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Interdependencies in the euro area derivatives clearing network: a multi-layer network approach

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Abstract

The global nature of derivatives markets, and the presence of large key financial institutions trading in several markets across the globe, call for taking a "macro" view on the interconnections arising in the clearing network. Based on the analysis of derivatives transactions data reported under the EMIR Regulation we reconstruct the network of relationships in the centrally-cleared derivatives market and analyse its topology providing insight into its structural features. The centrally-cleared derivatives network is modelled in the form of a multiplex network where each layer is represented by a derivatives asset class market. In turn, each node represents a single counterparty in that market. On the basis of different centrality measures applied to the collapsed aggregate and to the multiplex network, the critical participants of the euro area centrally-cleared derivatives market are identified and their level of interconnectedness analysed. This paper provides insight on how the collected data pursuant to the EMIR regulation can be used to shed light on the complex network of interrelations underlying the financial markets. It provides indications on structural features of the euro area centrally-cleared derivatives market and discusses policy relevant implications and future applications.

Keywords: Interconnectedness, CCP, multiplex network, derivatives markets, EMIR data
JEL Classification: G01, G15, G23

Non-technical summary

The global nature of derivatives markets and the presence of large key financial institutions, which trade different products in several markets across the globe, call for taking a "macro" view on the interconnections arising in the clearing network. This is in particular due to the fact that CCPs share a number of globally active common clearing members, as well as the fact that several CCPs rely on financial resources and liquidity provided by the same (large and globally active) banks. More specifically, the clearing members which participate in multiple CCPs and markets can act as connecting links across otherwise unrelated CCPs. Stress tests carried out by each CCP in isolation do not capture coordinated and potentially cumulative elements, and do not necessarily take into account the market impact of multiple CCPs running in parallel (un-coordinated) margin liquidation as part of their respective default management processes.

Analysis of the interdependencies is thus very important to understand the potential transmission (or amplification) of systemic risk within and across centrally-cleared markets. Against this background, in this work, the interdependencies existing in the euro area derivatives clearing network are mapped out and measured, exploiting the derivative transactions data reported under the EU EMIR Regulation. Focusing on those derivative transactions that have been cleared via a CCP, this paper analyses the network of relationships between market participants. In this network, the nodes are the counterparties of the reported transactions, and an edge exists between two nodes if there is at least one outstanding cleared transaction between the two counterparties. Edges are undirected and weighted with the gross mark-to-market value of all transactions between the two nodes/counterparties. Carrying out standard and multi-layer network analysis, the derivatives market of cleared transactions is reconstructed, and interdependencies due to common relationships between the nodes, including across distinct market segments, are analysed.

The analysis shows that the level of interconnectedness in the euro area cleared derivatives market is high. The systemic importance of a node is reinforced by its direct and indirect connections with the rest of the system, both via the same asset class and across asset classes. The latter arises because many clearing members participate simultaneously in several CCPs and markets, and can act as connecting links across otherwise unrelated CCPs and market segments. Moreover, there are nodes that despite maintaining few relationships and showing a relatively low exposure level towards other nodes, are nevertheless central because their presence in several market segments means they can potentially act as a channel of contagion across layers or communities in the same network. While interconnections may act as vehicles for the transmission of stress or contagion, it is worth emphasizing that interconnections can reinforce the resilience of the network by ensuring the impact of a shock is absorbed by a larger number of entities.

The analysis also shows the significance and concentration of client clearing. The identification of the main euro area and non-euro area clearing members acting as entry points to the cleared market and serving large communities may guide the selection of the most critical service providers to be included in a future stress test exercise. Such an exercise could focus, for example, on the porting of clients' positions in case of the default of a major provider. At the same time, the limited number of common clients shared by clearing members may signal some limited substitutability at the level of clients. In general, the area of client clearing is relatively unexplored in the literature and deserves further attention by researchers.

This analysis is useful for authorities and regulators from different perspectives: we found evidence of strong market integration (in the form of strong interdependencies due to common clearing members) across euro area and non-euro area CCPs, but also at the level of clearing members. This confirms the need to continue and encourage authorities' efforts to carry out supervisory-led, macro-prudential CCP stress testing, given that each CCP individually does not have and cannot integrate information on such interdependencies into its own stress tests. Macro-prudential stress testing should be seen as an important complement to the stress tests that each CCP conducts to calibrate the size of initial margin and guarantee funds that it needs to collect from members. Moreover, the significant interdependencies identified across the euro area and non-euro area call for a carefully designed geographical perimeter of macro-prudential stress tests, and show the limits of keeping a jurisdictional focus in a market that is intrinsically global. If authorities are to better understand and monitor risks in an increasingly interconnected world, it is imperative that obstacles to sharing data or intelligence are removed. In this respect, progress has been made with the adoption of international technical standards, but work remains to be done on the legal front.

1 Introduction

During the global turmoil in the aftermath of the 2008 Lehman Brothers collapse the centrally cleared global derivatives market continued to be resilient, i.e. the market where over the counter (OTC) derivatives are novated[1], netted and guaranteed by a central clearinghouse (or central counterparty, referred to as a CCP)[2]. CCPs basically functioned as shock absorbers and, despite not being totally immune from some limited problems or losses (see [27], p. 42-43), overall they were able to act very quickly (within a few hours of Lehman's default) and ensure the orderly liquidation of hundreds of thousands of derivatives positions. In most cases the process terminated without any losses or any need to allocate uncovered losses to their members ([9] and [22]).

At the Pittsburgh summing in 2009, G20 leaders pledged to reform OTC derivatives markets to improve their transparency and reduce systemic risks, i.a. by agreeing that: "All standardized OTC derivative contracts should be [...] cleared through central counterparties by end-2012 at the latest" ([23][3]). As a result, the share of centrally-cleared derivatives increased substantially, doubling between 2011 and 2016, and covering up to one third and even more than half of the global market (respectively in the credit derivatives and interest rate swaps ([8]). This brought CCPs to the centre of attention by regulators, as they have increasingly become a central pillar of the global market resiliency: a CCP can act as shock absorber and contribute to limit contagion and systemic risk, only insofar as it remains the strongest participant in the market and able to adequately manage and cover the risks it pools from the market. CCPs thus remain high on the agenda of policy makers and legislators. In 2015, the global standard-setting bodies (in addition to CPMI and IOSCO, also the FSB and the BCBS) set out together an ambitious Work Plan on CCPs, which resulted in the publication, in July 2017, of additional guidance on resilience, recovery and resolution of CCPs, together with an analysis of central clearing interdependencies ([12] and [11]). The latter work highlighted the high degree of interconnectedness of the global

[1] Novation is a process through which the original obligation between a buyer and a seller is discharged through the substitution of the CCP as seller to the buyer and buyer to the seller, creating two new contracts. See [6].

[2] The detailed analysis of a given CCP's functions, role and risk management as well as its performance during the crisis are covered at length in the specialised literature (i.a., see [10], [34], [14] and [8]) and is beyond the scope of this paper. However, some key concepts about CCPs functions and how they operate are recalled in the Appendix.

[3] In the same context the G20 leaders, in order to overcome the opaqueness of the bilateral OTC derivatives markets that had fuelled uncertainties on exposures and on creditworthiness of counterparties and contributed to amplify market disruptions, also agreed that OTC derivatives contracts should be reported to trade repositories. Indeed the empirical analysis presented in this paper would have not been possible without the mandatory reporting introduced in the EU pursuant to the EMIR Regulation.

derivatives market and the importance of the interdependencies to understand the potential transmission (or amplification) of systemic risk within and across centrally-cleared markets.

Considering this high degree of interconnectedness, stress tests carried out in isolation by each CCP cannot capture coordinated and potentially cumulative elements, and do not necessarily take into account the market impact of multiple CCPs running in parallel (un-coordinated) margin liquidation as part of their respective default management processes. For example: i) in the case of the default of one clearing member participating in several CCPs, the other "common" surviving clearing members might be called simultaneously by multiple CCPs to cover losses or contribute with additional resources, or ii) in the case of multiple CCPs liquidating large collateral positions in parallel, collateral prices may be impacted resulting in the overestimation of expected prices.

For these reasons, some authors (e.g., [26]) highlighted the need to complement the CCP "micro" stability perspective with a "macro" view on systemic risk originated by the clearing network interdependencies. ESMA in the European Union and the CFTC in the United States have indeed carried out stress tests at system level to assess the ability of CCPs to withstand a variety of stress scenarios [4] ([15] and [17]).

Against this background, in this work, we map and measure the interdependencies that exist in the euro area derivatives clearing network, relying on derivatives transactions data reported to Trade Repositories (TRs) and made available to the ECB, under the EU EMIR Regulation[5]. We focus on derivatives transactions that have been cleared via a CCP and we build the network of relationships between market participants. The nodes of our network are the counterparties of the reported transactions and an edge between two nodes exists if there is at least one outstanding cleared transaction between the two counterparties. In our analysis we consider undirected edges weighted with the gross mark to market value of all transactions between the two nodes/counterparties. As we aim to map the key interdependencies due to CCPs' common participants also across the distinct market segments, we carry out standard and multi-layer network analysis to characterise the derivatives market of cleared transactions that involve euro area counterparties. Our general approach for the analysis of interconnectedness in derivatives markets is as follows: first, we build the networks by analysing the transaction data. As a second

[4] In its 2016 EU CCPs stress test exercise ESMA also took into account to some extent the interdependencies created by the fact that the CCPs in scope share a number of members and key service providers.

[5] European Market Infrastructure Regulation (EMIR), i.e. Regulation (EU) No 648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories.

step, we identify the most “critical nodes” (CCPs and clearing members) on which to focus the interconnectedness analysis by ranking the nodes using network centrality measures. Finally, we look at the similarity of edges across critical nodes (to understand their degree of overlap) both at the level of the whole market (aggregate network) and at the level of individual derivatives asset classes.

The paper is structured as follows: Section 2 recalls the literature on which the analysis draws and to which it aims to contribute; Section 3 describes our dataset and provides a general picture of the size and structure of European derivatives markets, Section 4 presents the analysis as well as the results. Section 5 concludes reflecting on the policy implications of the findings and provides some indications for further research.

2 Related Literature

Two strands of literature are relevant for the present work, i.e. first, the literature on the structure of the derivatives markets and second, on the application of multi-layer network analysis to financial markets. Derivatives markets, in particular the OTC ones, have been traditionally opaque, and insights on their structure was derived mainly from analyses of data collected by the BIS via periodical surveys and from empirical works using trade repositories data (mainly from DTCC) for selected markets. The entry into force of the EU EMIR Regulation requiring i.a. that all derivatives transactions be reported to Trade Repositories and that various authorities shall have access to the data recorded in these databases marked a bit step towards a more comprehensive and detailed analysis of European derivatives markets. Reporting started in February 2014, and while quality issues have marked the collected data in the initial period of the reporting obligation, authorities have recently started to use the reported dataset to better understand the derivatives market structure and the relevance of its main players. Authors in [1] provide a first insight on the structure of two segments of the EU derivatives market, i.e. interest rate (IR), focusing on the plain vanilla fixed for floating swaps and on the credit default swaps (CDS), looking at single-name CDS that represent respectively 70% of transactions and 40% in their dataset. They find i.a., that the network of OTC bilateral trades is sparse, with only one fourth of market participants trading with more than 5 counterparties and more than 70% of trades taking place among G-16 dealers[6] and between these dealers and banks. Concentration

[6]The G-16 dealers include the most active financial institutions in global derivatives markets, i.e. Bank of America, BNP Paribas, Citigroup, Crédit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP

of trades in the G-16 dealers and banks groups is even higher in their CDS sample. This market segment is also highly concentrated in terms of referenced entities, in the sense that a substantial amount of CDS are written on a limited number of reference entities. In their subsequent study [2], the authors extend the analysis to the foreign exchange (FX) forwards sector and elaborate more on the network properties of the three segments. While confirming and expanding their earlier results, they also find that the FX derivatives market – which mainly trades OTC on a bilateral basis and is not subject to the clearing mandate – is relatively decentralised, with most trades involving a bank but several trades also involving non-financial counterparties. [21] focuses on the structure of the EU centrally cleared interest rate derivatives market by looking at both the direct clearing relation (CCP-clearing members) and at the client clearing one (clearing members-clients). They provide information on the relative importance of the various categories of counterparties active in the market, confirming the important intermediating role of the G-16 dealers and find that the network structure tends to be relatively less persistent over time in the client clearing segment. Interestingly, they analyse the geographical distribution of clearing members and their clients, finding e.g., a relatively relevant cross-border relation between UK clearing members and clients in Luxembourg, compared for example to the more national orientation of German banks which provide CCP access services mainly to their domestic clients. Furthermore, they analyse the network resilience to the withdrawal of nodes finding that the removal of a G-16 clearing member would create sizeable access restrictions for the indirect clearing clients. [16] provides an overview of the general features of all derivatives asset classes (including also commodities, equity and other derivatives), using data from six trade repositories authorised under EMIR. The report describes the market size and key statistics for each segment, providing i.a. information on the breakdown between Exchange Traded Derivatives (ETD) and OTC transactions. They highlight a prominent role played by non-EEA counterparties, and compare the market size and concentration observed in the various segments. They show that OTC transactions are predominant on FX, credit and interest rate derivatives markets, while they find a slight majority of ETD transactions on equity and commodity derivatives markets. They find higher concentration in the commodities and credit derivatives markets, despite the first having the largest number of counterparties and the second the lowest one. In terms of size, by looking at the number of transactions, they find that the equity derivatives market is the largest (almost half of the reported transactions), followed by foreign exchange

Morgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, Société Générale, UBS and Wells Fargo.

products (about one fifth of transactions), interest rate derivatives (15%), commodity derivatives (14%) and credit derivatives (4%). However, in terms of notional gross outstanding amounts, IR dominates, followed by the FX derivatives segment (while the equity, credit and commodity derivatives segments are much smaller). More recently, in [20], the authors study the exposure of insurance companies in the derivative market by analysing the EMIR dataset available at the ECB. They have found that at aggregate level the use of derivatives by euro area insurance companies is limited but concentrated in few participants that make transactions with a relatively small number of counterparties, mainly banks. Typically small companies trade only with one counterparty, while large ones trade with more counterparties. In terms of asset classes, interest rate derivatives account for almost three-quarters of the total notional amount. In [3], the activity of the German banks in the USD/EUR FX market is analysed. The authors find large variation in the cost of dollar hedging for contracts with the same counterparty and they show how the cost increase depends on bank-specific characteristics.
This paper adds to the above mentioned literature by characterising the various segments of the centrally-cleared euro area derivatives markets and providing insights into the main structural features of the network represented by CCPs and its direct and indirect participants (clearing members and clients).

The second strand of research relevant for this study is the growing literature applying multi-layer network analysis (sometimes referred to as multiplex analysis) to financial networks. As explained in Section 4, multi-layer networks are networks where different entities (nodes of the network) are linked one-to-another simultaneously via different types of relationships which are worth keeping separate for the analysis of the network structure. This class of models is therefore particularly useful to describe the relationship between financial counterparties which have contracts in place (and reciprocal exposures) in different market segments. Various applications of multi-layer analysis to the study of risk propagation in financial markets point to the existence of non-linear effects, with various authors showing how limiting the analysis to one market segment (layer) and generalising the results to the full network, or also relying on metrics computed on the aggregate network (sum of layers) can lead to underestimating the total risks (see for example [32], [5], [35] and [18]). More recently, in [4], the authors apply the multi-layer analysis to UK EMIR trade repositories data, analysing the propagation of a liquidity shock in three market segments. The authors also propose to assess the importance of nodes for the resilience of the multiplex by using an extension of the Functional Multiplex PageRank (FMP) centrality measure proposed by [29], showing how their extended metric outperforms alternative measures of multiplex centrality for their specific dataset.

This paper contributes to this strand of literature in two ways: first, it provides a full multi-layer characterisation of the centrally cleared euro area derivatives markets, thus including six layers for all the asset classes of transactions reported under EMIR: interest rates, credits, equities, foreign exchanges, commodities and other derivatives. Second, we employ an original methodology to identify, based on various measures of network centrality, the most significant clearing members which we consider the "backbone" of the market.

3 Data and methodology

EMIR establishes the requirements for the reporting obligation of derivatives transactions. In general EMIR requires that all derivatives transactions both bilateral contracts and centrally cleared ones, irrespective of whether traded ETD or OTC, are reported. The reporting obligation falls on both the counterparties (the so-called double reporting obligation) and applies to all financial intermediaries, to non-financial counterparties that are over a given threshold, but not to individuals. The counterparties shall report their trade activities to the Trade Repositories (TR) that ESMA has approved and registered. Reporting has to take place within the day after the transaction has been executed. TRs collect all the information reported by counterparties and make them available to the relevant authorities according to their jurisdictions as set up in EMIR. The ECB is entitled to receive all the transactions in which at least one of the two counterparties belongs to the euro area[7]. In addition to the daily activities, the TRs provide authorities with the consolidated view of the status of all the open transactions, the so-called trade states report: i.e., for each transaction reported and identified by a Unique Trade Identifier (UTI), the TR builds one trade state record on the basis of all activity records received from the same reporting entity, consolidating the status of the transaction at the end of the day. Each trade state record contains several details about the transaction: the UTI, the counterparties (the two counterparties of the trade, i.e., the seller and the buyer, but also information about other counterparties that can be involved in the transaction such as the CCP, the clearing

[7]E.g., transactions between German counterparties and French counterparties, between German and UK counterparties and between German and US counterparties are included in the ECB dataset. The dataset does not contains transactions between non euro area counterparties, for instance trades between UK counterparties, between UK and US counterparties or between Swedish and Japanese counterparties are not included.

members, the broker, etc.), the underlying asset, the price, the maturity data, information about collateral, the value of the transaction. Reporting counterparties have to maintain the trades updated by providing daily valuation of the mark-to-market (or mark-to-model) value of the transaction and of the collateral exchanged on an individual or portfolio basis.

We focus on the cleared derivative market and we build the network of relationships between market participants from information derived from the trade state EMIR data set. As a first step we build six networks, one for each underlying asset class category as defined in EMIR (i.e. equities, credit, interest rates, commodities, FX and other) where each node represents a CCP, a clearing member or a client (i.e. an entity that accesses a CCP indirectly, via a clearing member). A node is classified as clearing member whenever it has at least one direct relationship with a CCP and we classify as clients all parties (including credit institutions) that do not have any direct relations to any CCP. An edge between two nodes exists if there is at least one outstanding cleared transaction between the two counterparties. Edges can exist (a) between a clearing member and a CCP, (b) between two CCPs in case of a link arrangement, or (c) between a clearing member and its client (note that edges between two clearing members are also possible in case one of the two, in addition to directly accessing one or more CCPs, uses another clearing member to indirectly access a specific CCP). We explore the topology of the derivatives network by means of standard network analysis applied (i) on each market segment (ii) on the aggregate network and (iii) on the multi-layer network. We choose the multiplex network model as it allows the description of complex systems in which different entities (nodes of the network) are connected by different relationships that are worth keeping separate for the analysis of the network structure. For example, in our case a counterparty (clearing member or CCP, for that matter) may have contracts in interest rate derivatives, commodity and credit derivatives, and the multi-layer model allows us to take into account the existence of these three distinct positions (see example in Figure 1 panels (a) and panels (b)). In other words, in the multi-layer network the different asset classes are separate layers, where each node is connected to itself in the other layers to account for its presence in different market segments (e.g., a counterparty on the commodities layer is connected to itself on all the other asset class layers where it is active). In the visual representation we place each node in the same position across layers, and show intra-layers connections in dashed format. The aggregate network in obtained by overlapping each individual asset class networks and aggregating the weights of the edges between two nodes. The result is a network in which the nodes are the union of the derivative market participants across all asset classes and an edge between two nodes exists if there is at least one outstanding transaction in at least one asset class; the weight of the edge is the sum of the weight of the edges from the various asset classes networks (see Figure 1 panel (c)).

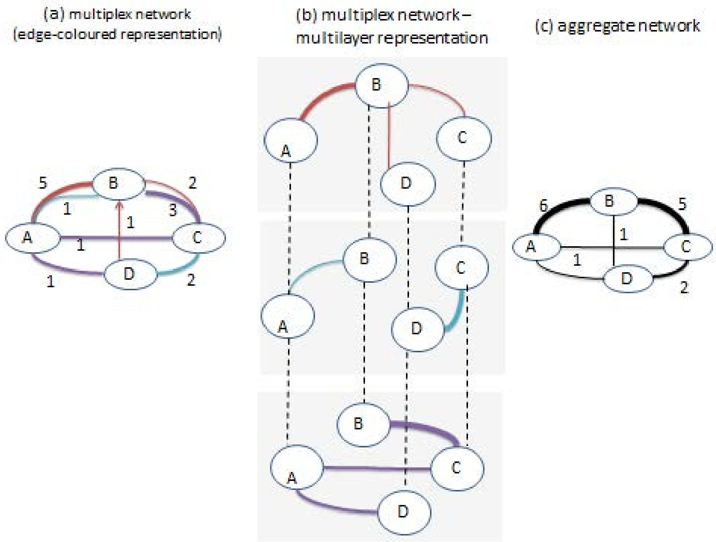


Figure 1: Multi-layer and aggregate networks

In our analysis we consider undirected edges weighted with the gross mark to market value of all transactions between the two nodes/counterparties[8] The (weighted) edge is built as the sum of the exposures between the two nodes, i.e. the sum of the weight of the two directed edges representing the gross exposure of counterparty A towards B and from B to A[9].

To recreate the clearing network that represents the status of relationship between nodes,

[8]Other weighting methods could be used for representing more appropriately the risk between the two nodes, e.g., the potential future exposure. However, due to data quality constraints, we considered not feasible to adopt other methodologies that would have requested the usage of non reliable information of the dataset. The same consideration holds for the choice not to consider the direction of the link, as in our data quality assessment we have identified that the information about the directionality of the mark to market value was not reliable. For the purpose of this paper, we consider the gross mark to market value as a good proxy for weighting the relationship between two nodes on the basis of the business between them. Further work will be done in the future to overcome those limitations.

[9]The exposures of A towards B and the exposure of B towards A are not netted, but the two absolute values are summed to obtain the weight of the undirected edge. Thus, the weight of the undirected edge is the gross value of the relationship between A and B independently of the direction of the exposure. For example, let us consider the case that three cleared transactions between counterparty A and counterparty B have been reported, two having negative mark to market values from A to B (exposure of A to B) and one with negative mark to market value from B to A (exposure of B to A). We compute two directed edges: one edge from A to B with a positive weight given by the absolute value of the sum of the two negative mark to market values from A to B and another directed edge from B to A with a weight given by the absolute value of the mark to market value of the exposure of B to A. Finally, the undirected edge connecting A and B is weighted with the sum of the two directed edges weights. The weights of the direct edges between A and B and between B and A indicate the exposures of A to B and of B to A respectively, whereas the weight of the undirected edge is the gross value of the relationship between A and B independently of the versus of the exposure.

we prepare a clean dataset of the bilateral exposures between counterparties by processing all the trade states in a given day. One of the main issues we faced in the processing of the trades has been the proper identification of the counterparties and of transactions in order to avoid double counting of the trade due to the previously mentioned EMIR double reporting obligation. In fact, while on the one hand the double reporting regime provides to the authorities the possibility to double check the data reported by the two counterparties increasing the global quality of the data, on the other hand it is challenging to work in a double reporting obligation environment, considering that i) not all the transactions are reported twice but this depends on the obligation of the two counterparties, i.e., in case transactions between European entities and non-European entities, only the European entity is obliged to report under EMIR, ii) it is not easy to couple the records that the two counterparties report about the same transaction since the two counterparties not always use the same transaction identifier, can report to two different TRs, can report transactions using different methodologies allowed by EMIR (e.g. some counterparties, in particular CCPs, adopted the possibility to report and maintain derivative transactions aggregating at position level, in line with the approach they adopt for the valuation of the mark to market of the trades). Without hampering the quality of the results, we adopted an alternative approach that attempts to obtain the aggregate information on the exposures between counterparties by exploiting the information about the reporting obligation of the counterparty. Details about the data cleaning process and the creation of the network are reported in the Appendix.

As a result of the cleaning and aggregation process we obtain a set of distinct networks for each EMIR reported asset class. In each asset class network, the nodes are the counterparties active in that market, the edges represent the existence in that specific layer of at least one open transaction between the two nodes and the weight of the edge represents the related aggregate gross exposure between nodes in the given layer. Note again that the aggregate exposures between two nodes are not netted. In addition to the single asset class networks, we build the aggregate and the multiplex networks. The aggregate network is obtained by overlapping all the asset class networks: a node represents a counterparty that is active in at least one asset class and an edge between two nodes exists if it exists in at least one asset class network; the weight of the edge is the sum of the weights across the various asset classes, i.e., the weight is the sum of the absolute market values of all trades between two nodes across all asset classes. The multi-layer network, instead, is a tri-dimensional network created connecting together the various asset class networks: each node in one layer is connected to itself in the other layers where it is active (e.g., a counterparty on the commodities layer is connected to itself on all the other asset class layers, etc.).

The mathematical representation of the cleared networks described above is as follows. Let L be the number of layers of the multiplex network where each layer represents a different asset class of the derivative market (6 asset classes) and N is the number of nodes in the cleared network. N represents the whole population of counterparties, but not all counterparties are active in all layers.

$A^{(\alpha,\alpha)}$ is the adjacency matrix representing the network for the asset class layer α: the element of the matrix $a_{i,j}^{(\alpha,\alpha)}$ is 1 if there is at least one outstanding transaction between node i and node j in the layer α (independently of the direction). The $A^{(\alpha,\alpha)}$ matrices are symmetric, i.e., $a_{i,j}^{(\alpha,\alpha)} = a_{j,i}^{(\alpha,\alpha)}$ for $i \neq j$, as we do not take into consideration the direction of the trade, with zero values on the diagonal, as nodes have no self links. The aggregate network, i.e., the network that is obtained by overlapping the single layer networks, is represented by the matrix O where the elements $o_{i,j}$ are 1 if $\sum_\alpha a_{i,j}^{(\alpha,\alpha)}$ is greater than 0 and 0 otherwise. We define $A^{(\alpha,\beta)}$ as the inter-layer adjacency matrices. The matrices are diagonal matrices where the value on the diagonal $a_{i,i}^{(\alpha,\beta)}$ is 1 if the node i is active in both layers α and β and 0 otherwise. As the edges are undirected $A^{(\alpha,\beta)} = A^{(\beta,\alpha)}$ for $\alpha \neq \beta$.

The multi-layer network is described by the supra-adjacency matrix $\mathbf{A}$ that represents all the possible relationships between the nodes and it is defined as:

$$\mathbf{A} = \begin{bmatrix} A^{(1,1)} & A^{(1,2)} & \dots \\ \vdots & \ddots & \\ A^{(L,1)} & & A^{(L,L)} \end{bmatrix} \tag{1}$$

Similarly we define the weighted adjacency matrices $W^{(\alpha,\alpha)}$ and $W^{(\alpha,\beta)}$, the weighted aggregated adjacency matrix $O^{(w)}$ and the supra weighted adjacency matrix $\mathbf{W}$. The elements of $W^{(\alpha,\alpha)}$ are $w_{i,j}^{(\alpha,\alpha)}$ and are computed as the absolute value of the gross mark to market value exposure between node i and j. The elements of $O^{(w)}$ are given by $o_{i,j}^{(w)} = \sum_\alpha w_{i,j}^{(\alpha,\alpha)}$. Regarding the inter-layer connectivity we associate a weight $w_{i,i}^{(\alpha,\beta)}$ of 1 when the node i is active on both layer α and layer β[10] and $w_{i,j}^{(\alpha,\beta)} = 0$ for $i \neq j$. Also in this case the matrices $W^{(\alpha,\alpha)}$

[10]In this paper we do not explore other possible ways to weight the inter-layer connections. This analysis is left for further work.

are symmetric and $W^{(\alpha,\beta)} = W^{(\beta,\alpha)}$ as we do not take into consideration the direction of the exposure.

4 Analysis of the cleared network

For this analysis we used the dataset available to the ECB containing all open transaction from the trade state reports at the date of 30 June 2017. After the cleaning process, the dataset size decreases from 20 to 12 million of records that represent the end of day status of the whole euro area cleared derivative market. Table 1 reports some basic information about the number of active nodes (CCPs, clearing members and other counterparties) in each layer and the number of bilateral relationships (edges). In total more than 26 thousand counterparties are identified in the dataset (N), 30 of which are CCPs, 190 are clearing members (i.e., are members of at least one CCP in at least one asset class layer) and the rest are clearing members' clients. The most populated market is the equity one in terms of CCPs, clearing members and clients, followed by the interest rate layer, while the FX and the Credit derivative markets are the most sparse ones, with few CCP and clearing members. The table reports also some basic statistics as well as the average degree of the CCP and clearing member nodes (i.e. the average number of edges per node). These averages are computed respectively for the complete network (i.e., the network that includes also the clients) and for the network limited to the relationships between clearing members and CCPs. In the reminder of the paper we will use the terms complete network and CCP-clearing member network to refer to those networks.

Figure 2 depicts the aggregate network where the red and yellow nodes in the centre represent the CCPs of euro area and outside the euro area respectively, the blue and light blue nodes are the (euro area and non euro area) clearing members. The inner circle represents the most significant clearing members as identified later in the paper. The figure on the left panel also includes green (and light green) nodes, i.e. other counterparties inside (and outside) the euro area identified as clients (i.e., which have access to CCPs via clearing members). It is evident already at visual inspection that some clearing members serve a large number (several hundreds) of clients, a result that will be analysed further later. Of the 30 CCPs, 8 established in a euro area country and 22 outside the euro area. As for the clearing members, 143 are in the euro area and 47 outside. Since the ECB dataset comprises reports by euro area counterparties, the information regarding the euro area counterparties (CCP, clearing members and clients)

	Aggregate	Equity	Commodity	IR	FX	Credit	Other
Number of nodes	26542	16340	1399	7172	3719	446	4814
Number of CCPs	30	19	13	15	8	5	10
Number of Clearing members	190	126	46	71	10	19	130
Number of edges	28101	16647	1500	7912	3725	726	4913
Density (edges/nodes)	1.06	1.02	1.07	1.10	1.00	1.63	1.02
Number of CCP-CMB edges	371	198	83	125	18	29	195
CCP-CMB density	1.69	1.37	1.41	1.45	1.00	1.21	1.39
Average CCP degree	12.4	6.6	2.8	4.2	0.6	1.0	6.5
Average Clearing member degree (complete network)	123.8	75.1	7.1	37.6	18.5	1.5	18.8
Average Clearing member degree (CCP-CMB network)	2.0	1.0	0.4	0.7	0.1	0.2	1.0

Table 1: Number of nodes and edges per each asset class network and for the aggregate one.

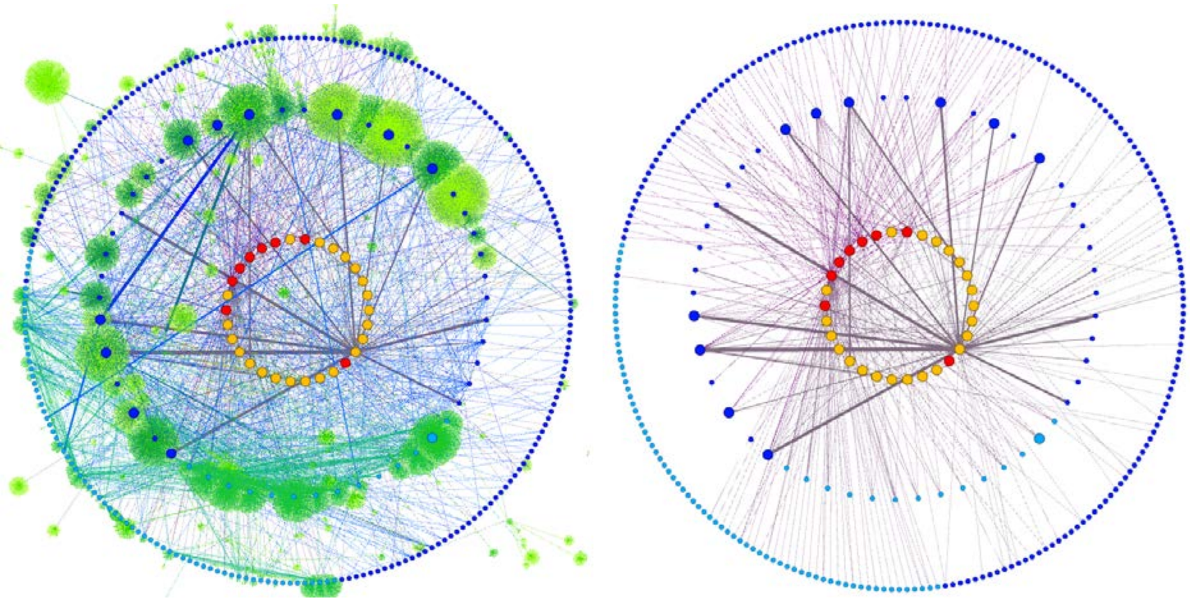


Figure 2: Mark to market network including CCP, Clearing Members and clients (left) and mark to market network limited to the relationships between CCP and Clearing Members (right)

should be complete, while the information regarding counterparties outside the euro area are not complete (according to the EMIR access criteria the ECB has access only non-euro area trades insofar as they involve on the other side a euro area reporting party).

Table 2 and Figure 3 report the number of layers in which the counterparties are active. For

Number of layers nodes are active	1	2	3	4	5	6	Total
CCP	13	4	5	6	2	0	30
Clearing members	34	44	29	22	40	21	190

Table 2: Number of asset class layers CCP and clearing members are active in.

CCPs, 13 out of 30 are active only in one layer, 4 are active in 2 layers, 5 in 3 layers, 8 in more than 4 layers. Regarding the clearing members, only few of them are active only in one layer (about 18%), whereas a large share of them (about 44%) are active in more than 4 layers and there are 21 clearing members that are active in all the asset class layers. Potentially those nodes are good candidates to move the contagion from one layer to the others. The situation differs when analysing the rest of the counterparties (the clients), for which the participation in more than one layer is low. In case of credit institutions the percentage of counterparties active in more than one layer is 35%, whereas for other counterparties the percentage is 20%[11]. This result highlights that the majority of clearing member's clients participate only in one layer, presumably using the derivative market for hedging against specific risks related to their core business and balance sheet.

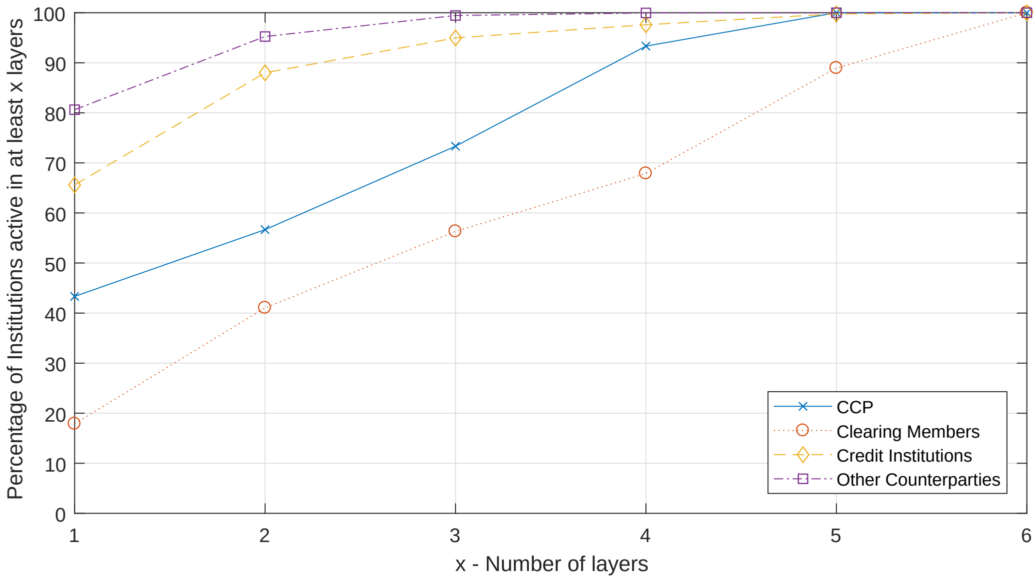


Figure 3: Percentage of counterparties active in one or more asset class layer simultaneously.

[11]Excluding the Other asset class category the percentage of counterparties active in more than one layer is respectively 29% and 18%

4.1 Identifying central nodes

Once we have reconstructed the networks of relationships between counterparties, we move on to identify the most critical nodes. We rank the nodes by different centrality measures and we compare the rankings to assess which are the main characteristics of the nodes we have to take into account when assessing their criticality for the whole derivatives network.

For the computation of node centrality, we use three different dimensions. The first dimension is the centrality measure itself: we include four different metrics that we consider relevant: the degree of the nodes, that gives an insight on the number of relationships that a node maintains with other nodes, the weighted degree of the nodes that provides information about the size of relationships by including the weight of the links (marked to market values of reported trades) in the computation, the eigenvector centrality and the weighted eigenvector centrality (explained further below in more detail) for which the centrality of a node is computed recursively taking into account the centrality of its neighbours. The second dimension is the network on which we compute the centrality metrics: we analyse both the aggregate and the multiplex network and both the complete and the CCP-Clearing members network. The third dimension is the nodes to which we apply the network centrality measure as we distinguish between CCPs and clearing members.

The weighted and unweighted centrality measures we use are defined as follows:

- The degree centrality of the aggregate network d_i measures the number of nodes, node i has relationships with and it is computed as $\sum_{j=1}^{N} o_{i,j}$ where $o_{i,j}$ are the elements of the aggregate adjacency matrix O.

- The degree centrality of the multiplex network $\mathbf{d}_i$ measures the number of relationships that node i has with the other nodes in the network, but taking into account that two nodes can have relationships in more than one layer. It is computed as $\sum_{k=1}^{L} \sum_{j=1}^{NL} \mathbf{a}_{i \cdot k,j}$ where $\mathbf{a}_{i,j}$ are the elements of the supra-adjacency matrix.

- The weighted degree centrality of the aggregate network s_i measures the centrality of the node as the sum of the weights of the links with its neighbours and it is calculated as $\sum_{j=1}^{N} o_{i,j}^{(w)}$ where $o_{i,j}^{(w)}$ are the weights of the edges and elements of the weighted adjacency matrix $O^{(w)}$.

- The weighted degree centrality of the multiplex network $\mathbf{s}_i$ is similar to weighted degree centrality on the aggregate network but it also includes the links that weights between the same node on different layers. It is computed as $\sum_{k=1}^{L}\sum_{j=1}^{NL}\mathbf{w}_{i\cdot k,j}$ where $\mathbf{w}_{i,j}$ are the elements of the weighted supra-adjacency matrix $\mathbf{W}$.

As mentioned above, in addition to the standard degree and the weighted degree, we compute the eigenvector centrality measured on the aggregate network on the multiplex network. The eigenvector centrality measures the centrality of one node on the basis of the centrality of its neighbors recursively[12].

Figure 4 shows the comparison of the ranking of the nodes obtained for different centrality measures (degree, weighted degree, eigenvector centrality and weighted eigenvector centrality) on the aggregate network (x-axis) and on the multiplex network (y-axis) for the CCP-clearing members network. Each dot represents one node where the x value is the rank obtained with the centrality measure computed on the aggregate network and the y value represents the rank resulting from the centrality measure computed on the multiplex. The colour of the dot follows the same standard we adopted above (see Figure 2): a red circle represents a CCP established in the euro area, a yellow plus sign a CCP outside the euro area, a blue cross is a euro area clearing member and the light-blue squares are the non-euro area clearing members. The four subfigures show the comparison for the degree centrality (upper-left), weighted degree (upper-right), eigenvector centrality (lower-left) and weighted eigenvector centrality (lower-right). Analysing the results obtained for the CCP-Clearing members network we notice that: i) for the degree centrality the first ranked nodes for the multiplex and the aggregate network are the same and CCPs (mainly those established in the euro area) are the most central nodes[13]. It is worth

[12] The eigenvector centrality is considered a standard measure for assessing the importance of nodes in a network and takes its name from the mathematical process used to compute it. The basic assumption behind the eigenvector centrality is the fact that a node in the network is central if its neighbours are central themselves. In mathematical terms the eigenvector centrality of node i on the aggregate network is given by $e_i = \frac{1}{\lambda}\sum_{j\in\mathcal{C}_i} e_j$ where $\mathcal{C}_i$ is the set of neighbors of i and λ is a constant. In turn the previous equation can be written as $e_i = \frac{1}{\lambda}\sum_{j=1}^{N} o_{i,j}e_j$, where $o_{i,j}$ are the elements of the aggregate adjacency matrix O. Imposing that e_i are non-negative implies, for the Perron-Frobenius theorem, that e_i is the i-th component of the eigenvector associated to the largest eigenvalue of O. Similarly the eigenvector centrality can be applied to the weighted adjacency matrix $e_i^{(w)} = \frac{1}{\lambda}\sum_{j=1}^{N} o_{i,j}^{(w)}e_j^{(w)}$, where $o_{i,j}^{(w)}$ are the elements of the aggregate weighted adjacency matrix $O^{(w)}$.
The extension of the eigenvector centrality (and the weighted eigenvector centrality) to the multiplex network is obtained by computing the eigenvector centrality on the supra-adjacency (and the weighted supra-adjacency) matrix. In this case, considering that the only edges between layers are between the same nodes in the different layers, the eigenvector centrality of a node in a given layer is influenced not only by its neighbours in that layer but also on its own centrality on the other layers. Finally, the multiplex eigenvector centrality of the node, is the sum of its eigenvector centrality on each of the layers, as we consider that all layers contribute equally to the centrality of the nodes.

[13] The CCP established in the euro area show a higher degree also because the dataset does not contain complete information for CCP established outside the euro area and in particular relationships between CCP outside the euro area and clearing members outside the euro area are not present in our dataset.

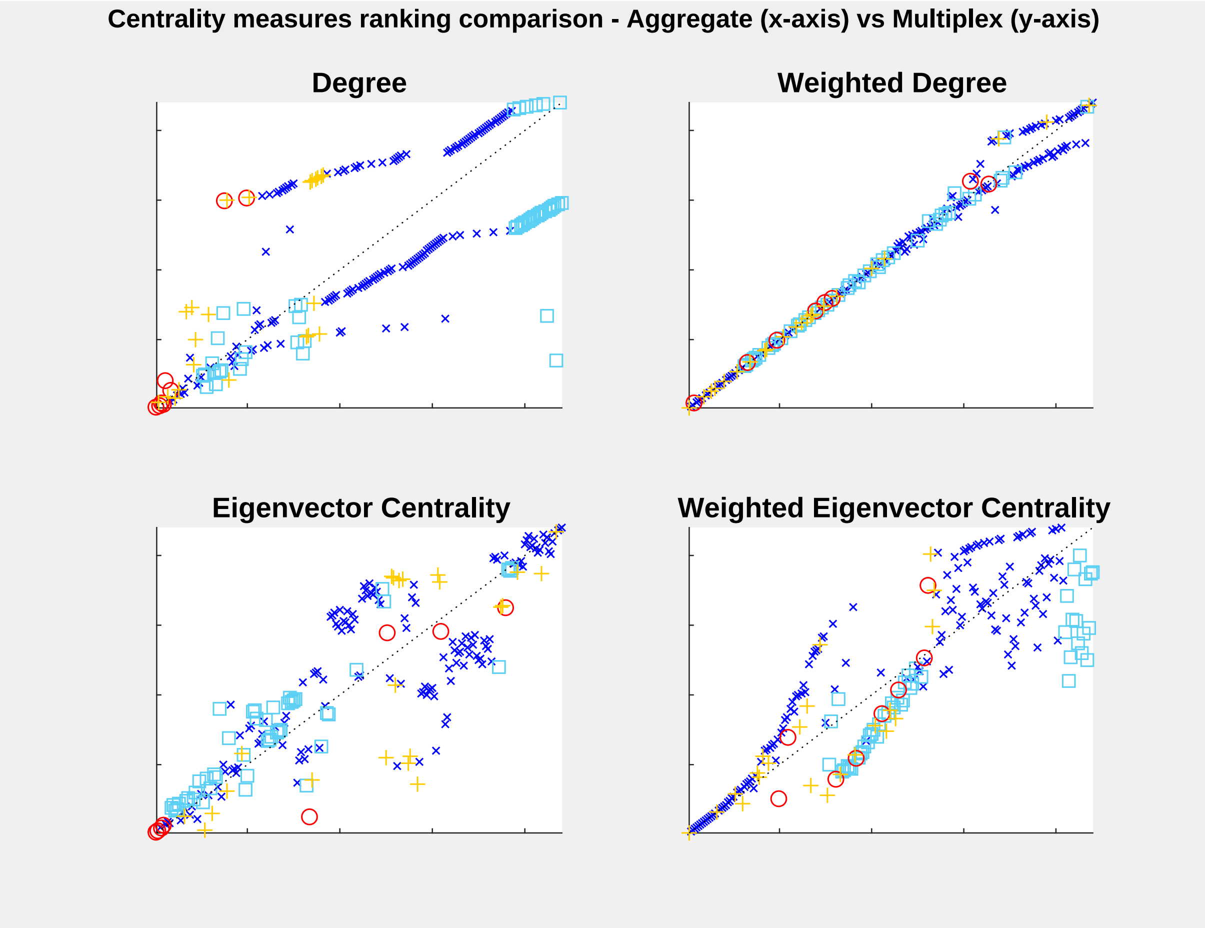


Figure 4: Centrality measures computed on the CCP-Clearing members network. Each dot represents a node sorted according to the ranking of the centrality measure on the aggregate network (x-axis) and on the multiplex network (y-axis). Colours of the nodes are consistent with Figure 2 (red for euro area CCPs, yellow for CCPs outside euro area, blue for euro area clearing members and light blue for non euro area clearing members).

noticing that there are also clearing members that have a very high degree (the two most connected clearing members participate simultaneously in 17 and 18 CCPs respectively). Not in the first ranking positions there are nodes for which the ranking on the aggregate network is much higher than the one obtained on the multiplex network: these are nodes that have the same number of relationships on the aggregate network, but are active in less layers. Comparing the weighted degree computed on the aggregate and the multiplex we notice high correlation and indeed the two ranking criteria obtain the same results; this is not surprising considering that the inter-layer links (the links of each node to itself in the other layers where it participates) have a weight equal to one, hence these intra-layer links do not affect these metrics where weights are represented by the marked-to-market values of exposures. Moving on to the comparison of the ranking of nodes obtained from the eigenvector centrality computed on the aggregate and on the multiplex, it is worth noting that the centrality measure on the aggregate tends to underestimate the centrality of some CCPs (in particular some outside the euro area) with respect to the centrality computed on the multiplex. Regarding the weighted eigenvector centrality, we observe that while for the first ranked nodes, the two measures bring the same results (they both rank first the same set of high central nodes), for medium ranked nodes, the centrality measure applied to the multiplex tends to classify as more critical some non-euro area clearing members compared to the euro area clearing members (pointing to the significant role of some sophisticated non-euro area banks active in several market segments). Moreover it is possible to notice that the weighted eigenvector centrality tends to increase the ranking of the clearing members with respect to the ranking of CCPs: only two CCPs (both outside the euro area) are classified in the top 20 central nodes list according to this metric. This indicates that the clearing members that serve multi-product markets have a sizeable business that in some cases is comparable to that of CCPs.

Figure 5 shows the same comparison of centrality measures for the complete network (i.e., including also client-clearing members relationships). The centrality degree measures (both weighted and unweighted) show a strong correlation between the ranking obtained in the multiplex and in the aggregate network. This means that in terms of number of connections, metrics computed on the aggregate network are good proxies for the multiplex, or put differently, that the multilayer analysis does not bring additional information when looking only at the number of edges of nodes. Moreover it is worth noticing that CCPs are not in the first ranking positions for the degree centrality because, as can be expected in the tiered access structure of CCPs, there are clearing members that have many more relationships. What is remarkable here is the extensiveness, concentration and international dimension of client clearing emerging from the analysis: the top ten ranked nodes exhibit a degree that varies from 800 to up to 3000 clients and among the top ten clearing members, three clearing members do not belong to the euro area. On the contrary, when the weight (i.e., the mark to market gross exposure) is taken into account, the most significant node is a CCP and 5 CCP are included in the list of top 20 nodes both for the aggregate and the multiplex (note that only one of them is established in the euro area, pointing to the sheer size of business cleared at non-euro area CCPs and the strong cross-border integration of euro area derivatives markets). Notably 15 clearing members of the euro area are in the list of top 20 nodes for mark to market exposure. Analysing the eigenvector centrality

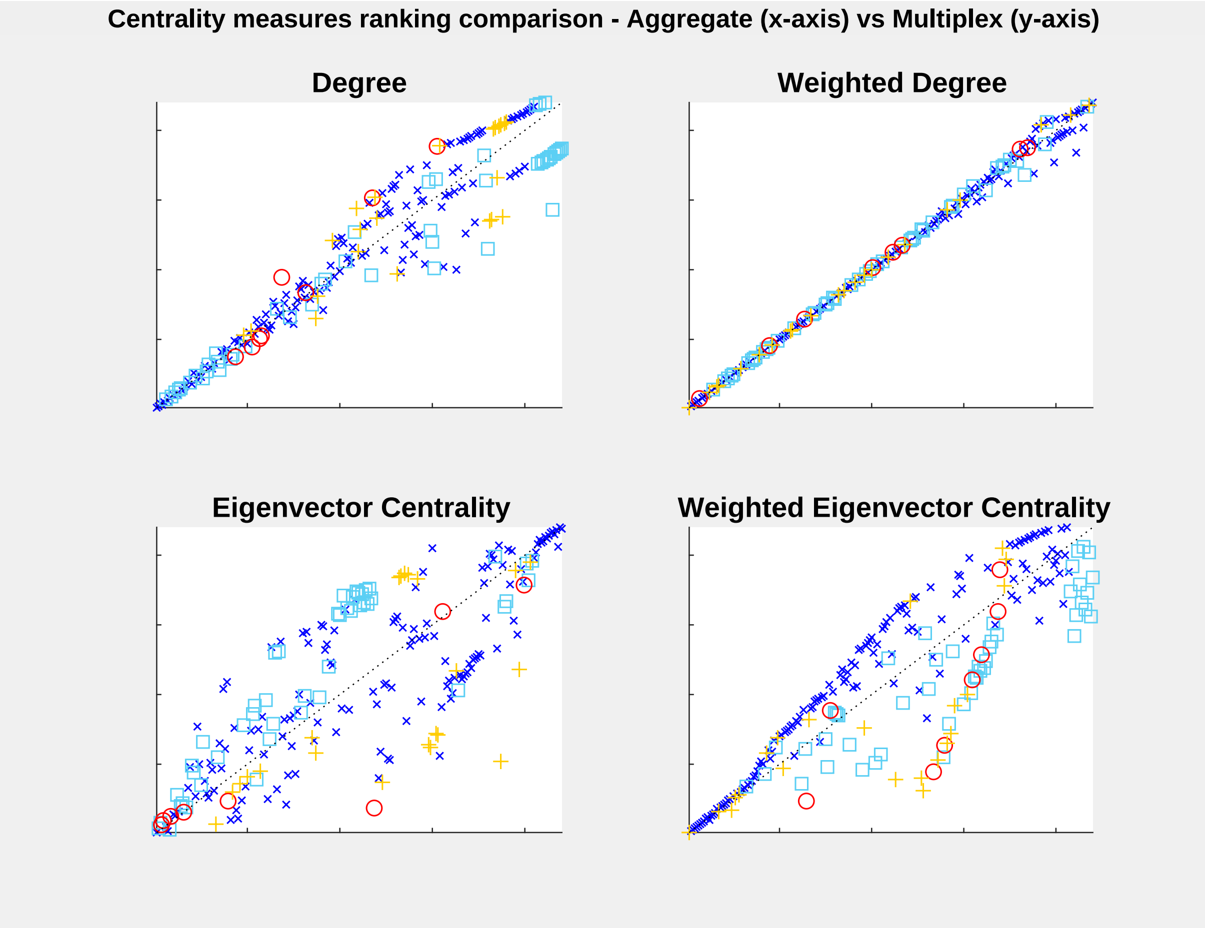


Figure 5: Centrality measures computed on the complete network. Each dot represents a node sorted according to the ranking of the centrality measure on the aggregate network (x-axis) and on the multiplex network (y-axis). Colours of the nodes are consistent with Figure 2 (red for euro area CCPs, yellow for CCPs outside euro area, blue for euro area clearing members and light blue for non euro area clearing members).

measures, we notice that the correlation of the ranking computed on the aggregate and on the multiplex is lower and that in general the measure applied on the aggregate network tends to underestimate the centrality of the CCP with respect to the measure applied to the multiplex. For completeness of information, Figure 6 reports the degree and the normalised weighted degree computed on the multiplex network for the CCP-clearing members network and the complete network. The plots are useful to see the distribution of the centrality measure values and the type of nodes.

From the analysis of the centrality measures on the different networks and considering the different types of nodes in our network, we conclude the following:

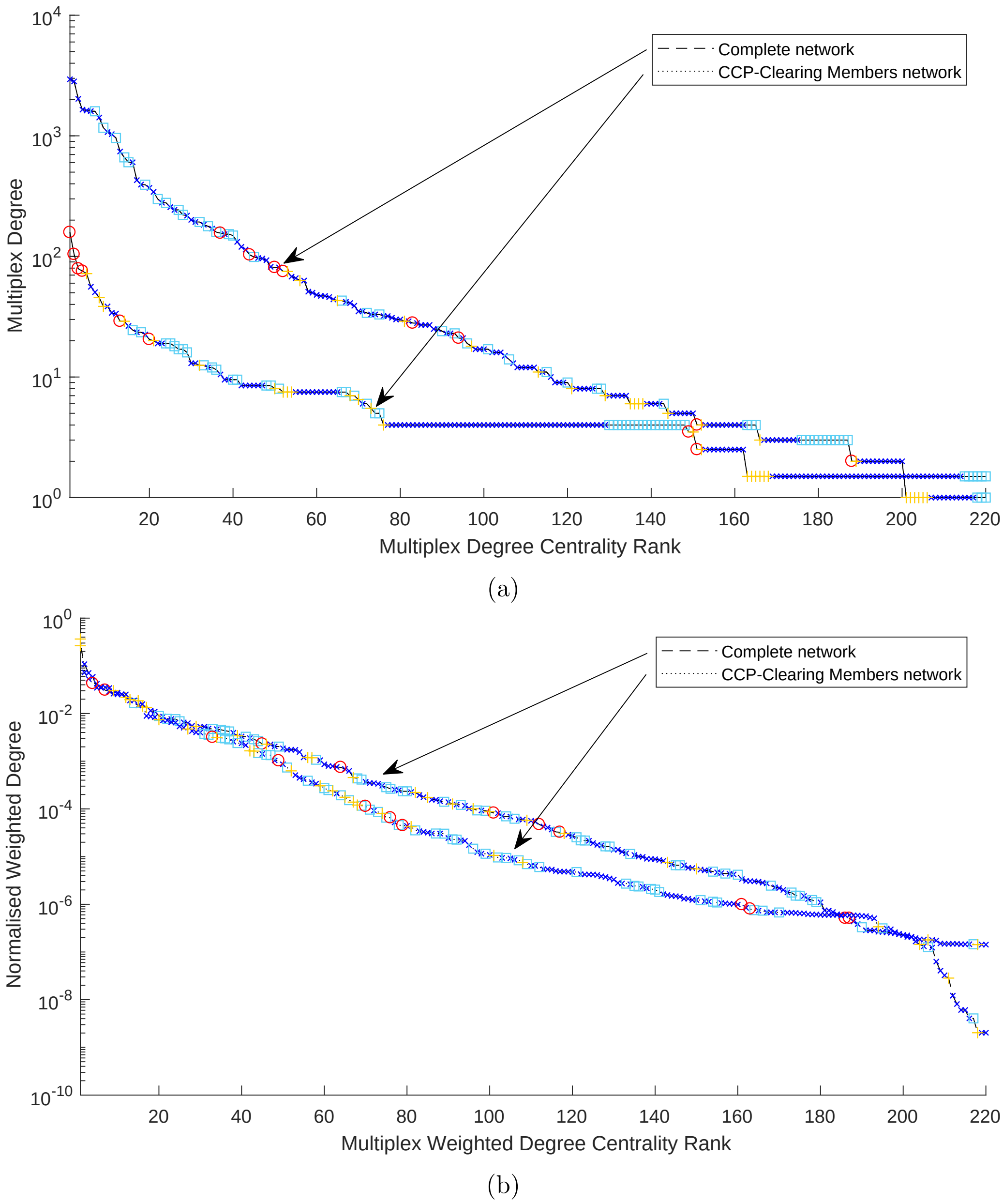


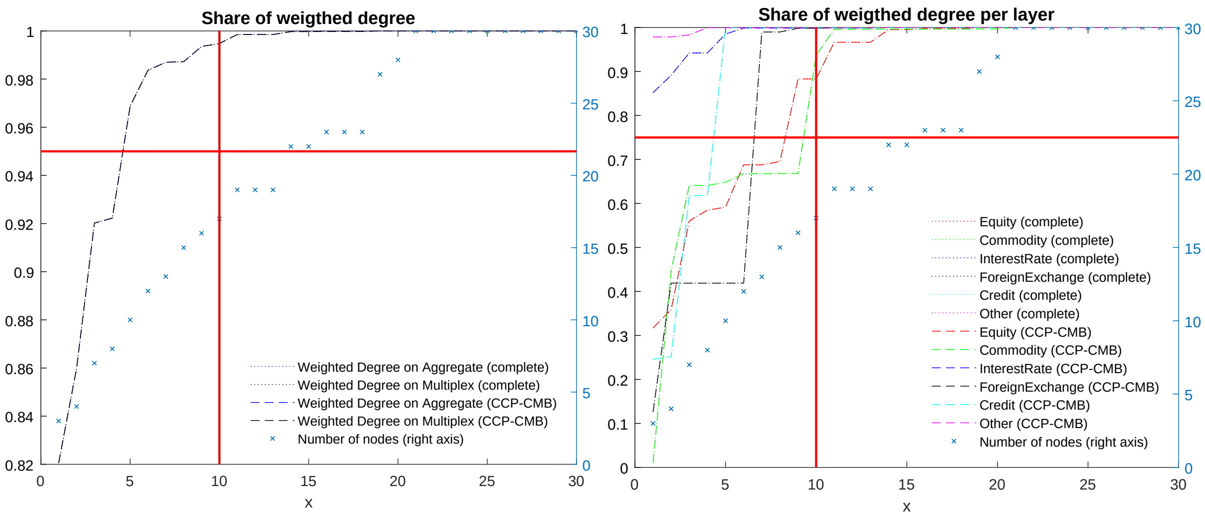
Figure 6: Multiplex centrality degree and weighted degree computed on the complete network.

- In term of degree centrality, as expected in a tiered access structure, CCPs are the most central nodes when we limit the analysis to the CCP-clearing members relationships, but when we include the clients in the network, there are clearing members that are more central than some CCPs. In general there are clearing members that some centrality measures identify as more central, both in terms of number of relationships (degree) and notably in terms of mark to market exposure (weighted degree), than CCPs (which, by definition, are central nodes of the cleared derivative network). Some clearing members established in the euro area have a business size comparable to the largest CCPs.

- For some centrality measures the correlation between the ranking obtained on the aggregate network and on the multiplex network is low, in particular when analysing the eigenvector centrality measures. This indicates that the aggregate network itself does not capture entirely the structure of the cleared network. In particular, the CCPs and the clearing members established outside the euro area are ranked first by centrality measures such as the weighted eigenvector centrality when applied on the multiplex compared to the aggregate network.
- There are nodes that despite not maintaining many relationships and not showing a particularly high exposure level towards other nodes, are nevertheless central in the (multiplex) network because their presence in several market segments means they can potentially act as a channel of contagion across layers or communities in the same network (we do not perform community detection analysis in this paper, and we leave this aspect for further exploration in a future work).

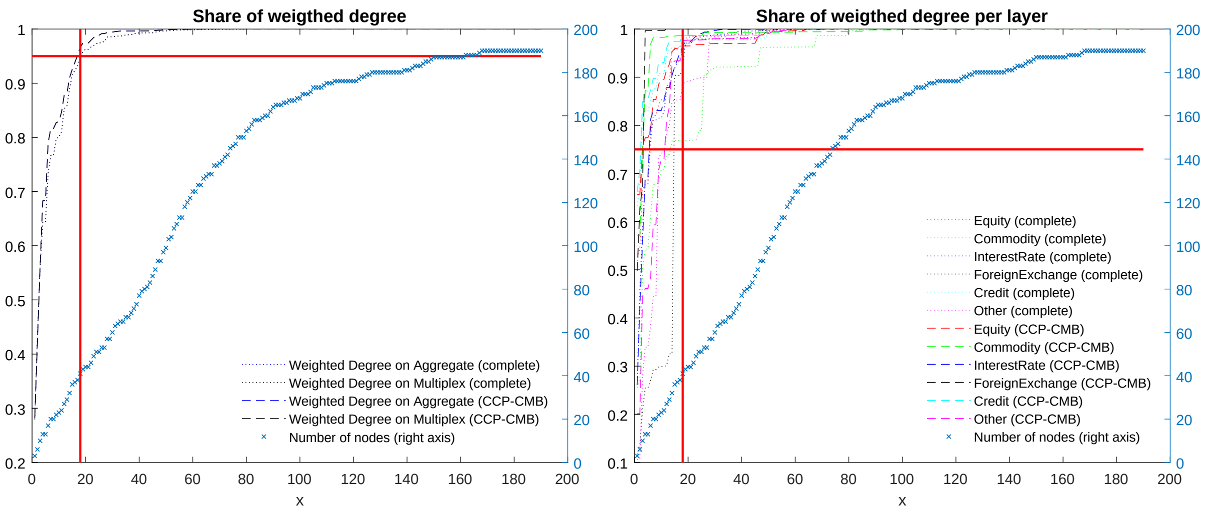
As the main purpose of this part of the analysis is to identify the most central CCPs and clearing members for focusing the subsequent analysis of interconnectedness, limiting the selection process on the first nodes ranked based only on one centrality measures creates the risk of omitting important nodes that are possible channels of contagion. Each of the selected centrality measures highlight different aspects of the nodes and in order to properly identify and classify the most critical nodes we consider important to take all the measures into account. For instance, the degree centrality identifies those nodes that maintain more relationships: on the aggregate network, the degree centrality selects those nodes that maintain the greater number of relationships (independently of the layer they are active in) while, on the multiplex network, the measure ranks first those nodes that maintains the same relationships over more layers; selecting only on the basis of the measure on the aggregate network or on the multiplex network would omit one of the two highlighted aspects that are both relevant. For this reason, we designed the process for the identification of the critical nodes by combining the information and the ranking provided by different centrality measures.

The process works as follows: first we create the lists of ranked nodes for the four centrality measures (degree, eigenvector centrality, weighted degree, weighted eigenvector centrality) applied to the aggregate and the multiplex networks. We do so both for the CCP-clearing members network and for the complete one. Then we select x nodes from the lists and create the set of nodes as the union. Varying x we compute the share of mark to market exposure on the total value of the exposure for the aggregate and the multiplex networks and for each of the asset class layer networks. We chose x, i.e. the number of nodes in the lists before the union, that guarantees that 95% of the total mark to market exposure is taken into account (for all networks) and 75% of the total mark to market value for each layer.



(a) (b)

Figure 7: Share of weighted degree vs. number of CCP nodes.



(a) (b)

Figure 8: Share of weighted degree vs. number of clearing members nodes.

Figures 7 and 8 show the share of weighted centrality that is taken into account varying

the number of nodes x for each ranking list to be included. Figures 7a and 8a show the share on the aggregate and multiplex networks for the CCP-Clearing members and for the complete networks, while figures 7b and 8b show the shares or weighted degree for each layer. Circles represent the number of nodes included after the selection process if x nodes for each ranking list is selected (e.g., choosing x equal to 10 corresponds to a final list of CCPs of 17 nodes).
Applying the above procedure, $x = 10$ for CCPs and $x = 18$ for clearing members are the values of x ensuring that the share of mark to market gross exposure for the whole network and the single layers is greater than 95% and 75% respectively. That corresponds to selecting 17 CCPs and 41 clearing members as the total of 58 most critical nodes.

		Aggregate	Multiplex	Equity	Commodity	IR	FX	Credit	Other
Degree	CCP	0.94	0.94	0.95	0.86	0.93	0.72	1.00	0.99
	CMB	0.86	0.85	0.90	0.67	0.88	0.92	0.82	0.66
Weighted	CCP	0.99	0.99	0.88	0.94	1.00	1.00	1.00	1.00
Degree	CMB	0.95	0.95	0.97	0.77	0.95	0.92	0.98	0.88

Table 3: Share of degree and weighted degree for the select nodes on the complete network.

		Aggregate	Multiplex	Equity	Commodity	IR	FX	Credit	Other
Degree	CCP	0.94	0.93	0.95	0.88	0.91	0.72	1.00	0.99
	CMB	0.51	0.54	0.52	0.64	0.56	0.89	0.90	0.48
Weighted	CCP	0.99	0.99	0.88	0.94	1.00	1.00	1.00	1.00
Degree	CMB	0.97	0.97	0.96	0.99	0.96	1.00	0.99	0.98

Table 4: Share of degree and weighted degree for the select nodes on the CCP-Clearing member network.

Tables 3 and 4 report the share of unweighted and weighted degrees that are covered by limiting the network to their 58 most critical nodes. By definition, in terms of weighted degrees this network captures more than 75% for the individual asset class networks and 95% for the multiplex and aggregate ones. As for the degree we observe that the CCP share of degree is above 86% for all asset classes except for the FX layer where the share is 72%. This is not surprising as this market is one where clearing is in general limited (there is no clearing obligation), and is served by a small number of CCPs and clearing members. For the clearing members the share of degree for the aggregate network in the CCP-clearing members network is about 50%, while for the complete network, the share remains higher. Now that we identified the most critical nodes, in the next section, we proceed with the analysis of the interconnectedness of the selected nodes as they represent what we consider the core of the cleared derivative market.

4.2 Interconnectedness due to common nodes

As before, we provide some basic statistics on the network limited to the most significant CCPs and clearing members; Figure 9 depicts the new network in a single layer layout and in a multi layer layout. The colours of the nodes are consistent with the previous network charts while the size of the nodes is proportional to the weighted degree of the nodes.

The network is composed of 17 CCPs, 7 established in the euro area (the red nodes) and 10 established outside the euro area (in yellow). As for the 41 clearing members, 28 are from the euro area countries (blue) and 13 from outside (light blue). Table 5 reports the number of layers

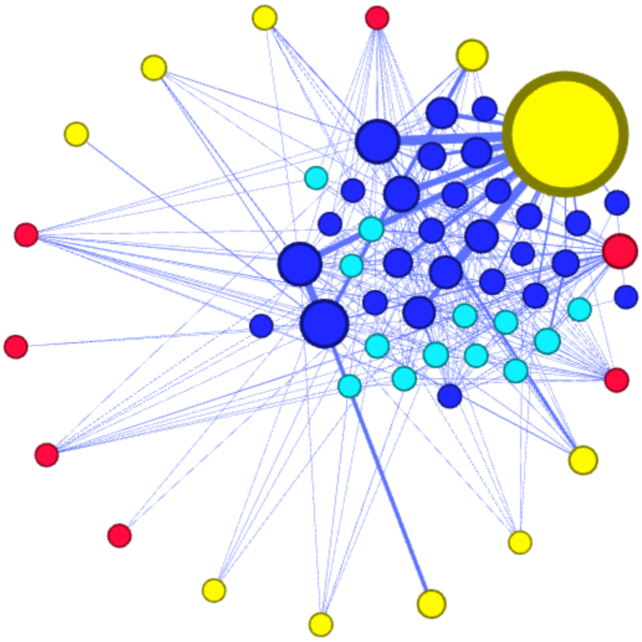
Number of layers nodes are active	1	2	3	4	5	6	Total
CCP	3	3	5	4	2	0	17
Clearing members	4	6	10	12	7	2	41

Table 5: Number of asset class layers CCP and clearing members are active in.

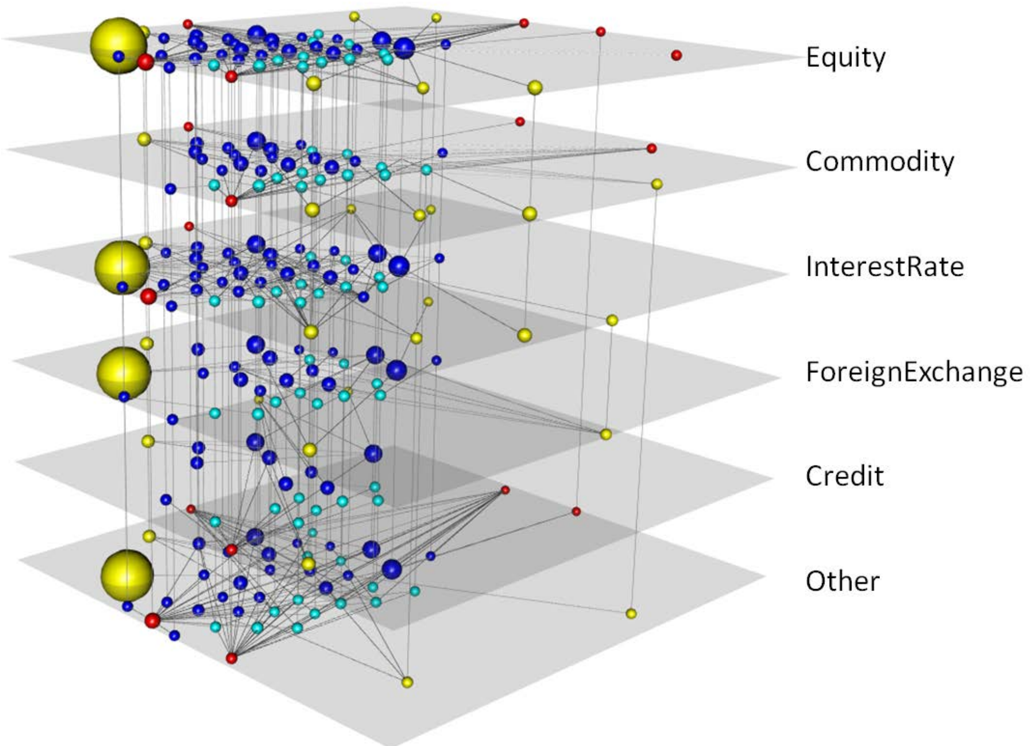
	Aggregate	Equity	Commodity	IR	FX	Credit	Other
Number of CCP	17	13	9	10	4	5	9
Number of Clearing members	41	34	23	26	7	16	35
Number of edges	171	94	48	59	11	26	92
Density (edges/nodes)	2.95	2.00	1.50	1.64	1.00	1.24	2.09
Average CCP degree	20.4	11.1	4.3	6.7	0.8	1.7	11.4
Average Clearing member degree (complete network)	493.4	314.1	21.8	153.9	78.9	5.6	57.4
Average Clearing member degree (CCP-CMB network)	24.6	2.5	1.3	1.7	0.4	0.6	2.3

Table 6: Number of nodes and edges per each asset class network and for the aggregate one.

the most critical CCPs and clearing members are active in, while Table 6 reports some basic statistics about which layers the CCPs and clearing members are active, the number of edges,



(a) Single-layer layout



(b) Multi-layer layout

Figure 9: The cleared network limited to the most significant CCPs and clearing members.

the density and the average node degree. Note that the average degree is computed averaging the degree computed on the original network (i.e. the one including also the less critical nodes) for the most critical nodes. Comparing Table 5 with Table 2, we notice that the procedure for the selection of the most critical nodes, included automatically those nodes that are active in more than one layer, however few CCPs and clearing members that are active only in one of the asset class layer are included, as they are critical for that layer.

In our analysis of interconnectedness, we want to understand how many relationships (edges) and the size of the relationships that the most critical nodes in the network share, focusing on

i) the clearing members that two CCPs share (i.e., common CCP participants; in case of a default of a common clearing member, these two CCPs will be counting on resources called from the same set of common surviving clearing members). Note that this view is bilateral, e.g. we take CCPs two by two, but in principle more CCPs have a certain set of common clearing members that are common to all of them. We are hence looking at a minimum measure of interconnectedness

ii) the CCPs that two clearing members share (i.e., both clearing members are participant of the same CCPs: in our example if one or more of these "common CCPs" initiates default management procedures or is anyway in distress, both clearing members will potentially face calls to provide further resources or absorb losses from the same CCP(s)) and

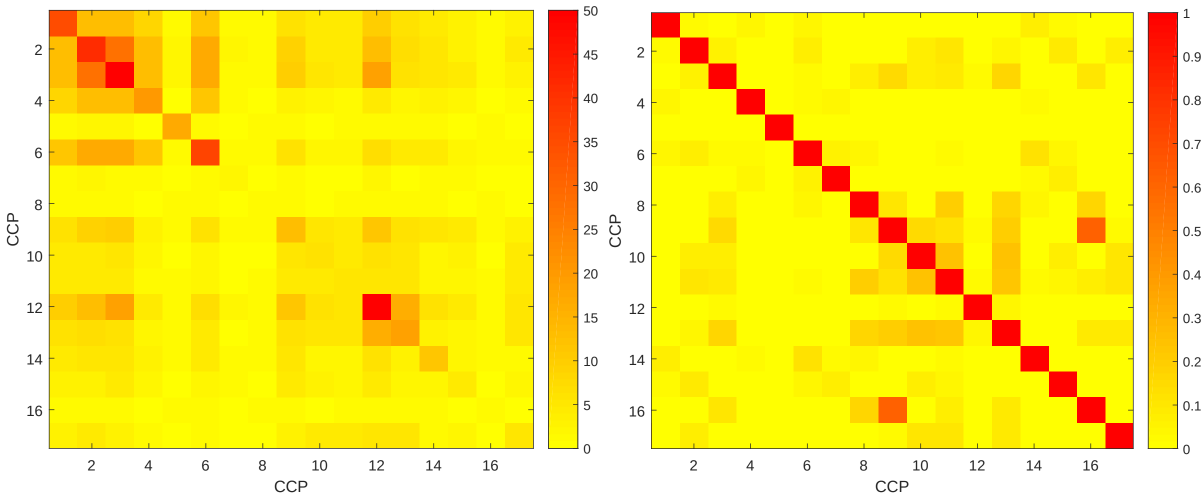
iii) the clients that two clearing members have in common. This gives a sense of the presence of clients that use different access points for clearing (in principle, this could be done to access different CCPs clearing in different market segments, or also a same CCP, if the client is subject to concentration limits applied by clearing members or by CCPs). This aspect has not been studied so far, and it may be important to understand interdependencies arising at the client clearing level.

To quantify the common relationships between two nodes, we compute the number of edges that two nodes have in common and the size of the relationships that two nodes share[14]. For instance on layer α, the number of common edges similarity between node i and j can be computed as $\sum_{k=1}^{N} a_{i,k}^{(\alpha,\alpha)} \cdot a_{j,k}^{(\alpha,\alpha)}$ where $a_{j,k}^{(\alpha,\alpha)}$ are the element of the adjacency matrix for layer α, $A^{(\alpha,\alpha)}$.

[14]This is equivalent to focus on the bipartite network composed of CCPs and clearing members and the one composed of clearing members and clients and to analyse respectively the projection of bipartite network on the CCP and on the clearing members.

To quantify the size of the relationships that two nodes share, we adopt the weighted Jaccard similarity that is defined as $\sum_{k=1}^{N} \min(w_{i,k}^{(\alpha,\alpha)}, w_{j,k}^{(\alpha,\alpha)}) / \sum_{k=1}^{N} \max(w_{i,k}^{(\alpha,\alpha)}, w_{j,k}^{(\alpha,\alpha)})$ where $w_{j,k}^{(\alpha,\alpha)}$ are the element of the weighted adjacency matrix for layer α, $W^{(\alpha,\alpha)}$.

Figure 10 reports the number of common clearing members that the most significant CCPs share (panel (a)) and the weighted Jaccard similarity index (panel (b)). Figure 11 reports the number of common clearing members for each asset class layer. The two similarity metrics are represented in the form of a correlation plot where the colour of each square represents the metric value between the CCP on the x-axis and the CCP on the y-axis. The nodes are not ordered by size, but note that the first seven CCPs are those established in the euro area and the remaining ones those established outside the euro area. For the interpretation of the plots, consider the following examples related to Figure 10(a): i) CCP2 and CCP3 (both established in the euro area) have 28 common clearing members. ii) CCP12 (outside the euro area) and CCP3 (in the euro area) share 18 clearing members. iii) CCP12 and CCP13 (both outside the euro area) share 16 clearing members.



(a) Number of common edges

(b) Weighted Jaccard Index

Figure 10: Jaccard similarity between the most significant CCP.

As the figures show, the number of common clearing members among the most significant CCPs is very high. Across euro area CCPs, there are 5 CCPs that share more than 13 clearing members and there are 3 euro area CCPs that share more than 10 clearing members with CCPs outside the euro area. Furthermore there are two non euro area CCPs that share 16 euro area clearing members and 4 that share between 4 and 5 euro area clearing members. Actually recall that the number of common clearing members between the CCPs outside the euro area could be

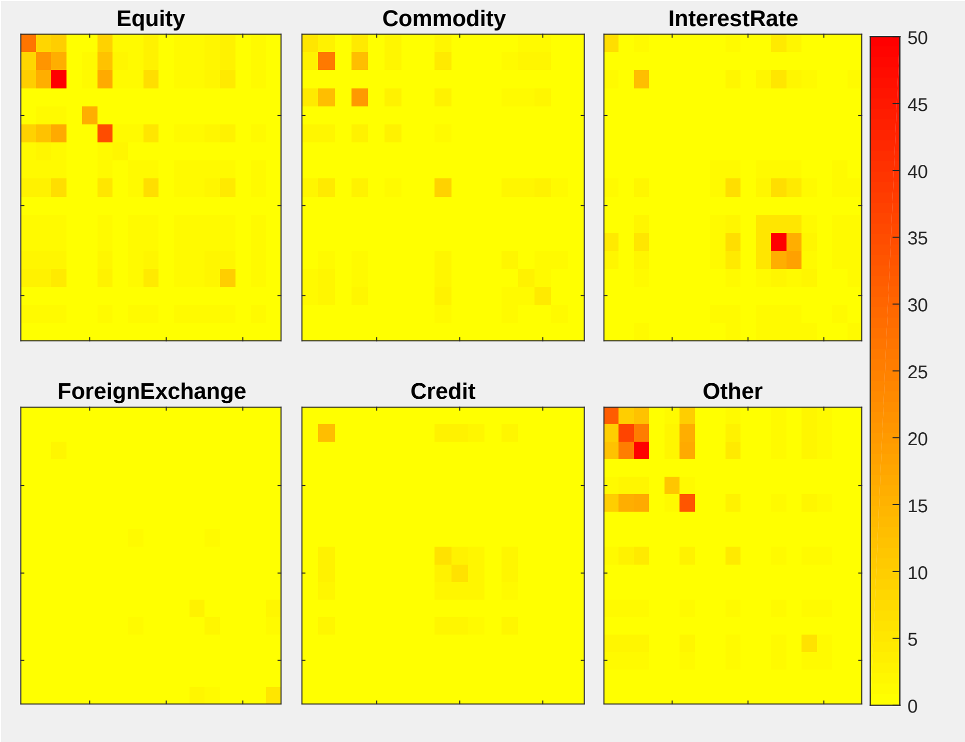
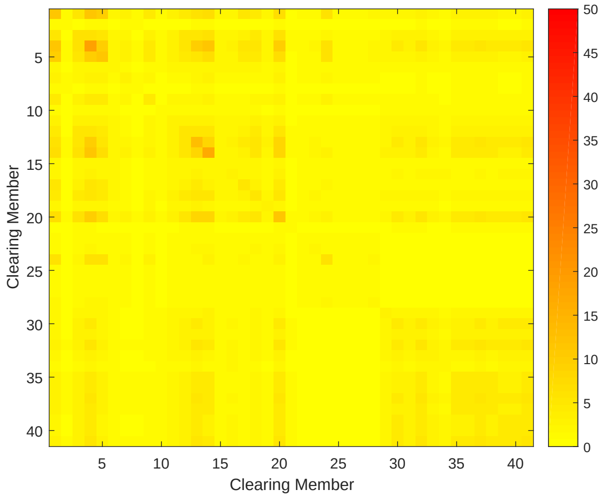


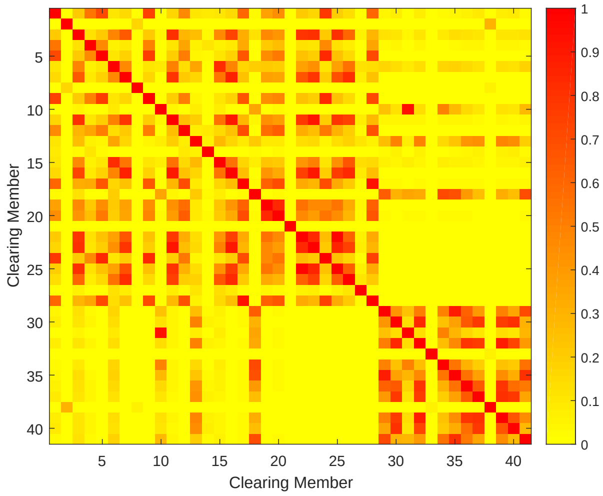
Figure 11: Number of common edges between the most significant CCP per layer.

even higher, considering that they may also share non-euro area clearing members that are not in our sample, because we only have access to transactions in which at least one counterparty is in the euro area. Also in terms of mark to market value the similarity between some CCPs outside the euro area is very high indicating the some CCPs have common clearing members with exposures comparable to the total exposure of the CCP. The analysis of individual asset class layers shows that highest number of common clearing members is in the equity layer, while in the interest rate layer there are two non euro area CCPs that share 16 euro area clearing members. It is worth noticing that the equity layer shows a pattern similar to the "other derivatives" asset class layer, which seems to indicate that transactions in the other asset class layer are highly correlated with the equity layer and could point to cases of misclassification of the other derivative transactions (a similar pattern can be identified in the next figures related to clearing member similarity). The high number of common clearing members between euro area and non euro area CCP points out the high level of integration of those markets, supporting the case for strong cooperation between the respective authorities for an effective monitoring of risks deriving from interdependencies due to common clearing members.

Figures 12 and 13 and Figures 14 and 15 reports the similarity measures between clearing members considering the network limited to the CCP-clearing members relationships and the complete network (including clients).



(a) Number of common edges



(b) Weighted Jaccard Index

Figure 12: Similarity between the most significant clearing members on the CCP-clearing member network.

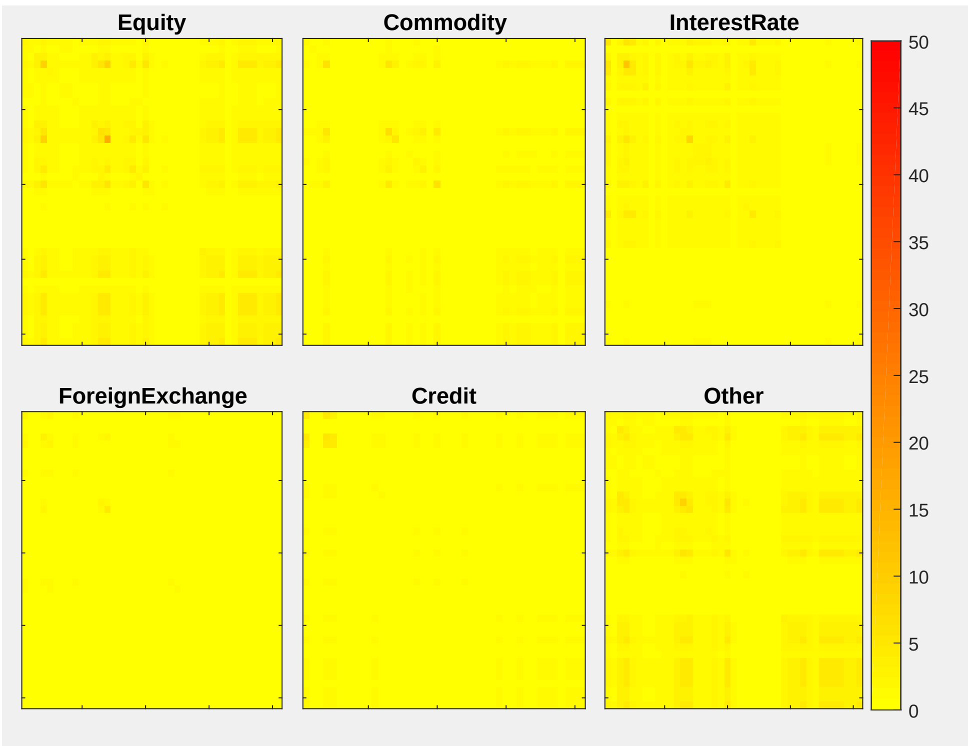
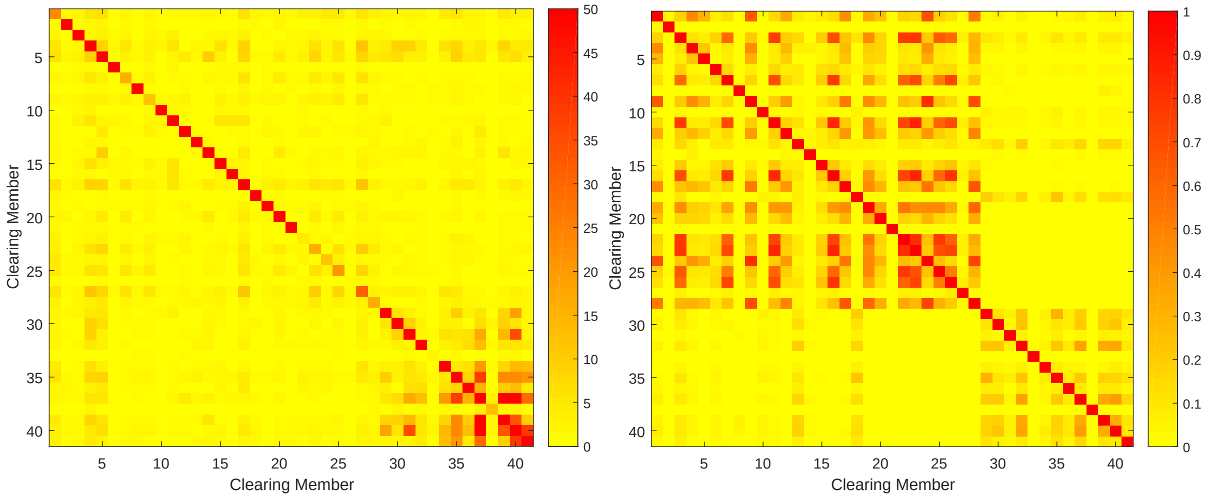


Figure 13: Number of common edges between the most significant clearing members on the CCP-clearing member network per layer.



(a) Number of common edges

(b) Weighted Jaccard Index

Figure 14: Similarity between the most significant clearing members on the complete network.

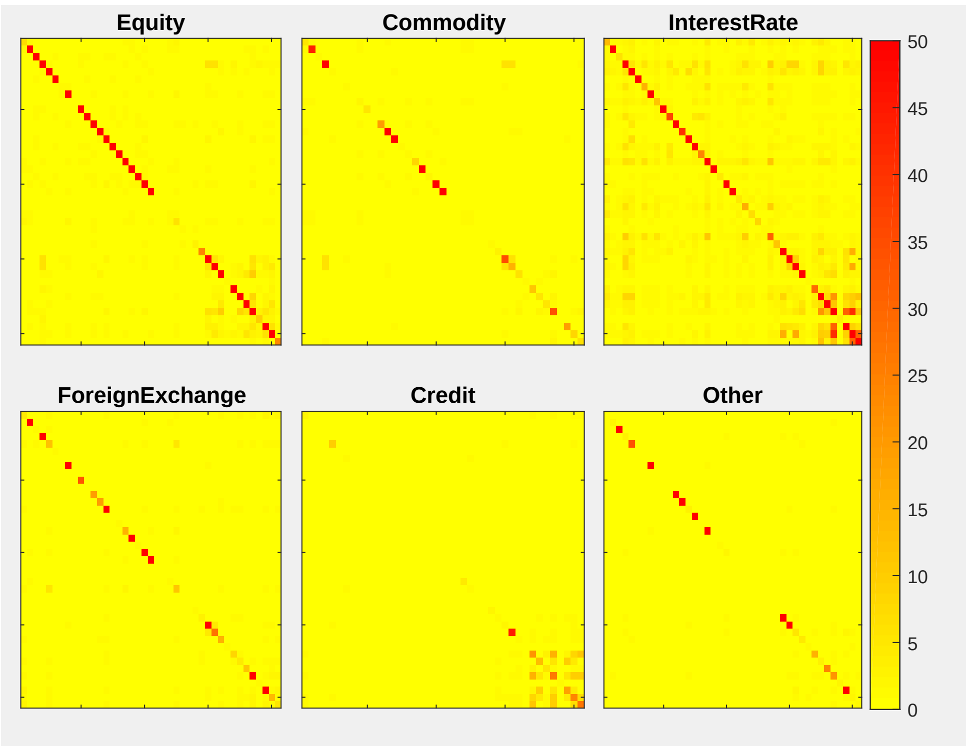


Figure 15: Number of common edges between the most significant clearing members on the complete network per layer.

From the first two figures (Figures 12 and 13, in which the network is limited to the CCP-clearing members edges) it is immediately evident the clearing members that are simultaneously participating to several CCPs. This information is fundamental for example when defining the scope of macro prudential stress testing as authorities may wish to define the perimeter of the test by capturing all or the most relevant common CCPs, including those outside their jurisdiction. There are 6 euro area clearing members that participate in the same 10 CCPs and there are 4 non euro area clearing members that participate in the same 5 euro area CCPs. Analysing the single layers, we see that the highest common CCP participation is in the equity layer (where the number of active CCPs is higher). The phenomenon is also present in the interest rate layer but it is relatively limited among euro area clearing members (i.e. few non euro area clearing members participate to the same euro area CCPs, denoting a possible product of country specialisation). Similarity is also very high when analysing the weighted Jaccard index.

Finally we analyse the similarity of the clearing members in the complete network to gain an insight on the phenomenon of common clients of clearing members (Figures 14 and 15). The overall picture is that the number of common clients is generally low. Euro area clearing members share a relatively small number of (presumably large) clients between them with the maximum number of common clients being below 20. This can point to the specialisation of clearing members either by product or by country. It is interesting to notice that non euro area clearing members share between themselves more euro area clients: there are three clearing members that share about 60 clients, pointing to the relatively larger presence of multi-homing or large clients that access the derivative market from outside the euro area. The analysis of the asset class layers individually shows that the common clients of non euro area clearing members phenomena is particularly relevant for the interest rate layer but also in the credit derivative layer where there are 6 clearing members sharing between 11 and 15 clients (the latter is not negligible considering that in the credit derivative layer the average degree is about 5). Analysing the weighted Jaccard similarity index, we notice a high level of similarity, both among euro area clearing members and among non euro area clearing members, indicating that although the number of common clients is low, there are few common clients that have a large exposure. Those clients are likely large clients such as large corporations or large financial institutions.

5 Conclusions

Based on the analysis of the data provided under the EMIR Regulation presented above, we reconstructed the network of relationships in the centrally-cleared derivatives market between clearing members and CCPs, as well as that between clearing members and their clients. We subsequently analysed the topology of this network providing insight into its structural features. On the basis of different centrality measures applied to the aggregate network and to the multiplex network, the critical participants of the euro area centrally-cleared derivatives markets were successfully identified. Our analysis provides a clear snapshot of the critical nodes (CCPs and clearing members) of the derivatives markets, including a quantitative estimation of their interconnectedness within and across the different market segments.

The analysis shows that the level of interconnectedness in the euro area cleared derivatives market is high. The systemic importance of a node is reinforced by its direct and indirect connections with the rest of the system, both through the same asset class and across asset classes: many clearing members participate simultaneously in several CCPs and markets, and can act as connecting links across otherwise unrelated CCPs and market segments. Moreover there are nodes that despite maintaining few relationships and showing a relatively low exposure level towards other nodes, are nevertheless central because their presence in several market segments means they can potentially act as a channel of contagion across layers or communities in the same network. While interconnections may act as vehicles for the transmission of stress or contagion, it is worth stressing that interconnections can reinforce the resilience of the network by ensuring the impact of a shock is absorbed by a larger number of entities and, in fact, the analysis of similarity points also to a good level of substitutability.

The analysis also shows the significance and concentration of client clearing. The identification of the main euro area and non-euro area clearing members acting as entry point to the cleared market and serving large communities may guide the selection of the most critical service providers to be included in a future stress test exercise focusing on the porting of clients' positions in the case of the default of a major provider. At the same time, the limited number of common clients shared by clearing members may signal some limited substitutability at the level of clients. In general, the area of client clearing is relatively unexplored in the literature and deserves further attention by researchers.

We believe that this type of analysis is useful for authorities and regulators from different perspectives: we found evidence of strong market integration (in the form of strong interdependencies due to common clearing members) across euro area and non-euro area CCPs but also at the level of clearing members.

This confirms the need to continue and upscale authorities' efforts to carry out supervisory-led, macro-prudential CCPs stress testing, given that each CCP individually does not have and can-

not integrate information on such interdependencies into its own stress tests. Macro-prudential stress testing should be seen as an important complement to the stress tests that each CCP conducts to calibrate the size of initial margin and guarantee funds that it collects from members. Moreover, the significant interdependencies identified across the euro area and non-euro area call for a carefully designed geographical perimeter of macro-prudential stress tests, and show the limits of keeping a jurisdictional focus in a market that is intrinsically global. If authorities are to better understand and monitor risks in an increasingly interconnected world, it is imperative that obstacles to sharing data or intelligence are removed. In this respect, progress has been made with the adoption of international technical standards, but work remains to be done on the legal front, e.g., in the form of establishing confidentiality safeguards and cooperative frameworks across all the relevant jurisdictions.
Finally on the methodological side, the application of multiplex network analysis confirms the existence of non-linearities, hence the risk of underestimating the centrality of nodes if the network is studied only at the level of a specific product class, or even only at aggregate level.

While the analysis performed in this paper is of a static nature, we leave to our future work the analysis of the dynamic properties of the network, i.e. the analysis of how the network structure may affect the potential transmission of financial shock across CCPs and their clearing members. As the network described above has multiple layers, corresponding to different derivatives product classes, a fully comprehensive analysis of this kind would involve the introduction of a financial stress to the network of CCPs and clearing members, followed by a coherent and robust method for monitoring the possible propagation of this stress throughout the full clearing network, including across product class layers. In this context it would be important to consider whether the assumptions made by each CCP about the liquidation prices of its collateral are conservative enough, considering the significant share of common participants and the likelihood that different CCPs may be liquidating positions in parallel.

A Key concepts on central counterparty clearing

A CCP is a financial market infrastructure that guarantees the execution of transactions of its members, hence eliminating the credit risk from original bilateral trade exposure and replacing it with a (netted) exposure versus the CCP alone. Following contract novation, the CCP becomes the seller to all buyers and the buyer to all sellers. The CCP also reduces the exposures of its members via multilateral netting and guarantees contract execution even in case of default of one of its members. This is possible because CCPs:

- Have a neutral market risk profile: they keep a "matched book" (as seller to all buyers and buyer to all sellers), hence do not take any proprietary positions on the portfolios they clear, and they are exposed to market risk for the replacement of the position only in case of a member's default (see below).
- Are specialised and sophisticated risk managers, and do not allow members' profit or losses to accumulate over time: they mark to market positions frequently (daily, and in some cases also intraday), and request members whose positions decreased in value to pay-in variation margin (and in turn the CCP pays out to members whose position increased in value).
- Collect collateral from members and have predefined procedures to manage a member's default in addition to a series of financial safeguards in place that can be mobilised to cover the related losses that may arise ("Default waterfall"). This allows CCPs to continue to fulfil their obligations versus the non-defaulting members, including when a default occurs in stressed market conditions. Positions at the CCP need to be collateralised, and CCPs collect "initial margin" from each member to cover potential future losses in the value of members' open positions; CCPs employ sophisticated models which are subject to comprehensive stress testing (including historical and hypothetical scenarios) in order to determine the amount of collateral needed. They only accept high quality and liquid collateral and apply conservative haircuts. The initial margin requirements are determined in a way that allows the CCPs to cover potential losses due to adverse market developments for a period until it successfully liquidates the position (the so-called "margin period of risk" whose duration depends on the liquidity of the cleared instruments and is subject to regulatory requirements). In more serious circumstances, if losses exceed the defaulted

counterparty's margin, the CCP would proceed to liquidate the position via a predefined default management process which may include carrying out auctions among members (to allocate parts of the position on a voluntary basis and facilitate the liquidation of the residual position in the market[15]). If the defaulted member was clearing on behalf of indirect clients, the CCP will also attempt to transfer these clients' positions to other clearing members willing to accept them (a process called "porting" of clients positions).

- Rely on an intrinsic mutualisation principle, meaning that residual losses that exceeded the defaulter's resources would be shared by multiple parties with each having to absorb a relatively smaller loss. When the defaulter's initial margin is insufficient, the CCPs would tap on additional resources according to their pre-defined waterfall sequence. Typically, this would include tapping first on the defaulter's contribution to the CCP guarantee fund, then a part of the CCP own resources ("skin in the game"), then potentially mutualised resources from the surviving members (i.e. their contributions to the default fund). CCPs also have under their Rulebooks, a right to call on further contributions from members (powers of assessment or cash calls). Usually a waterfall would envisage that before calling on unfunded resources from surviving members a CCP would have to commit another part of "skin in the game", i.e. its own capital equity. Eventually, a recovering CCP which reaches the end of the waterfall may resort to more extreme measures e.g. variation margin gains haircutting (where the CCP would not pay in full the variation margin to members with mark-to-market gains, irrespective of whether or not such members had any trade originally with the defaulter, or (voluntary or mandatory) partial tear-ups (where the CCP terminates the defaulted open contracts in order to restore a matched book so that it can restore normal operations and continue to perform its function[16]).

- Ensure transparency: the fact that CCPs manage central books with a complete overview of members' positions and have a set of clear, pre-defined procedures in place to manage the default of a member ("default management process") with detailed rules and a clear sequence of steps, ensures the needed transparency among members on how a pathological event such as a member default unfolds. This contributes to counter uncertainty in the

[15] The CCP would typically carry out macro-hedges of the portfolios or parts of it, in order to enhance its risk profile and facilitate its auctioning and liquidation. For these trading activities CCPs have a right to request the assistance of their members, including members' staff deployment at the CCP.

[16] For a more detailed discussion of CCPs loss allocation tools in recovery and resolution and their respective advantages and disadvantages see Gibson (2013) and CPMI-IOSCO (2017)

market (a condition that in itself has the potential to exacerbate fears during events of market stress, potentially spiralling into protective behaviours by market participants and exacerbating further the market stress).

B The data cleaning and preparation process

The process for the cleaning and preparation of the data set is composed of several actions described in the following. As explained above we analyse the trade state reports only.

- Asset class classification: transactions are classified according to the underlyer of the derivative transaction into six different categories defined in the EMIR Regulatory Technical Standards: Equity, Commodities, Interest Rates, FX, Credit and Other. The classification of the underlying asset class is based on information provided by the reporting counterparty. Counterparties are requested to report or directly the category of the underlying asset or using the ISO10962 CFI (Classification of Financial Instrument) code. In case of CFI code reporting, the category of the asset class cannot be always identified uniquely because the same code could refer to different asset classes. Transactions for which we are not able to uniquely identify the asset class are classified under the "Other" category that includes also transactions for which the asset class is not unique (as for instance derivative transaction based on basket of mixed asset classes) or the underlyer does not fall in any of the other category.

- Removal of spurious transactions: in the dataset several transactions have been identified as not correctly reported or maintained, but remained "alive" in the trade repository system. To avoid such spurious transactions, those transactions are removed from our dataset if the mark to market value of the trade was not updated since at least 100 days. Removing such transactions we assume that, since the valuation update is a mandatory requirement for the reporting counterparties under EMIR, they are closed or expired transactions that are still in the TR system by mistake.

- Creation of counterparty list: for dealing with the double reporting obligation we create the list of counterparties by processing all the transactions in the dataset and classifying the counterparties into four categories: CCPs, Clearing members, credit institutions, and other counterparties. To this aim, first, we build a static data set of CCPs' LEIs on the basis of the list of CCPs authorised to offer services and activities in the Union and the list of third-country CCPs that are recognised to offer services and activities in the Union. Both lists are maintained and published by ESMA according with Article 88(1) of EMIR. By using the list of CCPs, we identify all clearing members by collecting all counterparties that have at least one direct relationship (i.e. it is counterparty of at least one transaction) with a CCP. The remaining counterparties are clients of the clearing members and are classified as credit institutions or other counterparties on the basis of the sector classification provided by the reporting counterparty. In addition to the category, each counterparty is classified as belonging to the euro area or outside.

- Mark to market quality improvement: to improve the quality of the mark to market valuation of the trade, we exploit the fact that some transactions are reported twice (according to the double reporting obligation) and that some market actors are supposed to be more reliable than others. In particular we assume that the CCPs report better than other counterparties, that clearing members report better than the others and so on. Under this assumption, we compare information provided in all the transactions that are double reported (and that we are able to couple) and in case of mismatching in the reported mark to market value we retain the value reported by the counterparty we assume to be more reliable. In this step we also remove replicas of the same transaction that is reported more than once on behalf of the same reporting entity: we identified, in fact, several cases in which the reporting obligation is fulfilled by the reporting entity itself and by another entity on behalf of the reporting counterparty, e.g. we identified cases in which the CCP reports the transaction to fulfil its obligation, but reports the same transaction also on behalf of the clearing member; in addition the clearing member reports the transaction by itself.

- Double reporting avoidance: the last step we perform is the double reporting avoidance step that we use to avoid the double counting of double reported transactions. In order to avoid the double counting of transactions (and of the mark to market values) reported twice we follow a three-step approach by segregating the reporting entities into three categories: CCP, clearing members and others. In the first step we take into account all records reported by CCPs that are established in the euro area. As a second step we consider all the transactions reported by euro area clearing members excluding those against euro area CCPs as counterparties because they have already been processed in the first step. For all transactions between euro area clearing members we divide by two the value of the mark to market value because we know that such transactions are reported twice and accounted twice in this step, whereas for transactions with non euro area clearing members and with other counterparties independently of the country of residence, the mark to market value is considered entirely since the transactions are not reported twice and/or accounted twice in this step. In the third step, we process all transactions reported by other euro area counterparties (credit institutions and non) excluding those with euro area clearing members as counterparties since they have already been processed in the second step. Similarly to step two, the mark to market values of transactions between euro area counterparties are divided by two.

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