total granular gross exposures and 32.4% of LGD exposure amounts. This means that PD and LGD parameters towards the K sector tend to be smaller than for the other economic activities. Lastly, the manufacturing sector (C) stands out with £3.1 billion estimated losses (12.4%) and other non-negligible economic activities such as Information and communication (J) with 3.6%, and wholesale and retail trade (G) with 2%.

Table 5: Decomposition of Granular Exposures into 1-digit NACE codes for Q3-2021

NACE Tier 1	**K**	**UNK**	**O**	**C**	**J**	**G**	**B**	**ToT**
Exposures	3851	1658	635	327	66	59	41	6637
Expected Losses	5.5	11.5	0.3	3.1	0.9	0.5	0.4	22
Ratio EL %	0.1%	0.7%	0.1%	1.0%	1.3%	0.8%	0.9%	
NACE Tier 2	**D**	**H**	**L**	**S**	**M**	**Q**	**F**	/
Exposures	40	31	29	24	23	23	21	189
Expected Losses	0.4	0.5	0.2	0.3	0.3	0.0	0.2	2
Ratio EL %	1.0%	1.6%	0.8%	1.4%	1.3%	0.0%	1.0%	
NACE Tier 3	**E**	**N**	**U**	**I**	**A**	**R**	**P**	/
Exposures	18.1	16.4	7.1	2.7	1.4	1.2	0.00	47
Expected Losses	0.2	0.1	0.0	0.0	0.0	0.0	0.00	0
Ratio EL %	0.9%	0.8%	0.6%	1.2%	0.9%	3.8%	0.0%	
Grand Total Exposures								6873
Grand Total Expected Losses								25

2. Deep-dive into K Financial and Insurance Activities

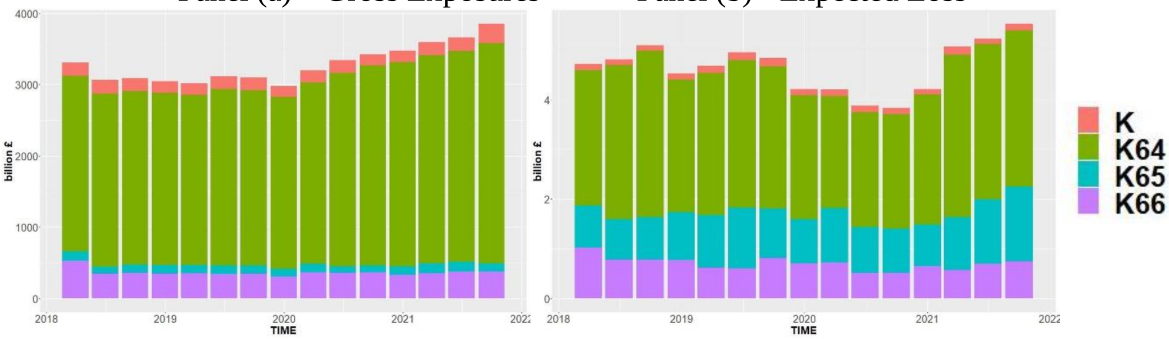
As we have seen, "K" financial and insurance activities account for 56% of total gross exposures and 22% of expected losses. Given its relevance, we provide a granular deep-dive into the group of economic activities based on a 2-digit NACE code classification, respectively "financial service activities, except insurance and pension funding" (K64), "insurance, reinsurance and pension funding, except compulsory social security" (K65), and "activities auxiliary to financial services and insurance activities" (K66).

Looking at Figure 5, we see that the majority of gross exposure amounts are directed towards K64, roughly 80% of the total or £3086 billion. This category encompasses a vast and heterogeneous group of financial corporates which can be further classified according to 4-digit NACE codes as reported in Figure 6. In this respect, we set a threshold of 1% of total exposures in order to select only the relevant sectors with 4-digit NACE code. As we can see by increasing the level of granularity, we are able to improve the accuracy of the mapping, but not hugely. Only 20% of exposure amounts previously allocated to K64 (Figure 10) can now be associated with sub-categories with 4-digit codes, respectively "Central banking" (K6411)

£415 billion, “Other monetary intermediation” (K6419) 144 billion, “Activities of holding companies” (K6420) £139 billion, “Other financial service activities, except insurance and pension funding” (K6499) £72 billion, and “Other credit granting” (K6492) £72 billion[83]. By looking at the loss side, Panel (b) attributes £3.1 billion of expected losses stemming from K64 Financial service activities (£2.8 billion to K6400), out of which £0.15 billion from K6499, £0.13 billion from K6420, £0.12 billion from K6419, and £0.1 billion from K6492.

Figure 5: UK Banks’ Expected Losses by 2-digit NACE code for K sectoral classification

Panel (a) – Gross Exposures Panel (b) - Expected Loss



The second relevant 2-digit NACE category for K industry is K65 or insurance, reinsurance and pension funding activities which account for £119 billion of gross exposures. Nevertheless, the 4-digit decomposition does not allow us to disentangle further between K6511 and K6512, respectively Life Insurance and Non-life insurance activities, K6520 reinsurance activities and K6530 pension funding. Although the K65 activity represents only 3% of total K exposures, it accounts for a large part of expected loss estimates, roughly 27% or £1.5 billion.

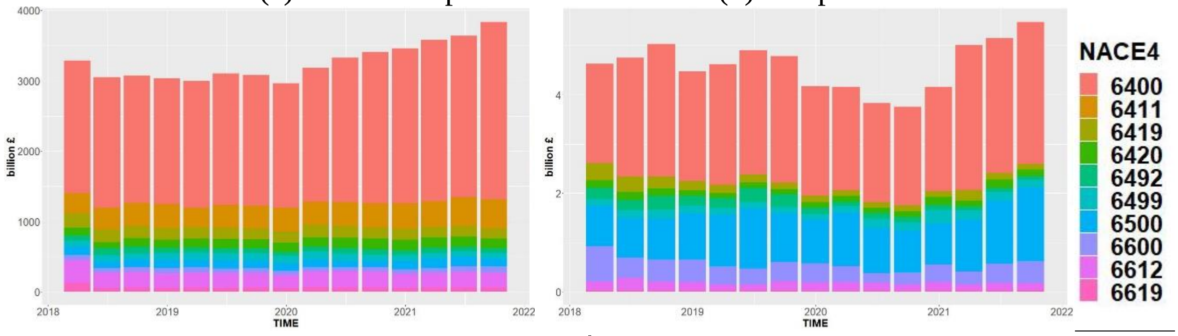
Finally the third relevant 2-digit NACE category for K industry is K66 or “activities auxiliary to financial services and insurance activities” which account for £375 billion of exposures, and only 0.75 billion of expected losses. By looking at the 4-digit NACE breakdown we are able to disentangle £211 billion of exposures towards “security and commodity contracts brokerage” (K6612) or £0.14 billion of estimated losses and £60 billion or £0.1 billion of losses towards “other activities auxiliary to financial services” (K6619).

Overall we can state that UK banks’ exposures can be comprehensively classified with a 2-digit NACE classification of financial activities, though more effort is needed for a full break-down into a more granular classification based on 4-digit NACE codes.

[83] Credit institutions such as banks, saving banks and credit unions are classified under K6419; holding companies’ activities (K6419) refer only to corporate units whose principal activity is owning the group; K6499 refers to factoring activities, writing of swap, options and hedging arrangements; and K6492 which comprehends a vast majority of lending activities not involved in monetary intermediation such as granting of consumer credit, international trade financing, provision of long-term finance to industry by industrial banks, money lending outside the banking system, credit granting for house purchase. See for more details Eurostat (2008).

Figure 6: UK Banks' Expected Losses by 4-digit NACE code for K sectoral classification

Panel (a) – Gross Exposures Panel (b) - Expected Loss

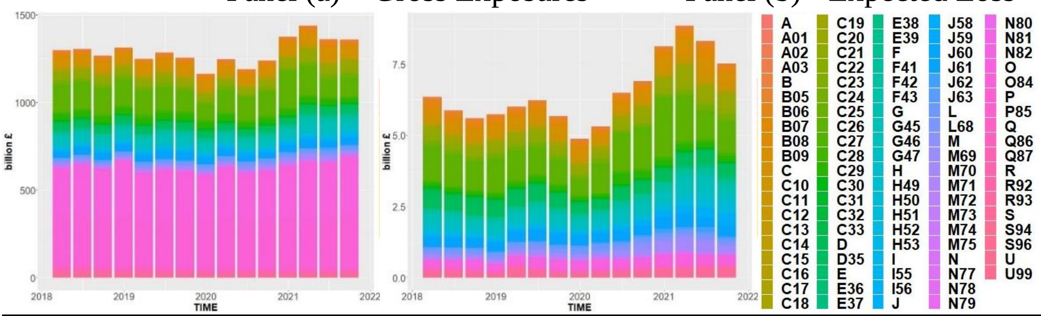


3. Deep-dive into Non-financial 2-digit NACE classification of Economic Activity

In this subsection, we analyse the subset of exposures towards economic activities which can be classified as non-financial or all categories except K activities. Hence, we subset the sample by removing all granular exposures towards financial and insurance activities and unmapped (UNK) activities. Thus, we end up with £1360 billion of gross exposures and £7.5 billion of expected losses. In this respect, we are able to decompose it into 2-digit sectoral components. Roughly half of the total (£635 billion) comes from exposures towards public administration and defence and compulsory social security activities (O or O84) which accounts for less than 4.2% (£0.32 billion) of expected losses as reported in Figure 7. The second largest component is exposures towards the manufacturing sector (C), roughly £327 billion. However, this sector includes the largest number of 2-digit NACE sub-categories. In particular, exposures towards "manufacture of computer, electronic and optical products" (C26) accounts alone for £109 billion and £1.1 billion of expected losses.

Figure 7: UK Banks' Expected Losses by Nace 2-digit Classification

Panel (a) – Gross Exposures Panel (b) - Expected Loss



Other relevant sub-categories within the manufacturing sectors are "manufacture of chemicals and chemical products" (C20) for £44 billion, "manufacture of motor vehicles, trailers and semi-trailers" (C29) for £23 billion, "manufacture of coke and refined petroleum product" (C19) for £15 billion, "manufacture of basic pharmaceutical products and pharmaceutical preparations" (C21) for £14 billion and "manufacture of other transport equipment" (C30) for £10 billion. Roughly 15% of exposures towards C categories could not be decomposed further into 2-digit classification. Other relevant sub-categories from other economic activities are "electricity, gas, steam and air conditioning supply" (D35) which account for £35 billion of exposures, "telecommunications" (J61) for £41 billion, "construction of buildings" (F41) for £18 billion, "extraction of crude petroleum and natural gas" (B06) for £24 billion, "real estate activities" for £12 billion (L68), and "wholesale trade, except of motor vehicles and motorcycles" (G46) for £12, billion.

Appendix C – Conditional Capital at Risk Estimates

Table I – Decomposition of UK Banks' CCaR Estimates (Severe Distress Scenarios)

Panel (a) – By Sector

Loss Ratio	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
CI	0.3%	0.4%	0.3%	0.3%	0.3%	0.3%	0.2%	0.2%	0.2%	0.3%	0.5%	0.3%	0.4%	0.4%	0.4%
GG	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%
NFC	6.0%	6.0%	5.6%	6.2%	6.4%	5.9%	5.8%	5.5%	6.5%	6.9%	6.8%	8.0%	9.0%	7.3%	6.8%
FC	0.5%	0.7%	0.9%	0.6%	0.7%	0.7%	0.6%	0.6%	0.5%	0.6%	0.5%	0.8%	0.9%	0.7%	0.7%

Loss Share	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
CI	3.0%	3.4%	2.6%	2.7%	3.0%	3.3%	1.7%	2.2%	2.1%	2.2%	3.7%	1.6%	1.9%	2.9%	3.1%
GG	1.2%	1.2%	1.2%	1.4%	1.2%	1.4%	1.2%	1.6%	1.2%	1.3%	1.0%	0.8%	0.9%	1.3%	1.4%
NFC	92.8%	92.5%	92.0%	93.3%	92.9%	92.0%	94.3%	93.4%	94.4%	94.3%	93.1%	95.1%	94.6%	92.9%	92.4%
FC	3.0%	2.8%	4.1%	2.6%	2.9%	3.3%	2.8%	2.9%	2.3%	2.3%	2.2%	2.4%	2.6%	2.9%	3.1%

Panel (b) – By Region

Loss Ratio	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
UNK	3.9%	4.4%	4.5%	4.7%	4.9%	4.8%	4.7%	4.7%	4.1%	5.2%	4.7%	3.7%	4.6%	6.1%	4.5%
Africa	3.6%	3.6%	3.9%	3.4%	2.3%	2.1%	2.6%	3.2%	2.6%	3.7%	4.3%	3.6%	3.9%	5.1%	5.3%
Europe	0.9%	0.9%	1.0%	1.0%	1.2%	1.1%	1.1%	1.3%	0.9%	1.1%	1.0%	1.2%	1.3%	1.5%	1.4%
Asia	4.2%	3.8%	3.4%	3.8%	3.8%	3.4%	3.0%	2.3%	4.0%	4.0%	4.4%	4.3%	3.9%	3.1%	2.9%
Americas	0.9%	1.1%	1.1%	1.0%	1.1%	1.1%	1.1%	1.3%	2.1%	1.3%	1.2%	5.5%	7.3%	2.1%	3.0%
Oceania	0.5%	0.5%	0.6%	0.6%	0.8%	0.8%	0.8%	0.8%	0.6%	0.9%	1.1%	0.9%	0.9%	0.9%	0.8%
UK	1.3%	1.4%	1.3%	1.5%	1.5%	1.4%	1.6%	1.5%	1.3%	1.3%	1.3%	1.0%	1.2%	1.6%	1.1%

Loss Share	Q1-2018	Q2-2018	Q3-2018	Q4-2018	Q1-2019	Q2-2019	Q3-2019	Q4-2019	Q1-2020	Q2-2020	Q3-2020	Q4-2020	Q1-2021	Q2-2021	Q3-2021
UNK	31.2%	34.5%	37.2%	35.8%	34.7%	35.0%	37.6%	41.5%	31.0%	37.6%	32.9%	20.2%	19.8%	36.3%	28.7%
Africa	0.8%	0.8%	0.8%	0.8%	0.6%	0.5%	0.7%	0.9%	0.6%	0.7%	1.0%	0.6%	0.5%	1.0%	1.0%
Europe	6.5%	6.3%	6.9%	6.6%	7.6%	7.7%	8.2%	8.9%	5.5%	6.3%	6.0%	5.4%	5.0%	8.4%	7.5%
Asia	44.8%	41.4%	38.0%	40.4%	39.0%	38.5%	33.4%	27.0%	39.2%	37.0%	41.9%	35.1%	29.2%	29.5%	31.6%
Americas	6.9%	7.4%	8.0%	7.0%	7.5%	8.5%	8.8%	10.7%	15.7%	8.9%	8.4%	32.8%	39.6%	13.8%	22.6%
Oceania	0.2%	0.1%	0.2%	0.1%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.2%	0.1%	0.2%	0.2%
UK	9.8%	9.5%	9.0%	9.3%	10.5%	9.5%	11.1%	10.8%	7.9%	9.3%	9.6%	5.7%	5.8%	10.9%	8.4%