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An assessment of the Portuguese OTC Market Network Structure under EMIR

Bringing light to the Portuguese OTC CDS Market

Project Work proposal presented as partial requirement for obtaining the Master's degree in Information Management, with a specialisation in Knowledge Management and Business Intelligence

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
Universidade Nova de Lisboa

AN ASSESSMENT OF THE PORTUGUESE OTC MARKET NETWORK STRUCTURE UNDER EMIR

BRINGING LIGHT TO THE PORTUGUESE OTC CDS MARKET

by

Sónia Alexandra Baptista Pedro

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Supervisors: Flávio L. Pinheiro (NOVA IMS) / Tarik Roukny (Leuven University)

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DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.
This work has not been previously evaluated or submitted to NOVA Information Management School or elsewhere.

Lisbon, 22/11/2019

Sónia Pedro

[The original has been archived by the NOVA IMS Services]

To R., "*my counterparty in life*"…

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ABSTRACT

Here we provide a data-driven network analysis of the *Over-the-Counter* (**OTC**) Portuguese Market under the European Market Infrastructure Regulation (**EMIR**). We do it so from the point of view of the Regulator, thus focusing in how different regulation instruments can be improved through a network abstraction and analysis of the **OTC** market. Such approach, we argue, can allow regulators to answer complex questions: Who are the players in the Portuguese **OTC** *Credit Default Swps* (**CDS**) Market, and how is it structured?

In this paper we provide, as a starting point, the study and characterisation of the **OTC CDS** Derivatives Market. By using a multi-segment approach, we were able to build three networks that represent the Portuguese **OTC CDS** Market: (1) **PT Products + PT Participants** segment; (2) **PT Products** segment; and (3) **PT Participants** segment. The analysis of the first two networks showed that activity, at its scale, is very similar to the European landscape, highly clustered in a small number of counterparties, with the *Central Counterparties* (**CCPs**) and the entities of the *Group of 16* (**G16**) assuming the leading positions while the counterparties of the United Kingdom have the lion share in the **OTC CDS** Derivatives Market. However, when we place the focus only on the **PT Participants** segment, e.g., Portuguese players active in the **OTC CDS** the **CCPs** are replaced by Banks and there is a clear preference for the non-domestic Market and non-cleared transactions.

KEYWORDS

EMIR; Portugal; Trade Repository; OTC Derivatives Regulation; Network analysis

RESUMO

A nossa análise de rede baseada em dados do Mercado de Balcão (**OTC**) português ao abrigo do Regulamento Europeu de Infraestrutura de Mercado (**EMIR**) do ponto de vista do regulador, com enfoque em como diferentes instrumentos de regulamentação podem ser aprimorados por meio de uma abstração de rede e análise do Mercado **OTC**.

Argumentamos que essa abordagem pode permitir que os reguladores respondam a perguntas complexas: quem são os participantes no Mercado **OTC** *Credit Default Swaps* (**CDS**) português e como está estruturado?

Neste documento, fornecemos, como ponto de partida, o estudo e a caracterização do Mercado **OTC CDS** português. Recorrendo a uma abordagem multissegmento, permitiu-nos construir três redes que representam o Mercado **OTC CDS** português: (1) ***PT Products* + *PT Participants*** *segment*; (2) ***PT Products*** *segment*; e (3) ***PT Participants*** *segment*. A análise das primeiras duas redes mostrou que a atividade, à sua escala, é muito semelhante ao panorama europeu, altamente concentrada num pequeno número de contrapartes, em que as *Contrapartes Centrais* (**CCP**s) e as entidades do *Grupo dos 16* (**G16**) assumem as posições de liderança, enquanto que as contrapartes do Reino Unido ocupam um lugar primordial no Mercado de Derivados **OTC CDS**. No entanto, quando o foco são as transações de contrapartes portuguesas em Mercados de Derivados **OTC CDS** (***PT Participants***), as CCPs são substituídas pelos Bancos e a preferência recai sobre os mercados não domésticos e transações sem compensação.

PALAVRAS CHAVE

EMIR; Portugal; Repositórios de Transações; Regulamentação Derivados OTC; Análise de redes

LIST OF ABBREVIATIONS AND ACRONYMS

ID	Identification
BIS	Bank of International Settlements
BdP	Portuguese Central Bank (*Banco de Portugal*)
CCP	Central Counterparty
CMVM	Portuguese Market Supervision **(***Comissão do Mercado de Valores Mobiliários*)
EMIR	European Market Infrastructure
ESRB	European Systemic Risk Board
ESMA	European Securities and Market Authority
EU	Europe
G16	Group of Sixteen
G20	Group of Twenty
GLEIF	Global Legal Entity Identifier Foundation
ISIN	International Securities Identification Number
ITS	Implementation Technical Standard
LEI	Legal Entity Identifier
MiFID II	Markets in Financial Instruments Directive II
MiFIR	Markets in Financial Instruments Regulation
NCA	National Competent Authority
OTC	Over-the-Counter
Q&A	Questions and answers
PT	Portugal
RTS	Regulatory Technical Standard
TR	Trade Repository
TRACE	ESMA system for EMIR data
UK	United Kingdom
US	United States of America

GLOSSARY

Central Counterparty (CCP)	A legal entity that interposes between the counterparties to the transaction (the buyers and the sellers) on derivative contracts (e.g. becomes de seller for each buyer and vice versa).
CMVM	The Portuguese Market Supervision (*Comissão do Mercado de Valores Mobiliários*), was established in 1991 as an independent public institution, benefiting from financial and administrative autonomy from the Portuguese Government, to supervise and regulate the Portuguese financial market, its products and market players.
Dodd-Frank	The Wall Street Reform and consumer protection act, of 21 July 2010. This Regulation was the answer of the US government to the financial crises of 2008 and bought changes to the American financial regulatory environment.
EMIR	The Regulation nº 648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories. The Regulation is in force since 2014.
ESMA	The European Securities and Markets Authority is an independent European authority with the objective of improving the investor protection, and promote stable, orderly financial markets.
GLEIF	The Global Legal Entity Identifier Foundation is a supra-national non-profit organisation based in Switzerland. Established in 2014 by the Financial Stability Board its aim is to support the implementation and use of the Legal Entity Identifier. GLEIF is supported and overseen by the LEI Regulatory Oversight Committee (LEI ROC), which represent public authorities from around the globe.
Group of Sixteen (G16)	Group that includes the sixteen largest derivatives dealers across the globe: Bank of America, Barclays, BNP Paribas, Citigroup, Crédit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, Société Générale, UBS, and Wells Fargo.
Group of Twenty (G20)	International forum constituted by the world's 20 leading industrialised and emerging economies.
ISIN	The International Securities Identification Number is a 12 character alphanumeric code that uniquely identifies a financial instrument worldwide. It has three parts: first two letters identify the country code (as per ISO 3166), followed by 9 alphanumeric characters identifiers of the financial instrument assigned by the competent entity in each country. The last character is a check, which will validate the ISIN code.
LEI	The Legal Entity Identifier is an unique global identifier of the entities participating in the financial markets. The LEI is a 20 alphanumeric character based on ISO 17442.
MiFID	The Markets in Financial Instruments Directive (Directive 2004/39/EC of the European Parliament and of the Council of 21 April 2004 on markets in financial instruments amending Council Directives 85/611/EEC and 93/6/EEC and Directive 2000/12/EC of

	the European Parliament and of the Council and repealing Council Directive 93/22/EEC). The Directive was implemented in 2007.
MiFID II	The revamped version of the MiFID. The Directive complements the MiFIR and pertains to bring more transparency to all asset classes (equities, equities look alike and non-equities) in the financial markets (Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments and amending Directive 2002/92/EC and Directive 2011/61/EU).
MiFIR	The European Regulation (Regulation (EU) nº 600/2014 of the European Parliament and of the Council of 15 May 2014 on markets in financial instruments and amending Regulation (EU) No 648/2012) applicable to securities markets across the European Union aimed to protect the markets and its investors. The Regulation is in force since 2014.
Over-the-Counter (OTC)	Transactions outside an organised financial market (commonly known as Stock Exchanges) where the parties bilaterally agree all the terms of the transaction.
Trade Repository (TR)	A legal person that centrally collects and maintains the records of derivatives transactions**.**
Counterparty	An entity that is part of a transaction.
Clearing Members (CM)	An entity that is member of a CCP and takes responsibility for the financial commitments of customers that clear through their firm.
Financial Counterparty (FC)	According to EMIR, are credit institutions, investment firms, investment funds or their management companies, institutions for occupational retirement provision and undertakings in insurance, assurance, and reinsurance established in the EU.
National Competent Authority (NCA)	(or Regulators) Organisations that have the legally delegated or invested authority, or power to perform a designated function, normally monitoring compliance with the national statutes and regulations.
Non-Financial Counterparty (NFC)	According to EMIR, are entities established in the EU other than a CCP or a FC, which includes small and medium-sized companies.
TRACE	ESMA systems that provide a single access point to the European NCAs to the TR data (transaction data reported to these entities in compliance with EMIR).

QUOTES

All the quotes within this work are summarised (authors and year of publication).
The reader should refer to the **Section 6** of this work for the complete list of the bibliographic references.
All the references in that section are ordered in alphabetical order.
Additional footnotes within provide short and complementary information to the text.

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1. INTRODUCTION

The 2008 financial crisis resulted in a sequence of events that shook the financial system worldwide. Losses resulting from the crisis are estimated to top up to as much as 22 Trillion US Dollars (United States Government Accountability Office (GAO), 2013). It represented the collapse of the *Over-the-Counter* (**OTC)** Derivatives Market.

One of the most well-known and reported events that unfolded during the crisis was the downfall of the Lehman Brothers and the consequent chain of events that followed it. At a first glance, those events could be seen as random. However, a closer look reveals complex web of interdependences between financial institutions that dictated the sequence of events, with Lehman at its core. The story of the 2008 financial crisis is that of the inherent systemic risk embedded in a complex but fragile financial system, the story of a cascade of events, and in particular, of the vulnerability of a system to the collapse of a few, but central, elements.

The **OTC** Derivatives Markets are markets where the parties involved in each transaction pre-agree totally or partially all the characteristics of the financial instrument as well as the terms of the transactions to meet their hedging or business needs (**OTC** Derivative contracts) and cost reductions, not achievable through the standardise Regulated Market (Exchange derivative contracts) (McGill & Patel, 2010). In Stock Exchanges worldwide such hedging is not always possible as the contract characteristics are pre-defined and standardised leaving a very limited optionality for its participants when trading Exchange derivative contracts: price (except its granularity) and volume of the transactions. The flexibility and the possibility to create a contract that fits the hedging needs of the counterparties make the **OTC** Derivative Markets very popular amongst the major players of the financial markets worldwide (Group of Sixteen – **G16** or major international banks).

As a matter of example, generally in a Stock Exchange (i) all prices of the financial instruments are publicly disclosed and updated in real-time providing information across all participants; (ii) anyone with access to the market can enter into a transaction at the publicly available prices; (iii) the maturity date (date at which the seller delivers the underlying to the buyer and receives the pre-agreed amount) is a fix date defined and published by the Stock Exchange; (iv) once a transaction takes place in a Stock Exchange its data (price, volume, maturity) is publicly disclosed. On the complete opposite side, the players in the **OTC** Markets agree the prices between themselves as well as the maturity (i and iii). Moreover, prior to *European Market and Infrastructure Regulation* (**EMIR),** no one apart from those involved in such agreement had access/knowledge about the price or even that the transaction has taken place. Such opposite characteristics lead to the surge of several labels when referring to Stock Exchange Markets (**SE)** and **OTC** Markets (**OTC**) over the years: transparent (**SE**) vs dark (**OTC**), regulated (**SE**) vs unregulated markets (**OTC**), standardised (**SE**) vs non-standardised (**OTC**).

The story of the **OTC** Derivatives Market collapse is in many ways similar to story of many other complex systems, and of the type of cascade events of failures that can stem from the collapse of a few of its elements. Classical examples in the literature include, the risk of large scale blackouts from the overload of individual components (i) in power grid structures (Chassin & Posse, 2005); (ii) in the internet, the incorrect load balancing in the elements of its infrastructure can greatly impair internet traffic (Apps Team, 2012); (iii) in electronics the failure of individual components can result in large scale fail of the entire system (Schroeder & Gibson, 2005); (iv) in ecology regime shifts (e.g., the extinction of a specie) in one ecosystem can lead to a string of events along interdependent ecosystems (Rocha, Peterson, Bodin, & Levin, 2018).

Underlying a cascade of failures in complex systems is always a well-defined network of interdependences along which failures will spread and scale. Hence, to truly understand the susceptibility of the system to the failure/collapse of a few individual elements we need to first understand the underlying interaction structure between its elements. In the context of financial markets, these ideas have already been pushed forward (Abad et al., 2016; D'Errico, Battiston, Peltonen, & Scheicher, 2018; Daron Acemoglu, Asuman Ozdaglar, & Alireza Tahbaz-Salehi, 2015; Levels, van Stralen, Kroon Petrescu, & van Lelyveld, 2018) to help identify, or better understand, the complex patterns that emerge from events such as the 2007/2008 crisis.

In the aftermath of the 2007/2008 crisis, the *Financial Crisis Inquiry Commission Report* (Federal Crisis Inquiry Commision, 2011) stated that there was not sufficient information available regarding the systemic risk of **OTC** Derivative Markets. Nowadays, data has been made available through new market-wide regulations (such as the **EMIR**) in Europe or the Dodd-Frank Act in the United States. Regulators are now empowered with the necessary data to more effectively develop the necessary regulatory instruments to regulate the **OTC** Derivatives Markets (Benos, Wetherilt, & Zikes, 2013). One important aspect of the newly available data is the level of transparency it brings to a previously opaque market, which was mainly due to the bilateral nature of the transactions carried out. The basis of **EMIR** relies on the willingness of the *Group of Twenty* (**G20**) to ensure more transparency to the OTC Derivatives Markets

Regulators can now apply data-driven approaches to:

- Understand the undergoing activity on the **OTC** Derivatives Market;
- Test ongoing supervision action plans;
- Develop new regulatory instruments; and
- Reinforce measures that promote orderly and fair markets;

In that context, here we focus on the study of the Portuguese **OTC CDS** Market (see **Section 3**). While past works have focused in data from a single *Trade Repository* (**TR**), by looking at the **OTC** Derivatives Market at the European Level, and/or using **EMIR** data sets from before its revision in November 2017 (Abad et al., 2016; European Securities and Markets Authority, 2017, 2018a). It is noteworthy to mention a study dedicated to get insight on the Irish *Credit Default Swaps* (**CDS**) Market by exploring the **EMIR** state report from the **DTCC** before November 2017 (Kenny, Killeen, & Moloney, 2016), and the study dedicated to the Dutch **CDS** Market using a daily time-series data set from **DTCC** instead of a snapshot (transaction report rather than state report) (Levels et al., 2018). We believe that such studies as well as the work developed herewith, can be key for supervisors, market players, and policymakers EU-wide. To that end, in this work we use the trade reports from 2018 to explore the quality of the existing data, and the Steps necessary to perform a network analysis with regulatory purposes as the goal. In particular we approach the following questions:

- Who are the players in the Portuguese **OTC CDS** Derivatives Market under **EMIR**?
- What type of market players exist in the Portuguese landscape?
- How the different market players are interconnected?
- How is the market structured?
- Are there any players that can represent a risk to the network (e.g. in case of failure)?

With this work we hope not only to contribute to complement the existing studies on the **CDS** using **EMIR** data with more recent data sets (2018) but also to kick off the usage of a data science approach for better regulation. In order to achieve that we took a multi-segment approach that consist in the segmentation of the data sets into 3 segments all linked to the Portuguese **OTC CDS** Market: (1) starting from a broader view where we took into consideration all reports where the transaction involved a Portuguese **OTC CDS**, and at least one of counterparties is Portuguese – **Portuguese Product and Portuguese Participants** segment **(PT Products + PT Participants** segment**)**; (2) **Portuguese Product** segment **(PT Products** segment**)**, where we looked at the reports with transactions involving a Portuguese **OTC CDS** (e.g., a product identified with a Portuguese **ISIN**) ; and (3) the strictest segment – **Portuguese Participants** segment **(PT Participants** segment**),** where we look only to the network where at least one of the counterparties involved in the transaction in an **OTC CDS** is Portuguese.

This working paper is organised as follows: **Section 2**, provides a brief overview of the literature focused in contextualising the financial crisis of 2007/2008 and the **EMIR**, summarising past studies, and introducing the necessary network science methods to understand the work developed; **Section 3**, discusses the pre-processing of the data used in this work; **Section 4**, discusses the cleaning process as well as the network analysis of a sub asset class of Credit Derivatives: the Credit Default Swaps; **Section 5** presents the conclusion and remarks also mentioning the main limitations of this work and future opportunities.

2. OVERVIEW

Here we provide a brief overview to the elements necessary to understand the work conducted for this work, the background context, and its implications. **Section 2** is divided in four subsections: (i) in **Subsection 2.1** we introduce the background to the financial crisis of 2007/2008 as well as the *European Market and Infrastructure Regulation* (**EMIR)** that resulted from the crisis in an attempt to better regulate the *Over-the-Counter* (**OTC**) Derivatives Market; (ii) **Subsection 2.2** discusses the background of **EMIR**, its main objectives, and participants; (iii) **Subsection 2.3** provides a brief review of what are **OTC** Derivatives, including a dedicated section to the Credit Default Swaps, which we studied in more detail in this work; (iv) **Section 2.4**, introduces the key fundamentals of network science necessary to understand and replicate the analysis performed later in this work, with a special focus to past applications to the study of financial markets.

2.1. THE FINANCIAL CRISIS 2007/2008

In the aftermath of the financial crisis of 2007/2008 policymakers, governments, and the *Group of Twenty (***G20**) committed to improve transparency of derivatives markets across the world. However, long after the crisis, the extent of its damage continued to be based only in rough estimates and much is still left to uncover. The reason being the lack of transparency to clearly identify the existing bilateral agreements between Lehman Brothers and its counterparties, and consequently link losses and bankruptcies that resulted from the Lehman's collapse. Due to the opacity of bilateral agreements between parties in the **OTC** Derivatives Markets, very common on the **OTC** landscape, some authors like (Duffie, 2012) labelled these "markets" as "*dark markets*".

As pointed by (Cielinska, Joseph, Shreyas, Tanner, & Vasios, 2017) opaque markets, such as the **OTC** Derivatives Market, do not share information about counterparty and network exposure to both the financial market players and the Regulators.

The derivative transactions, in particular those bilaterally traded such as the **OTC**, were considered as the fuse (see **Subsection 2.3** for more details) to the financial crisis, as highlighted by (Yellen, 2013) in her speech to the *American Economic Association*. As presented by Yellen, the **OTC** Derivatives proven to be an important channel for the transmission of risk during the financial crisis.

In face of the crisis, the **G20** members, in their 2009 statement in Pittsburgh (Leaders' Statement, 2009), endorsed the draft of new regulations to bring more transparency to the **OTC** markets and its products.

The mandate from the **G20** members seems natural as several authors pointed the crisis and the need for more transparency as an important Step to the opaque Derivatives Markets and the **OTC** Derivatives in particular (Abad et al., 2016; D'Errico et al., 2018; Daron Acemoglu et al., 2015; Levels et al., 2018). Whereas, (Garslian, 2016) in its paper reminded that the role of these products in the financial crisis was controversial as the convergence of opinions leaded to "*endless debates regarding the role OTC derivatives played in that crisis and, thus, the necessary extent of OTC derivatives regulation*."

2.2. The European Market and Infrastructure Regulation (EMIR)

The *European Market and Infrastructure Regulation* (**EMIR**) aims at meeting the goals set by the *Group of Tenty* (**G20**) recommendations, and focuses in four main areas: (i) transaction reporting and record keeping; (ii) trading on trading venues[1]; (iii) central clearing; and (iv) margining and capital requirements hence the reduction of the systemic risk.

EMIR brought harmonised rules across the European Union's Member States and facilitated regulatory coordination, that is, coordination between regulators from different European (**EU**) Member States, integration in the international financial system, and the enforcement of the rules to counterparties with a cross boarder operation. As stated by (Godwin, Ramsay, & Sayes, 2017), the **OTC** Derivatives are global in the general sense but also as they relate to financial markets hence the need to have a solution that is cross-border "*both regional and global*" to be more overarching.

The entities under **EMIR** are identified and labelled consistently across Europe according to their type (European Comission, 2012): (i) *Financial Counterparties* (**FC**) that include banks, brokers, asset managers, and insurers; (ii) *Non-Financial Counterparties* (**NFC**) consisting mainly of corporates, (iii) *Central Clearing Counterparties* (**CCP**) and their *Clearing Members* (**CM**).

New players joined the Derivatives Markets such as the *Trade Repositories* (**TR**). These players have the responsibility to collect and maintain the records of all Derivative transactions in the **EU** reported by the aforementioned entities, as well as to make such information available to the *European Securities and Markets Authority* (**ESMA**) and to each of the national competent authority (the regulators of each **EU** Member State[2]). The **Figure 1** below represents

[1] Stock Exchange or trading platforms.
[2] Each National Competent Authority (**NCA**). In Portugal the supervision of EMIR is of the responsibility of the Portuguese Market Supervision (CMVM), the Portuguese Central Bank (BdP) and the Funds and Insurance Association (ASF) has the mandate to apply, supervise and monitor the application of the EMIR to the OTC Derivatives Market and the market players under its supervision. On a daily basis, the NCAs access the information allowing these supervisors to monitor the compliancy of the Regulation.

the flow of data between the counterparties, the **TR**s, ESMA and the *National Competent Authorities* (**NCA**s). Each counterparty sends the reports to at least one **TR** (for the complete list please refer to **Table 13** of **Section 7**). After data consistency validations the **TR** sends the data to **ESMA**, and then the latter makes the data available to each European **NCA**. **ESMA** hub centralises all the information in a single place, however the **NCAs** only have access to the data it concerns, and basket[3] data.

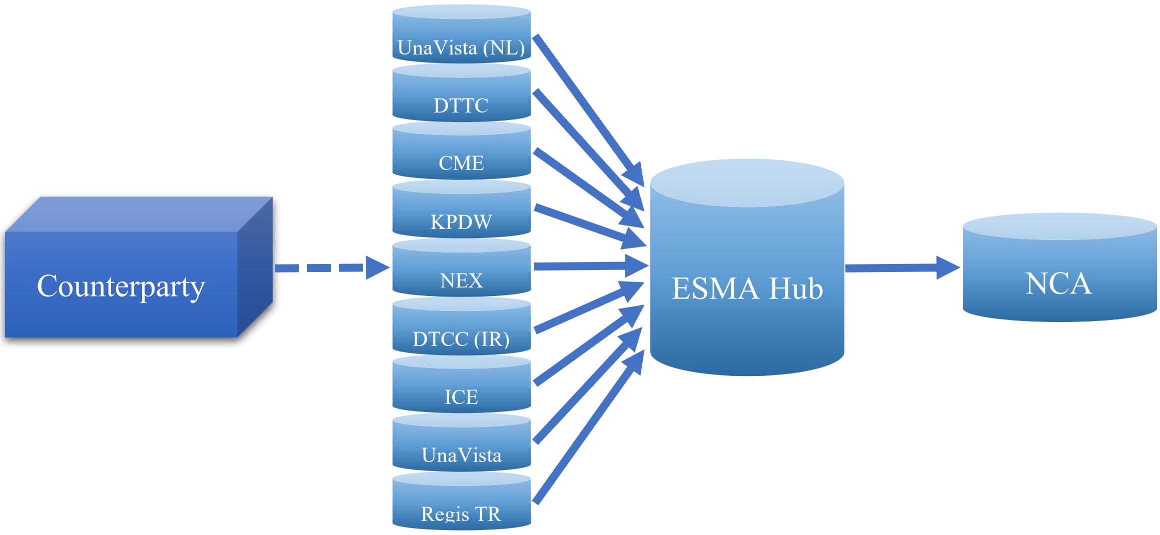

Figure 1 – Authorised Trade Repositories (**TR**) under **EMIR** as of March 2019

In the period in hands, the **TRs** provide data of two types: (i) the detailed data available through the daily transaction reports, and (ii) the aggregated data available through the state report. In the first 22 months of the **EMIR**, 27 billions of records were received by the **TRs** (European Securities and Markets Authority, 2017) and each of those records had more than 80 fields/variables, which contained relevant information to understand the overall European Derivatives Markets.

As pointed out by (Cielinska et al., 2017) with **EMIR**, policymakers, regulators, and researchers can now observe the trading activity and the network of exposures close to its execution, which provides them the ability to identify the systemic risk within the financial system. The downsize, however, is posed by the new challenges and limitations that the mix of the high volume of data and its complexity brings to its potential users.

The huge data sets on Derivatives that are now available to the European national competent authorities only possible due to the Regulation in force (**EMIR** and its related *Regulatory*

[3] basket of assets – group of assets.

Technical Standards – **RTS** and *Implementation Technical Standards* - **ITS**), can be used by the European regulators in its supervision indicators (Ali, Vause, & Zikes, 2016).

2.3. OVER-THE-COUNTER DERIVATIVES

Credit Derivatives are derivative assets classes. In order to understand these assets and, more importantly, their link to the 2007/2008 financial crisis we first need to clarify what are Derivatives and, in particular, what are **OTC** Derivatives. We start this **Subsection** by answering the question of "what is a derivative?", and later discuss what *Credit Default Swaps* are (a sub-asset class of Credit Derivatives).

2.3.1 Derivatives

According to (Garslian, 2016), Derivatives are financial instruments that depend on an asset[4] (a share, a commodity, an interest rate, a currency, a credit, among others). Derivatives can be either traded in a Stock Exchange or privately between parties. The latter represents the *Over-the-Counter* (**OTC**) Markets, which serves to transfer the financial risk between counterparties (Duffie, 2010).

Derivatives have become, according to (Gofman, 2017), a major slice of the global financial markets pie. Their rapid growth jointly with the link to the 2007/2008 financial crisis pressured governments to intensify the powers of regulators over the **OTC** Derivatives Markets. Hence, the *European Market and Infrastructure Regulation* (**EMIR**) and its related legislation[5] was created in Europe, sanctioned by the *European Commission* (**EC**).

2.3.2 *Over-the-Counter* (OTC) Derivatives

Before **EMIR**, there was no pressure to impose standardisation, clearing and/or margin requirements to the **OTC** Derivatives Markets. While such requirements were well established for derivative products traded in the Stock Exchange (Garslian, 2016). Such specificities were explained in the paper of (Duffie, 2010) as a characteristic of a private negotiated contract, that allows counterparties to customise it to the client's needs, e.g., the terms could be agreed one by one between each party involved in it.

[4] Also referred as an "*underlying*".
[5] The Regulation has three levels: Level 1 – EMIR; Level 2 – RTS and ITS; Level 3 – Q&A (Questions and Answers), Guidelines.

In the **OTC** Derivatives Markets the parties involved in each transaction pre-agree totally or partially all the characteristics of the financial instrument as well as the terms of the transactions to meet their hedging or business needs or achieve cost reductions. Such efficiencies are often not achievable through a standardised derivative available through a Regulated Market (McGill & Patel, 2010). The standardisation imposed by the Regulated Markets worldwide leave a very limited optionality for the parties involved in a derivative transaction apart from price (except its granularity) and volume of the financial instrument.

The flexibility inherent to the **OTC** Derivatives Markets which is well recognised by several authors does not exist in the Stock Exchanges where the terms of the financial instruments and agreements are standardised and often applied across Stock Exchanges, making the Stock Exchanges liquid pools, transparent, highly regulated and somewhat pricier for its participants (Garslian, 2016).

Due to the flexibility that is associated to the **OTC** Derivatives, it does not come as a surprise that in 2017, according to the *European Securities and Markets Authority* (**ESMA**) in its statistical report (European Securities and Markets Authority, 2018b), the transactions of **OTC** Derivatives kept hegemony versus the Derivatives transactions on the Stock Exchanges. However, there was an increase on the reporting of transactions in the Stock Exchanges.

As mentioned above, the **OTC** Derivatives Markets are an historical decentralised and opaque market without a source of information apart from the counterparties to the transaction. This lack of a wider channel of information creates uncertainty among market participants (Coudert & Gex, 2013).

There are a few definitions of **OTC** Derivatives from several authors that we read in preparation to this work from which, one was selected: "*an OTC derivative is a privately negotiated contract between two counterparties to exchange future cash flows that depend on the performance of an underlying"* (Yellen, 2013).

Through the transfer of the acquisition of the underlying asset to a later stage in time, **OTC** Derivative products require that at least one of the counterparties performs payments in a pre-agreed future date, which adds a key element to the transactions involving such type of contracts: counterparty risk. The counterparty risk linked to its globalism (cross-border products) has implications in the economy worldwide as pointed by (Yellen, 2013). Moreover, (Godwin et al., 2017) reinforced its wide scope and urged the need for regulatory coordination between regulators.

2.3.3 Credit Derivatives and Credit Default Swaps

Credit Derivatives are products that transfer the credit risk related to a single underlying, or an underlying portfolio with the transfer of such underlying and without the need of the counterparties to own it.

Credit Default Swaps

Many authors suggested that *Credit Default Swaps* (**CDS**) were the root cause for the financial crisis of 2007/2008, but what are they?

The sub-asset class of Credit Derivatives: **CDS**, is an **OTC** Derivative linked to credit (underlying asset) used to protect the buyer against loss of principal (notional) due to a certain entity facing a credit event (Mengle, 2007). In return for such protection, the buyer of such contracts has to pay to the seller a pre-determined premium/spread (Benos et al., 2013).

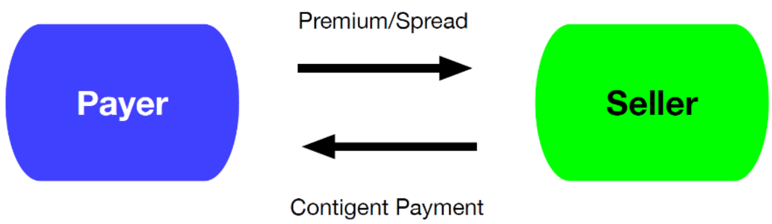

Figure 2 – Credit Default Swap Flow[6]

The **CDS** Markets, once considered as a niche, become an important market for the transfer of credit risk and are considered by (Oehmke & Zawadowski, 2016) as one of the most significant financial innovations of the last decades.

These contracts bear a recognised credit risk that arise from the counterparties to the transaction as well as the underlying risk of assuming the position in the transaction (Arora, Gandhi, & Longstaff, 2012; Bardoscia, Bianconi, & Ferrara, 2018; Benos et al., 2013). Moreover, the **CDS** have been linked to a certain degree of opacity, which led to the financial crisis in 2007/2008, the failure of the Lehman Brothers, and the AEG bailout (Morrissey, 2008).

The overall **CDS** market is highly concentrated in a few counterparties (Brunnermeier, Clerc, Gabrieli, Kern, & Memmel, 2013) with a high degree of intermediation. Major banks resell the credit risk to other market participants, generating a network topology characterised by a so-called "core-periphery" structure (Peltonen, Scheicher, & Vuillemey, 2014). Such

[6] Contingent payment, in case of a credit event (when a person or an organisation are unable to meet the terms of an agreement), the seller has to pay the pre-agreed amount.

specificity of the Market is the root of the systemic financial distress, that is, in case of failure of one of its most important participants (Duffie, 2010).

In case of a credit event of the reference entity, the buyer can claim payment from the seller minus the recovery value of the underlying asset. **CDS** were widely used prior to the crisis mainly due to their liquidity compared to the underlying (Kenny et al., 2016)

Several authors (Abad et al., 2016; Benos et al., 2013; Kenny et al., 2016) concluded that the **CDS** Derivatives Market is highly concentrated in a small group of counterparties as it was also observed in the snapshot presented in this paper for the Portuguese **OTC CDS** Derivatives market.

Situations where high concentration exists in a few counterparties, bring, according to some authors (Kenny et al., 2016), uncertainty to the market and its participants, which ultimately leads to an increase of counterparty credit risk within the financial system.

2.4. NETWORK SCIENCE

A Network is a model made up of two independent but interrelated sets: a set of nodes/vertices and a set of links/edges. Nodes represent the atomic elements of the system under study, while links connect pairs of nodes. A network can thus be used to abstract the structure of many different systems, while providing a common ground for their analysis. In the study of social systems, nodes would correspond to individuals and the links with a social relationship (e.g., friendship, co-workers, collaborators, family, influence, and cooperation). The **Figure 3** shows the graphical representations of networks.

A useful way to represent a network is through the so-called Adjacency Matrix (A), whose entries (a_{ij}) encapsulate the connectivity information between a pair of nodes (say, i and j).

Networks can be Undirected (A is symmetric along the diagonal) or Directed (A is not symmetric along the diagonal), Weighted (entries of A are real numbers that correspond to either a measure of similarity or distance) or Unweighted (entries of A are one or zero if pairs of nodes are, respectively, connected or not) depending on whether links are considered to carry information about the direction of relationships (e.g., information flows from node i to node j, but not in the reverse direction), and whether the strength of relationships need to be taken into account (e.g., the link between nodes i and j is n times stronger than the relationship between nodes $j$and k). The later needs to consider that the strength, or weight, of the relationship can be a measure of similarity/proximity (e.g., heavier links imply that nodes are closer) or a measure of distance (e.g., heavier links imply that nodes are farther away). Self-links, links that start and end in the same node, are often ignored in network analysis, in such case the diagonal of A equals zero. In the following of this **Subsection**, and for the sake of simplicity, we will discuss descriptive methods associated to the analysis of both Undirected and Unweighted networks.

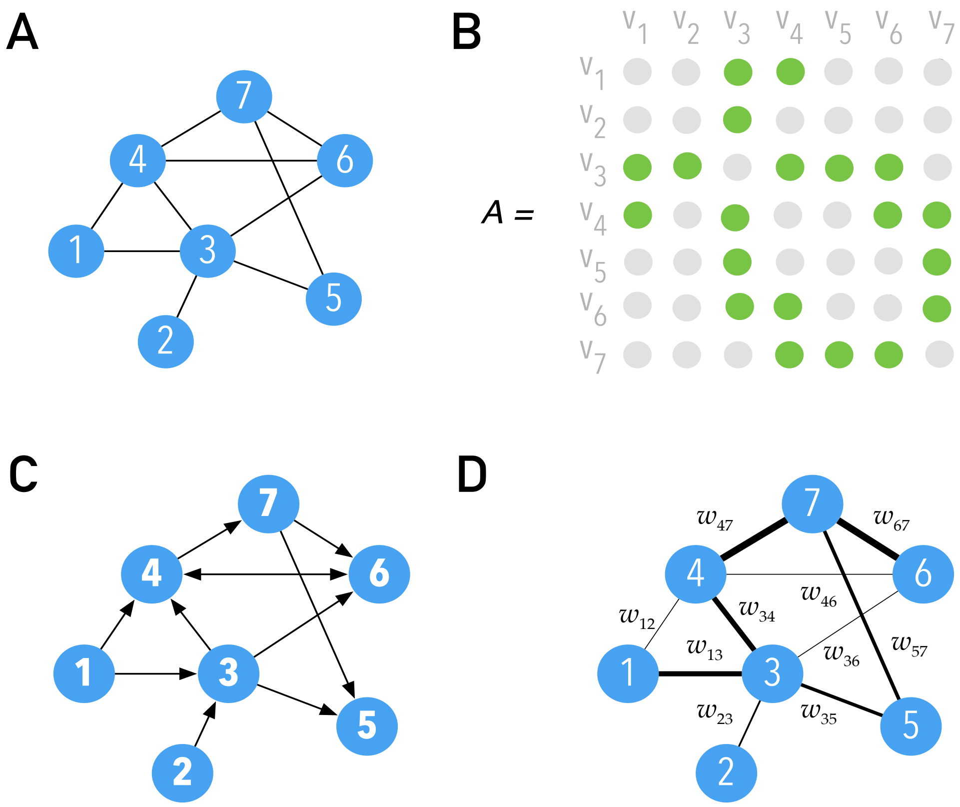

Figure 3 – Examples of different types of Networks and its different representations. **A)** shows a graphical representation of a network with 7 nodes and 10 edges; **B)** the Adjacency Matrix representation of the network in A); **C)** graphical representation of a directed network; **D)** graphical representation of a weighted network.

By abstracting the structure of a system as a network it is possible to obtain a rich set of descriptive metrics that offer valuable insights into its organisation and functioning (Jackson, 2008; Ribeiro, Pinheiro, Santos, Polónia, & Pacheco, 2018). For instance, the number of links node i participates defines his degree k_i. The simplest characterisation of a network is obtained from its degree distribution, $D(k)$, that captures the fraction of the nodes that have degree k. Hence, the average degree of the population is computed as:

$$\langle k \rangle = \sum D(k)\, k \tag{1}$$

and the variance of the degree distribution is:

$$var(k) = \langle k^2 \rangle - \langle k \rangle^2 \tag{2}$$

which is often a measure of the level of heterogeneity of the network. Other descriptive measures include the maximum degree.

Networks provide a natural metric to measure distances between elements in the system . For instance, the distance between any two elements/nodes, say i and j, in a network can be thought as the minimum number of links necessary to transverse in order to draw a path that connects the two nodes. Hence, the shortest path d_{ij}, or distance, corresponds to the shortest length (measured in the number of links) from all paths between nodes i and j. The *average path length* ($\boldsymbol{APL}$) of a network measures the average shortest path, d_{ij}, between all pairs of nodes. The diameter of a network is the largest shortest path in the network, that is max (d_{ij}).

Another measure of interest in the characterisation of a network is the level of clustering, that is the number of triangle motifs in the network. In that sense, the *average clustering coefficient* ($\boldsymbol{CC}$) measures the probability that two random nodes with a common linked third node are also a link between each other (D. Watts & Strogatz, 1998), and can be formally computed as:

$$CC \equiv \langle c \rangle = \frac{1}{N} \sum_{i=1}^{n} c_i \tag{3}$$

where N represents the number of nodes in the network, and c_i is the fraction of closed triangles formed between a node i and every possible pair of its nearest neighbors.

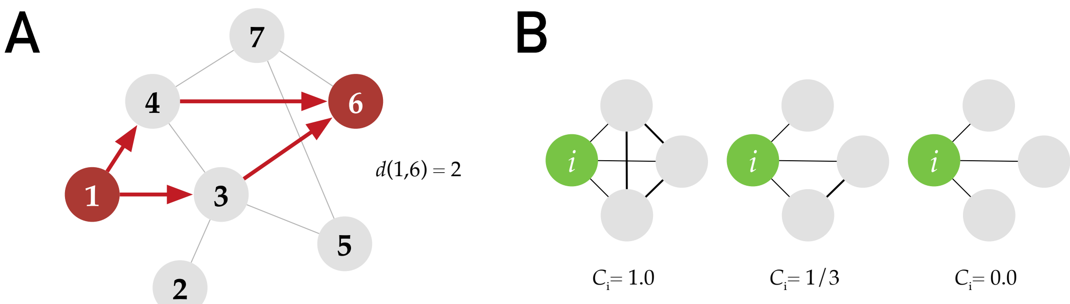

Figure 4 – A) example of two paths of length two between node 1 and node 6 in a network. **B)** different clustering coefficients measured at individual level for three network different motifs.

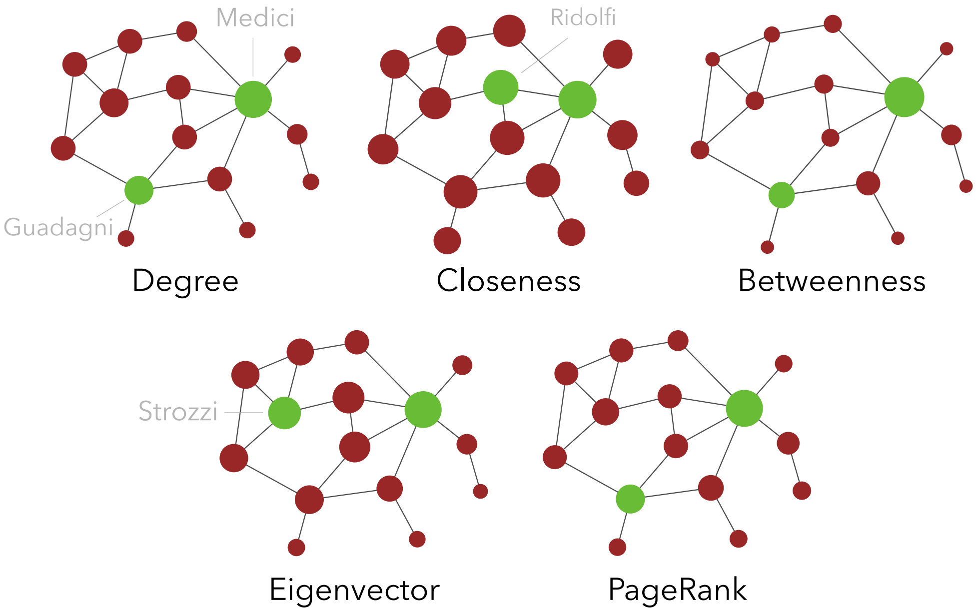

Figure 5 – Examples of the different centrality measures in a network of family ties among Italian families of the XVIth century. Larger nodes indicate higher centrality; green nodes correspond to the two most central individuals according to each metric.

Networks provide an opportunity to quantify the importance of individual elements of a system by their location in the network. Such measures are commonly associated with the centrality of nodes in the network, in that more central nodes are more important. Different measures of centrality try to account for different roles and systems, some of the most popular include:

- **Degree centrality** (k_i) states that most central nodes are the nodes with the highest number of connections, and it is given by:

$$k_i = \sum_{i \neq j} a_{ij}\,, \tag{4}$$

  where a_{ij} are the entries of the adjacency matrix.

- **Closeness centrality** (C_i) states that the most central individuals are the ones that minimise the geodesic distance to all the other nodes within a network, and can be represented as:

$$C_i = \frac{1}{N-1}\sum_{i \neq j} \frac{1}{d_{ij}} \tag{5}$$

  where d_{ij} is the length of the shortest path connecting i and j.

- **Betweenness centrality** (B_i) states that the most central nodes are the ones that lie more often in the pathway between many shortest paths, or in other words the node that plays more often the middleman role. This quantity can be formally computed as:

$$B_i = \sum_{i \neq j \neq k} \frac{\sigma_{kij}}{\sigma_{kj}} \tag{6}$$

where σ_{kj} measures the number of shortest paths that connect k to j, and σ_{kij} the number of those shortest paths that pass by i. In a network, the nodes with a high level of betweenness will have greater influence over the flow of information that connects different partitions that are weakly connected.

- **Eigenvector centrality** (E_i) states that a node is more central if it is connected to other central nodes. It usually involves a recursive process that can, in general, be represented as a eigenvector problem of the form:

$$E_i = \frac{1}{\gamma} \sum_{j=1, t \neq i}^{N} a_{ij} E_j \tag{7}$$

where γ is a constant. This measure has been popularised, for instance, as an alternative to the Impact Factor in measuring the importance of different research journals. A popular example of a centrality measure that is a particular case of the Eigenvector centrality is the PageRank centrality (Page & Brin, 2003), which become popularly used by Google to rank web pages according to their relevance in searchers.

2.4.1 Models of Networks

Past works have delved into identifying prototype network models that can result from different scenarios and conditions. Of these, it is noteworthy to mention the following examples: Complete, Regular Networks, Random Networks; Exponential Networks; and Scale-Free Networks.

Complete networks are structures in which each node is connected to all the other nodes in the network.

Regular Networks, such as right structures or lattices, are characterised by highly symmetric structures in which all nodes have the same degree (number of connections). Nodes are connected depending on their position in an Euclidian space.

Random Networks are often taken as the null model of network analysis. A popular algorithm to generate random networks is the Erdős–Rényi model which is as follows: starting from a N set of unconnected nodes, for each pair of nodes a link is created connecting them with probability p. The choice of p will define the connectivity of the network. For a sufficiently large N, the degree distribution resembles a Poisson distribution, that is

$$D(k) = \frac{\langle k \rangle^k e^{-\langle k \rangle}}{k!} \tag{8}$$

Exponential Networks have a degree distribution that follows an exponential distribution. To generate an exponential network, one can employ an algorithm of growth with a linear attachment, for instance: starting from a core of 3 nodes, iteratively add a new node that connects to two pre-existing nodes at random. This process is repeated until the desired network size is achieved. In the limit of large N, the degree distribution follows

$$D(k) = \lambda e^{\lambda k} \tag{9}$$

Scale-Free Networks have been widely popularised the late 90s and early 2000's when many real-world system networks were thought to follow this particular structure. Scale-free networks are characterised by a fat tailed degree distribution, indicating that a few nodes accumulated many connections, while the vast majority of the nodes only have a few. An algorithm often used to generate Scale-Free networks is the Barabási-Albert algorithm of growth and preferential attachment, which works as follows: starting from a core of m nodes, iteratively add a new node that connects to m-1 pre-existing nodes.

$$D(k) \approx k^{-\alpha} \tag{10}$$

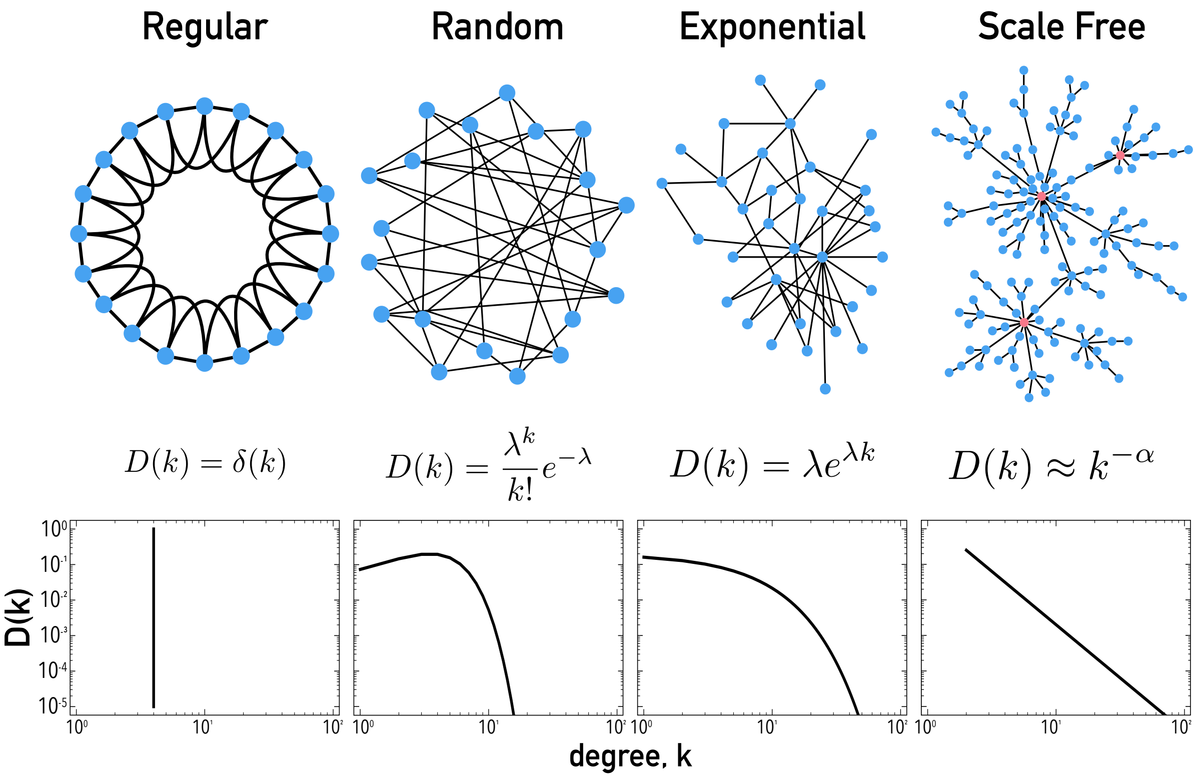

Figure 6 – Examples of the different popular network models in the Network Science literature. Graphical depiction of the networks above, and representative degree distributions bellow.

2.4.2 Network Analysis of Financial Markets

"The origin of large but rare cascades that are triggered by small initial shocks is a phenomenon that manifests itself as diversely as cultural fads, collective action, the diffusion of norms and innovations, and cascading failures in infrastructure and organizational networks." (D. J. Watts, 2002). In financial systems, cascade events can lead to large scale failures that network analysis can help to identify in advance, thus flagging, for example, to a regulator as a "*keep an eye*" on the counterparty/entity or potential risky situation (in case of a failure that can affect the network).

From the **Section 2.2** it is already clear that the *Over-the-Counter* (**OTC**) Derivatives are complex products that were in the shadow until the *European Market Infrastructure Regulation* (**EMIR**) brought transparency and more predictability about the activity of its participants.

(Yellen, 2013) stated that complex links among financial market participants and institutions are embedded in the modern global financial system, where different agents' active in the financial system engage in transactions with cross-border participants. Such kind of interactions apply a degree of complexity into the network, which may amplify existing market frictions, information asymmetries, or even external factors.

Complete networks, where banks benefit from diversified funding streams, can be more robust. Hence, a liquidity shock is less likely to cause harm to another bank since, due to its completeness, the shock could be disseminated through all banks within the network. In incomplete networks, on the other hand, institutions can be more exposed to failures due to shocks in one of its players. However, depending on the topology of the underlying network of interdependences between institutions, the system can be more susceptible to random or targeted failures/external shocks. For instance, in heterogeneous networks (e.g., Scale-Free networks), in which a few players accumulate the majority of the relationships and play a central role, the system is resilient to random failures but largely susceptible to failures that target the few most central elements in the network. Which in case of a failure would lead largely to the collapse of the system. In contrast, networks lacking degree heterogeneity are more resilient to targeted failures (since there is no particular set of players in the system that accumulates a strong relevance in its functioning) and more susceptible to random failure events.

Financial markets have a diverse set of market participants from big banks, to big corporate companies, and hedge funds up to individual investors than can be more sophisticated (called professional investors) or less sophisticated (called non-professional investors). The risks linked to the occurrences that harm the relationships between the participants within the financial market are called systemic risk. (Cont, 2010) highlights that the dimension of contagion lies on the structure of the network rather than the size of its largest participants.

(Caccioli, Barucca, & Kobayashi, 2018), highlighted the use of the network analysis in the study of systemic risk in the financial markets because the interactions between the counterparties/entities within the market can be represented as "*a network of financial linkages between institutions*".

In this work, we followed a similar approach to the previous taken by other authors (Abad et al., 2016; Kenny et al., 2016) and the *European Securities and Markets Authority* (**ESMA**) in its first overview of the Derivatives Market in 2017 (European Securities and Markets Authority, 2017) and its statistical report (European Securities and Markets Authority, 2018b). The similarities reflect the different approaches in what relates to the (i) time frame; and/or (ii) the *Trade Repository* (**TR**) from which the data set was retrieve; and/or (iii) the asset classes subject to the analysis; and/or (iv) the scope; and/or (v) the data set type. **Table 1** shows a comparison between each of the aforementioned studies.

Table 1 - Other studies using EMIR reporting data

Item	**Levels et al, 2018**	**ESMA, 2018**	**ESMA, 2017**	**Abad et al, 2016**	**Kenny et al, 2016**
Time Frame	1 Dec. 2015/ 31 Dec. 2016	Jan./Oct. 2018	24 Feb. 2017	22 Nov. 2015	1 Sep. 2015
TR	DTCC	All	All	DTCC	DTCC
Asset Class	CDS	All	All	CDS, FX, and IRS	CDS
Scope	Dutch Market	EU Market	EU Market	EU Market	Irish Market
Data set type	Transaction Report	State Report	State Report	State Report	State Report

As this is the first time the data is used to get insight on the Portuguese **OTC** Derivatives Market and considering the expected dimension of the Market, it was decided to use all the data available from all the **TRs** on the pre-selected dates (detailed in the following section - **Section 3**).

The decision to use data from all the **TRs** that receive the reports of entities active in the Portuguese **OTC** Derivatives Market provides a wider view; as it (i) will be the first snapshot of the Market; and (ii) will allow to start the quality data assessment for regulatory purposes. (Kenny et al., 2016) highlighted in its paper the importance of the use of this data as a tool to monitor financial and stability risks.

Moreover, it will allow to assess the Portuguese **OTC** Derivatives Market in comparison with the *European* (**EU)** landscape presented in ESMA statistical reports (proximity only at this stage due to the different time frames used for the data collection in both reports: data from the year of 2017 – **ESMA** versus 2018 – this paper).

Additionally, in those cases where there was not a harmonised approach regarding the aforementioned papers, towards the variables or the values to be excluded, all choices taken in this work are explained in the **Section 4**.

3. DATA, COLLECTION AND VARIABLE SELECTION

Here we describe the pipeline used for the data collection and feature selection performed ahead of the network inference of the Portuguese *Over-the-*Counter (**OTC**) *Credit Default Swaps* (**CDS**) Derivatives Market. The pipeline includes the identification of the different types of active entities in the Portuguese **OTC CDS** Market and subject to the transaction reporting under the *European Market Infrastructure Regulation* (**EMIR**). A detailed discussion of the data processing and the network inference is done in **Section 4**. The main data sets used in this work were collected via the *Transaction Reporting and Compliance Engine* (**TRACE)**. The **TRACE** contains Derivative positions and transactions of European entities, reported in *eXtensible Markup Language* (**XML**) format since February 2014. Given the large volume of data available we decided to extract only one representative day per month for the year of 2018: 26th January, the 23rd February, the 30th March, the 27th April, the 25th May, the 29th June, the 27th July, the 31st August, the 28th September, the 31st October, the 30th November and the 28th December.

The **Figure 7** below shows the process taken to perform this study.

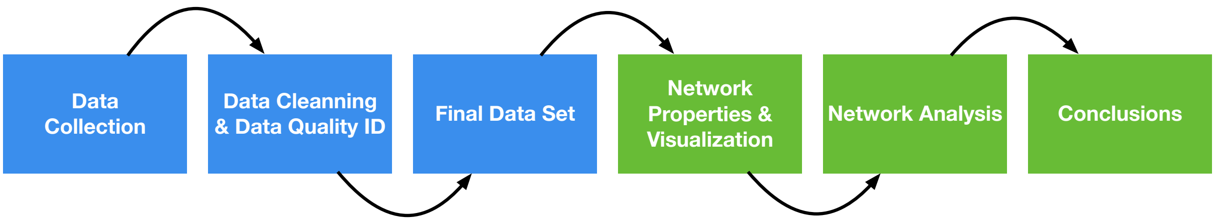

Figure 7 – Diagram of depicting the flow of the methodology adopted, Step by Step

Three additional data sets were used to complement the data collected from **TRACE**: **(1)** Exchange Rates published periodically by the Portuguese Central Bank (Banco de Portugal[7]); **(2)** Portuguese *International Securities Identification Number* (**ISIN**) codes from the **CMVM** internal data base; and **(3)** all the issued *Legal Entity Identifier* (**LEI**) codes from the *Global Legal Entity Identifier Foundation* (**GLEIF**) website[8]. A breakdown of the possible status for a **LEI** Code is shown in **Figure 19** of the Annex.

After the collection of all data from the different sources, the data was anonymised due to the obligation of professional secrecy applied to all persons who work or have worked for the competent authorities, or for auditors and experts instructed by the competent authorities or the

[7] https://www.bportugal.pt/taxas-cambio.
[8] https://www.gleif.org/en/.

European Securities and Markets Authority (**ESMA)**. No confidential information shall be divulged, except in an aggregated form to prevent the identification of the entities - Article 83 of **EMIR** (*Professional secrecy*). The full raw data set includes a list of 129 variables (Regulatory Technical Standard (European Comission, 2017)/Implementation Technical Standard (European Commission, 2017)). To perform our analysis, we extracted a subset of 24 variables that prove to be adequate for the inference of the Portuguese **OT CCDS** Derivatives Market network and its analysis. The variables considered are: *Reporting Counterparty ID*; *ID of the other Counterparty*; *Country of the other Counterparty*; *Type of ID of the Other Counterparty*; *Report submitting entity ID*; *Clearing member ID*; *Beneficiary ID*; *Counterparty side*; *Value of contract*; *Contract type*; *Asset class*; *Product identification type*; *Product identification*; *Underlying identification type*; *Underlying identification*; *Trade ID*; *Venue of execution*; *Notional*; *Execution timestamp*; *Maturity date*; *Confirmation timestamp*; *Cleared*; *CCP*; *Reference Entity*; and *Intragroup*.

A description of the above listed variables can be found in the **Section 7** – Annex (**Table 14**). Even though from the 24 variables only a smaller number were used, the remaining were crucial in the cleaning process and in the engineering of new explanatory variables.

To meet the objectives of this working paper, we have further included the following variables created:

- "*Country of the Reporting Counterparty ID*", identifies the country of the counterparty that submitted the report with a two-character encoding (**PT**[9], **UK**[10], **US**[11], …) that follows the **ISO** 3166 standard code defined by the *International Organization for Standardization*, obtained from cross referencing the **LEI** code of the reporting counterparty in the data set from **TRACE** System and the LEI code in the data set retrieved from *Global Legal Entity Identifier Foundation* (**GLEIF**) website;
- "*Product_Country*", identifies the country of the financial instrument object of the transaction with a two-character encoding (**PT**[12], **UK**[13], **US**[14]**,** …) following the **ISO** 3166 standard code defined by the *International Organization for Standardization*, we used data from the **TRACE** System and the **CMVM** internal data base;

[9] Portugal.
[10] United Kingdom.
[11] United States of America.
[12] Portugal.
[13] United Kingdom.
[14] United States of America.

- "*Gross_Notional*", the data in the raw data set can be presented in different currencies. For comparison, we converted the notional amount ("*Notional*[15]") to Euros. The date used for the conversion was the date of the submission of the state report to the *Trade Repository* (**TR**). We used data from **TRACE** System and Banco de Portugal data set to generate this variable.

An example of all the variables information (both original and created) can be found in the **Section 7** – Annex (**Table 15**).

[15] Field 20 (Section 2c) of RTS 2017/104 and ITS 2017/105.

4. CREDIT DEFAULT SWAPS ANALYSIS (CDS)

In the following **Subsections**, all the *European Market Infrastructure Regulation* (**EMIR**) data refers to the state reports obtained from the *Trade Repositories* (**TR**s**)** in twelve days of 2018: 26th January, 23rd February, 30th March, 27th April, 25th May, 29th June, 27th July, 31st August, 28th September, 31st October, 30th November, and 28th December. However, it should be noted that for the purposes of the network visualisation, it was selected only one of those days: the 28th of December as it provides a snapshot of the market on that moment in time.

Currently only six (6) **TR** provide the service to the Portuguese **OTC** Derivatives Market[16]: CME Trade Repository Ltd. (**CME**), DTCC Derivatives Repository Plc (**DTCC**), ICE Trade Vault Europe Ltd. (**ICE**), Krajowy Depozyt Papierów Wartosciowych S.A. (**KDPW**), Regis TR, S.A. (Regis-TR), UnaVista Limited (Unavista). The full list of the approved **TR**s is in **Table 15** of the Annex to this paper.

4.1. PROCESSING OF CREDIT DEFAULT SWAPS DATA

Here we discuss the processing of the data from the different **TR**s necessary to perform the network analysis of the Portuguese **OTC CDS** Derivatives Market. In our work we considered reports eligible to represent the Portuguese **OTC CDS** Derivatives Market, as all reports related to transactions that are executed (i) by at least one Portuguese counterparty, thus any non-Portuguese counterparty involved in an **OTC** transaction with a national counterparty will be included; or (ii) between foreigner counterparties on a Portuguese financial instrument, e.g. **CDS** identified with a Portuguese *International Securities Identification Number* (**ISIN**). Not within the scope of this work, but also available via the **TRs**, are derivative transactions of foreign counterparties on derivative products within a Portuguese Stock Exchange (Regulated Market).

The preparation process will follow the approach conducted in previous works at the *European* (**EU**) level by the *European Securities and Markets Authority* (**ESMA**) (European Securities and Markets Authority, 2018b) and the *European Systemic Risk Board* (**ESRB**) (Abad et al., 2016). These Steps aim at: (i) identify inconsistencies; (ii) data selection; and (iii) treatment of the data sets for the year of 2018. Each observation corresponds to one day of each month: 26th January, 23rd February, 30th March, 27th April, 25th May, 29th June, 27th July, 31st

[16] From a total of nine registered TRs, but only six of them have useful data on the Portuguese Derivatives Market. The updated list of TRs can be found at ESMA website: https://www.esma.europa.eu/supervision/trade-repositories/list-registered-trade-repositories.

August, 28th September, 31st October, 30th November, and 28th December. **Table 2** summarises the number observations for each month, before and after the data processing (initial data set, final data set, and variation in percentage). Overall, after the cleaning process the resulting data sets account for less than 1% of the corresponding original monthly data set. To obtain the working data set the Steps described below need to be performed sequentially.

Table 2 – Number of observations per data set in the Credit Default Swaps.

	Initial	Final	Percentage
January	213,551	1,617	0.76%
February	200,696	1,687	0.84%
March	199,933	1,569	0.78%
April	222,858	1,849	0.83%
May	220,503	1,898	0.86%
June	268,361	1,416	0.53%
July	245,863	1,476	0.60%
August	264,346	2,042	0.77%
September	250,596	1,965	0.78%
October	262,423	2,076	0.79%
November	266,019	2,135	0.80%
December	254,049	1,871	0.74%

The cleaning process starts by compiling each data set from the 6 Trade Repositories into a single data set.

Step one, we kept only the reports related to the transactions in Credit Derivatives, meaning all transactions identified by a CR in the field "*Asset Class*[17]".

Step two, all transactions that did not refer to the **OTC** Derivatives Market are discarded, e.g., all transactions not identified as "*XXXX*" or "*XOFF*" in the "*Venue of Execution*[18]" field were deleted.

Step three, we have dropped all reports where the fields of the counterparty of the trade (either the "*Reporting Counterparty ID*[19]" or the "*ID of the other Counterparty*[20]") were left blank or did not have a valid *Legal Entity* Identifier (**LEI**). The only exception being the counterparties identified with a client code (**CLC**) in the field: "*ID of the other Counterparty*[21]" as long as it fulfilled one of the report requirements that makes such report identifiable within the Portuguese **OTC** Derivatives Market: the transactions refers to a Portuguese **CDS** or if the

[17] Field 2 (Section 2a) of RTS 2017/104 & ITS 2017/105.
[18] Field 17 of RTS 2017/104 & ITS 2017/105.
[19] Field 2 of of RTS 2017/104 & ITS 2017/105.
[20] Field 4 of RTS 2017/104 & ITS 2017/105.
[21] Field 4 of RTS 2017/104 & ITS 2017/105.

counterparty to the transaction ("*Reporting Counterparty ID*") had a Portuguese **LEI** code (see **Section 4.2** above). We include this data in the first analysis and deviated from the cleaning process performed by (Abad et al., 2016) as we considered that for the first insight on the Portuguese **OTC** Derivatives Market it should be used the "biggest" sample of data as possible. Moreover, this data could also be used at a later stage to identify the weight of the CLC by the market players and consider a dedicated supervision action plan. Later on (**Subsection 4.2.2**) we have excluded the reports containing **CLC**, and performed a new analysis for comparison purposes with other studies published.

Step four, all observations where the variable that represents the *mark-to-market* "*Value of Contract*[22]" is missing are discarded from the analysis (Abad et al., 2016).

Step five, to be able to aggregate the transactions after the pre-processing phase and make them comparable (transactions are reported in different currencies) the notional amount of the transactions was converted to the Euro. To that end, we have used the exchange rates published by *Banco de Portugal*, using the exchange rate for the date of the state report. At this stage we performed an inconsistency check. All the observations with a *Notional*[23] below 10^3 Euros were considered as a misreporting (Abad et al., 2016; Kenny et al., 2016) and those above 10^9 Euros were considered as outliers (Abad et al., 2016). In both situations, the observations were discarded.

Step six, we discarded the duplicated reports in a few Steps. Since under the *European Market Infrastructure Regulation* (**EMIR**) all European counterparties must report the side of the transaction in which they are involved (the buyer shall report its side of the transaction and the seller shall report its side of the transaction), it introduces a duplication of reports whenever the transaction involves two European counterparties. Hence, we need to accurately treat these duplications. First, we select the unique transactions per "*Trade ID*", secondly match transactions with the same "*Trade ID*", third aggregate the information. Concerning the last point, all transactions with the same "*Trade ID*" are identified and a consistency check is performed, e.g., the notional amount reported, the counterparties and the maturity date had to coincide, additionally, the counterparty side could not be equal (the buyer should be identified with a "B" and a seller with a "S"). For the network analysis a unique report is used, as describe in the following **Subsection**.

[22] Field 17 of RTS 2017/104 and ITS 2017/105.
[23] The notional amount of an over-the-counter derivative contract is typically measured as the market value or, in the case of bond derivatives, the face value of the asset whose risk is transferred by the derivative.

The reports discarded during Steps four to seven were stored for future internal in-depth analysis. These might in the future allow to: (i) understand the degree of misreporting; (ii) identify the counterparties that are responsible for the misreporting; and (iii) implement dedicated supervision actions. It is noteworthy to mention that if this work had not required such an exhaustive treatment of the data, many of these situations would have, most likely, remained unaccounted.

Four additional Steps were performed to ensure that the data sets obtained would be consistent for aggregation and for the network analysis focused on the first phase on the Portuguese **OTC CDS** Derivatives Market.

Step seven, reports without a maturity date are discarded as they do not allow to verify if the contract is still open and, thus, its effective weight in the network.

Step eight, reports flagged with "*Y*" in the "*Intragroup*[24]" field that refer to transactions between entities from the same group are discarded as they do not pose the same risk as the interactions between distinct counterparties.

Step nine, all reports that are related to *Credit Derivatives* but not to its sub-asset class: *Credit Default Swaps* are also discarded.

Step ten, reports that are not related to transactions that are executed (i) by at least one Portuguese counterparty; or (ii) between foreigner counterparties on a Portuguese **OTC CDS**, e.g. a financial instrument identified with a Portuguese *International Securities Identification Number* (**ISIN**) in the "*Underlying Identification*[25]" *are* discarded as fall out the scope of this paper – Portuguese **OTC CDS** Derivatives Market.

We have eliminated the **CDS** indexes and baskets while performing the analysis of its **OTC** Portuguese Market. Such approach follows the same path as the *European Systemic Risk Board* (**ERSB**) paper (Abad et al., 2016), where it was decided to exclude those reports as it is not identified by an **ISIN**, hence difficult to link to a country.

At this point we had the necessary data set to draw the networks on the **PT Products + PT Participants** segment (counterparty, and country), and to identify the active players within. Before moving a Step forward, we made a *sanity check* to all reports identified with a "N" or left blank in the "*Cleared*[26]" field and checked if it was accurate, e.g., the transaction did not fell under one of the following conditions:

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[24] Field 38 (Section 2e) of RTS 2017/104 and ITS 2017/105.
[25] Field 8 (Section 2b) of RTS 2017/104 and ITS 2017/105.
[26] Field 35 (Section 2e) of RTS 2017/104 and ITS 2017/105.

- One of the counterparties to the transaction was identified with a **LEI** of a *Central Counterparty* (**CCP**); or
- The field "*CCP*[27]" is filled with an accurate **LEI** of a **CCP**.

Sixteen reports, representing 0,86% of the data set fulfilled at least one of the conditions. We replaced all the flags from "N" to "Y" since a report involving a **CCP** always refer to a cleared transaction. Nevertheless, we took note of the misreports, and saved the data for future analysis.

On a second stage, we further restricted the data set in order to be able to compare the results with existing studies (please see **Table 1** in **Subsection 2.4.2** for better reference on the studies). Noteworthy to remember that this restriction did not made us deviate from the initial goal: focus on the Portuguese **OTC CDS** Derivatives Market. Such exercise took four more Steps and provided us with two smaller data sets: (i) only focused on **CDS** identified with a Portuguese **ISIN** (Portuguese **CDS**), and (ii) only focused on Portuguese counterparties, e.g. reports where the transactions involved at least one Portuguese counterparty.

Step eleven, we dropped all reports were the counterparty was identified with a client code: **CLC** as the **ERSB** paper (Abad et al., 2016).

Step twelve, we identified all reports that were flagged with a "Y" in the "*Cleared*[28]" field and a **LEI** code in field "*CCP*[29]" but none of the counterparties was a **CCP** (e.g. identified with the **LEI** of a **CCP**) and rebuild the transactions. Reports falling under this situation accounted for 1% of the data set. Each report was replaced by two reports where all details were kept unchanged apart from the counterparties where the CCP assumed an intermediate role:

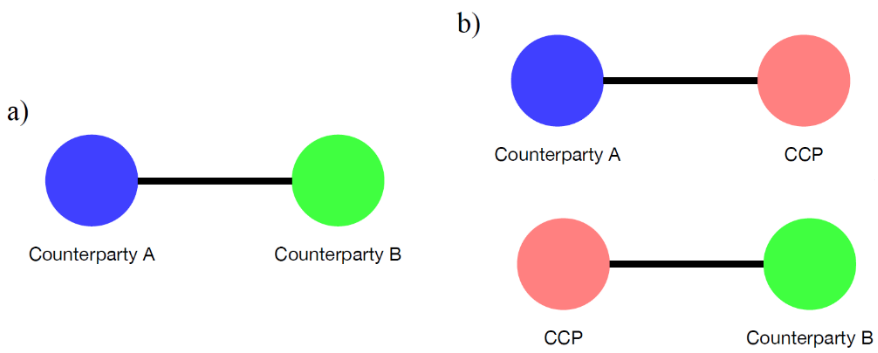

Figure 8 – Different types of relationships. **a)** Initial transaction report involving two counterparties that cleared through a CCP. **b)** Transaction report involving two counterparties that cleared through a CCP after the "rebuilding process".

[27] Field 37 (Section 2e) of RTS 2017/104 and ITS 2017/105.
[28] Field 35 (Section 2e) of RTS 2017/104 & ITS 2017/105.
[29] Field 37 (Section 2e) of RTS 2017/104 & ITS 2017/105.

To allow the accurate mapping, we rerun the cross check of the country of each of the counterparties. It is not only important for the clear identification of the reports to keep in the last Step of the cleaning process (Step fourteen) by considering the country of the counterparties but also to draw the country network in the following **Subsection**.

Step thirteen, we dropped all reports where the product was not a financial instrument identified as a Portuguese **CDS**, e.g. a **CDS** with a Portuguese *International Securities Identification Number* (**ISIN**). At this point we obtained the data set to build the network that represents the **PT Products** segment.

Step fourteen, we dropped all reports where the transactions were not performed by at least one Portuguese counterparty. Finally, we obtained the data set to build the network that represents the **PT Participants** segment.

All the Steps described above were taken for all the twelve data sets. **Table 3** summarises the above-mentioned Steps and indicates the number of reports remaining after each Step.

Table 3 – Processing of Credit Default Swaps data from the data set of 28th December. The Steps show how the number of reports were filtered from raw data to the working data set. Each Step was implemented in a sequential order (from top to bottom). The number of observations tracks the size of the working data set after each Step.

Step	Number of observations
0. Bulk data (all asset classes)	1,400,172
1. Raw data (Credit Derivatives)	254,049
2. Removal On-Exchange trades	228,812
3. Removal blank Counterparty **ID**	226,744
4. Removal erroneous value of contract	187,416
5. Removal notional below 1k and above 1bn Euros	185,745
6. Removal of Duplicates	150,015
7. Removal blank maturity date	149,832
8. Removal intragroup flag set to "Y"	128,978
9. Removal all non-**CDS** reports	117,850
10. Removal Non-Portuguese **OTC CDS**[30] (**PT Products + PT Participants** segment	1,871
11. Removal all reports where the counterparty is identified with a CLC	1,850
12. Rebuild the network	1,869
13. Removal non-Portuguese ISIN (**PT Products segment**)	1,814
14. Removal non-Portuguese counterparties (non-**PT Participants** segment)	55

[30] Single name Portuguese **OTC CDS**.

Due to the reduced number of liable data[31], the final data sets (e.g. the ones to be used in the network analysis) were considered only as a sample of the population (**EMIR** data representing each segment of the Portuguese **OTC CDS** Derivatives Market). Each data set that was labelled for better reference, and are discussed in the following **Subsections**:

- **PT Products and PT Participants** segment (e.g., data set obtained in Step 10 above) - 1,871 reports (observations) submitted by 156 counterparties to the **TR**s, which represents all the transactions involving any non- Portuguese counterparty involved in a transaction of a Portuguese **OTC CDS** Derivatives, or at least one Portuguese counterparty in an **OTC CDS** Derivatives Market;
- **PT Products** segment (e.g., data set obtained in Step 13 above)– 1,814 reports (observations) submitted by 133 counterparties to the **TR**s, which represents all reported transactions by counterparties involving a Portuguese **OTC CDS** Derivatives, irrespectively of the country of origin, and excluding counterparties identified with the **CLC**; and
- **PT Participants** segment (e.g., data set obtained in Step 14 above) – 55 reports (observations) submitted by 15 counterparties to the **TR**s, which represents all the transactions involving at least one Portuguese counterparty in an **OTC CDS** Derivatives.

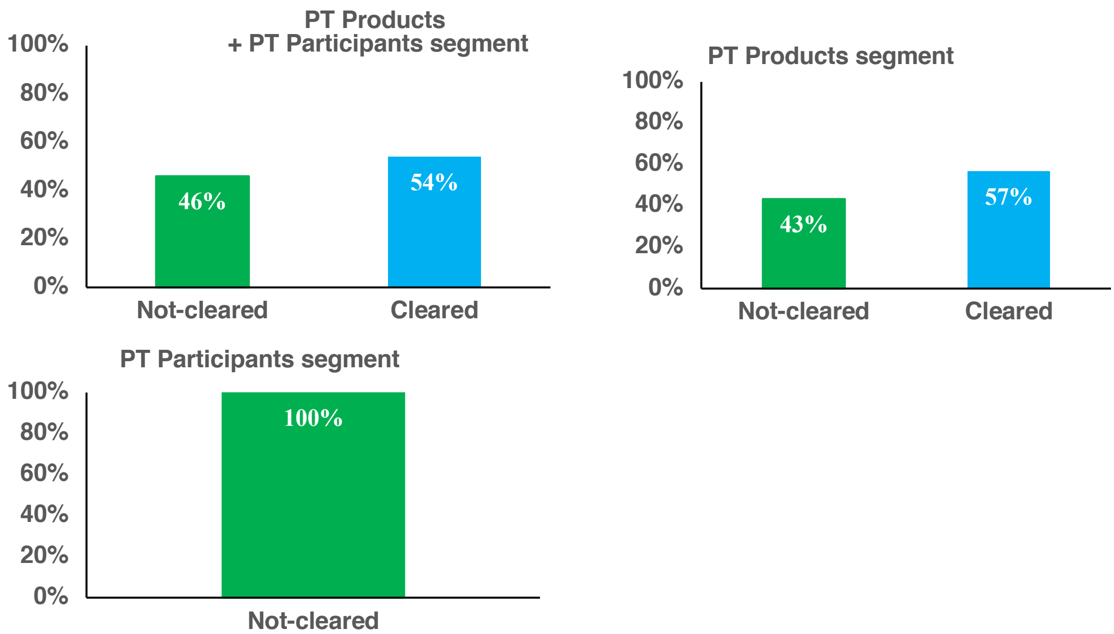

Figure 9 – Reports per clearing type in the (1) **PT Products** + **Portuguese** segment, (2) **PT Products** segment; and (3) **Portuguese Participants** segment in the 28th December 2018 type

[31] Data obtained after the pre-processing phase.

The **Figure 9** shows that there is a balance between the "*Cleared*" and "*Not-Cleared*" transactions within the state report of 28th December of 2018 for two of the final data sets representing the **PT Products + PT Participants** segment and the **PT Products** segment. However, the cleared transactions are slightly higher and accounts for more than 53% in both cases. There is a marginal number of reports submitted to the **TRs** without information in this field, which by cross referencing the information with the field "*CCP*[32]" we realised refer to cleared transactions and therefore we replace the blank field by a "Y". Those reports account for 0.21% of the data set. Our values are in line with the *Bank of International Settlements* (**BIS**) report from the end of 2018 on **OTC** Derivatives (Bank for International Settlement (BIS), 2019), which reported 55% of outstanding **OTC CDS** Derivatives cleared through a *Central Counterparty* (**CCPs**) during the analysis period.

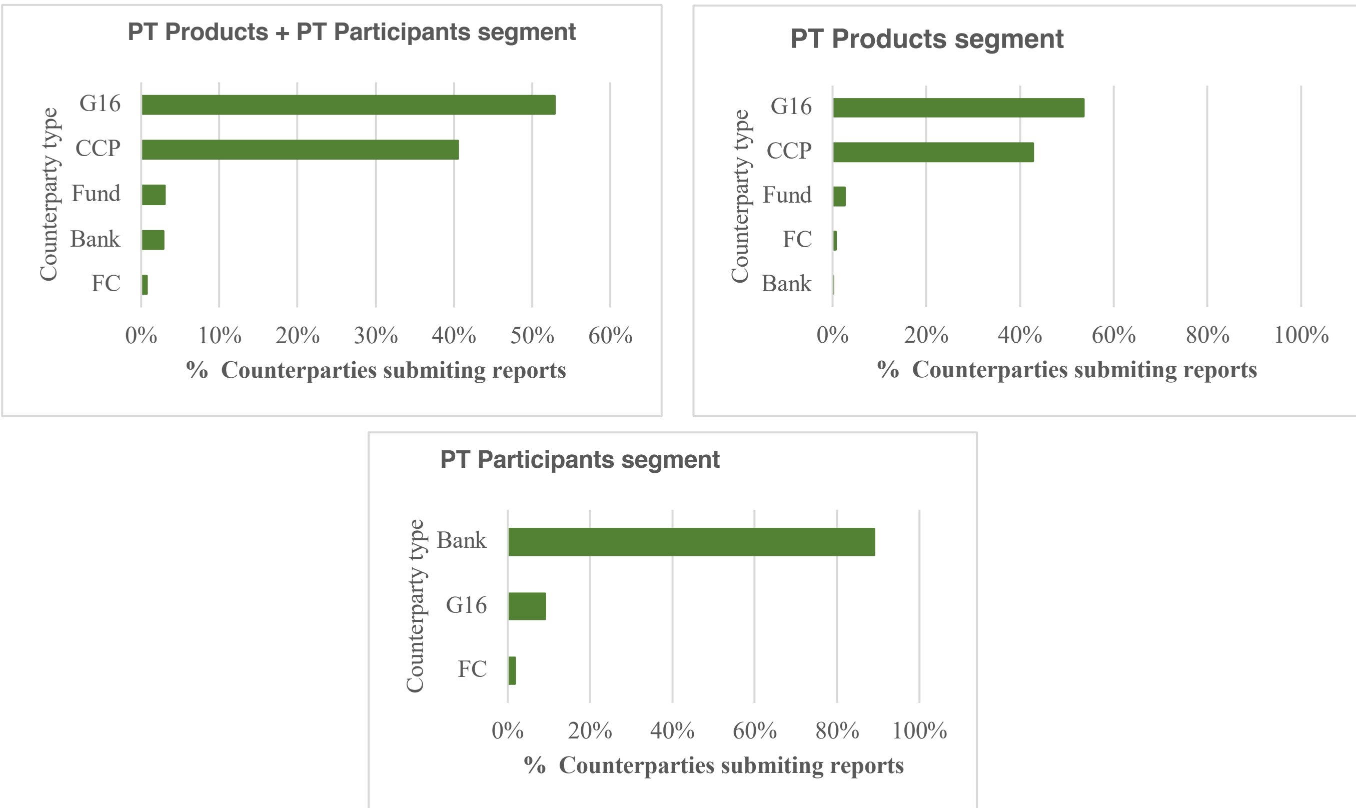

Figure 10 – Percentage of entities submitting reports in the (1) **PT Products + PT Participants** segment (2) **PT Products** segment; and (3) **PT Participants** segment, per counterparty type in the 28th December 2018

The **Figure 10** highlights the distribution per counterparty type of the active players on the Portuguese **OTC CDS** Derivatives Market. As it may be seen there is the hegemony of the members of the *Group of Sixteen* (**G16**) and the **CCP**, that account for more than 50% and 40% respectively for the data sets representing the **PT Products + PT Participants** segment, and

[32] Field 37 (Section 2e) of RTS 2017/104 and ITS 2017/105.

the data set representing the **PT Products** segment. On the other hand, the data set focused on the **PT Participants** segment is dominated by the Banks which account for almost 90% (89.1%). These findings are complemented in **Subsection 4.2** where we represent and discuss the network structure of the three segments defined to represent the Portuguese **OTC CDS** Derivatives Market.

Table 4 - Matrix of share of interaction between counterparty types, per transaction report on the 28th December (**CLC** – *Client Code;* **FC** – *Financial Counterparty;* **NFC** – *Non-Financial Counterparty*; **G16** – *Group of Sixteen*; **CCP** – *Central Counterparty*) for three data sets

PT Products + PT Participants segment

	Bank	CCP	CLC	FC	Fund	G16	NFC
Bank	0.1%	0%	0%	0.9%	0%	2.2%	0%
CCP	0%	0%	0%	0%	0%	56.7%	0%
FC	0%	0%	0%	0%	0%	0.7%	0%
Fund	0%	0%	0.1%	0%	0%	0.8%	0%
G16	2.6%	13.1%	0.2%	0.5%	2.6%	19.2%	0.2%
Total	2.7%	13.1%	0.3%	1.6%	2.6%	79.5%	0.2%

PT Products segment

	Bank	CCP	FC	Fund	G16	NFC
Bank	0%	0.2%	0%	0%	1.4%	0%
CCP	0.06%	0%	0.04%	0%	58.1%	0%
FC	0%	0.04%	0%	0%	0.6%	0%
Fund	0%	0.2%	0%	0%	0.6%	0%
G16	2.5%	13.4%	0.5%	2.7%	19.5%	0.2%
Total	3%	14%	1%	3%	80%	0%

PT Participants segment

	Bank	FC	G16
Bank	7.7%	32.3%	44.5%
FC	0.0%	10.5%	0.0%
G16	4.9%	0.0%	0.0%
Total	12.7%	42.8%	44.5%

A closer look into the relationships per counterparty types of the **PT Product + PT Participants** segment (represented by the gross notional of the transactions between them) allowed us to see that the market is concentrated in two main group of players: the **G16**, and the **CCP** where more than 70% of transactions took place between the **G16** players and the **G16** players and the **CCPs** (see **Table 4** above) for two of the data sets: the one representing the **PT Products + PT Participants** segment and the **PT Products** segment. The smaller data set, e.g. the **PT Participants** segment is dominated by the banks and the **G16** that account for more than 55%.

4.2. CDS NETWORK ANALYSIS

In this **Subsection**, each counterparty (or the country of a counterparty) to a *Credit Default Swap* (**CDS**) transaction is represented by a node in the network and the relationships between counterparties or the country of a counterparty (nodes) are represented by a link. For simplification, and visualisation reasons, links connecting the same counterparties were aggregated by the notional amount of the transactions ("*Gross Notional*").

As previously identified by other authors (Abad et al., 2016; Kenny et al., 2016) and by the *European Securities and Markets Authority* (**ESMA**) in its Derivatives statistical report (European Securities and Markets Authority, 2018b), the network analysis provides regulators a tool to map the interconnectedness of derivative transactions, their possible contagion paths, while allowing to understand the systemic risk across a range of financial systems and sectors.

The network analysis will use different samples (data sets) for the analysis. All of those data sets went through the same data cleaning process as described in **Table 3** of **Subsection 4.1** and exemplified for the final data set: 28th December 2018 Hence, we have: thirty-six files representing each month of 2018 (12 for each subset): (i) **PT Products + PT Participants** segment; (ii) **PT Products** segment, and (iii) **PT Participants**, from which we performed the network inference and characterisation; and three single files representing each final data set (dated of 28th December 2018) representing the three aforementioned data sets that will be used for the networks visualisation.

Additionally, we considered that the networks (focused on the counterparty interactions or in the country of those counterparties) are (i) **Undirected** as for the study in hands we assumed that two counterparties/countries are related in some way. These relationships exist, irrespectively of the balance of their transactions (e.g. who has the biggest position, or who was the seller and who was the buyer in the transaction); and (ii) **Weighted** by the value of the "*Gross Notional*" involved in the transactions between two counterparties/countries. The "*Gross Notional*" of each transaction was aggregated and used to measure the weight of the relationships.

It is noteworthy to mention that for ease of providing a graphical representation of the networks, unweighted versions of the same structures were used instead. The unweighted networks were obtained by conserving that links between counterparties only exist if at least one transaction was observed between them irrespectively of the position held by each one (buyer or seller of the transaction) or the amount ("*Gross Notional*") involved in the transaction.

4.2.1 PT Products + PT Participants segment

This **Subsection** will provide details of the network analysis for the data set focused on the Portuguese Product and Portuguese Participants , meaning that we used the monthly data sets of **Section 4.1**, that includes reports related to transactions executed by at least one Portuguese counterparty or reports related to transactions on Portuguese **OTC CDS** Derivatives irrespectively of the country of origin of the counterparties involved in such transaction to perform the network inference and the characterisation using the data set of 28th December 2018.

On average, there were 149 active counterparties on the **PT Products + PT Participants** segment network in the year of 2018. Being the month of April the one that registered the lowest number of active counterparties (127), and July the highest (168). **Table 5**, summarises the main network metrics per month.

Table 5 – Network analysis metrics for the **PT Products + PT Participants** segment, including the number of nodes in the network (**N**), the average degree ($\langle \boldsymbol{k} \rangle$), the density of links, the maximum degree ($\boldsymbol{max}(\boldsymbol{k})$), the diameter of the network (**diam**), the average path length (**APL**), the Cluster Coefficient (**CC**), and the variance of the degree distribution ($\boldsymbol{var}(\boldsymbol{k})$)

	N	<k>	Density	max(k)	diam	APL	CC	var(k)
January	148	3.176	0.022	39	5	3.004	0.28	33.91
February	152	3.211	0.021	36	6	2.998	0.27	34.22
March	137	3.309	0.025	33	6	2.907	0.29	38.47
April	127	3.559	0.028	34	6	2.838	0.28	35.48
May	132	3.561	0.027	34	6	2.818	0.31	36.77
June	139	3.295	0.024	42	6	2.831	0.23	37.06
July	168	3.238	0.019	49	6	2.807	0.38	46.09
August	152	3.553	0.024	49	6	2.746	0.43	49.57
September	152	3.553	0.024	49	6	2.754	0.44	49.56
October	163	3.656	0.023	49	6	2.825	0.34	50.16
November	165	3.636	0.022	51	6	2.816	0.37	50.83
December	156	3.679	0.024	52	6	2.835	0.4	49.88

The diameter of the network, which represents the maximum shortest distance between two nodes in a network (number of links separating two nodes), in this case the longest path that a counterparty has to run to its furthest counterparty was constantly at six for the last eleven months, and five for the month of January 2018.

The average degree of the **PT Products+ PT Participants** segment increased during the year of 2018, being December the month that registered the highest value. This means that the number of counterparties for each participant active in the Market registered fluctuate during the year and ended with a slight increase. Such increase was mostly due to the increase of diversification in the relationships of the *Group of Sixteen* (**G16**). The maximum degree also increased along the year, which consolidated the previous statement. The **G16** players and the *Central Counterparty* (**CCP**) assumed the main roles in the networks in 2018.

The networks exhibit a very sparse connectivity structure, as only an average lower than 3% of the possible links between counterparties exist. Such a low value indicates that the market might be highly susceptible to the existing relationships and be susceptible to the collapse of some of its central elements.

The average path length, which measures the average shortest path between all pair of nodes, was approximately three in all the data sets analysed.

The papers of (Abad et al., 2016; Kenny et al., 2016) highlighted that the main players of the **CDS** market are the **G16** and the **CCPs**, which is also the case for the **PT Product + PT Participants** segment network, despite the extended conditions (see **Section 4.1** for details). Indeed, we observe that the **G16** players (i) have the highest number of relationships with other counterparties and between themselves; (ii) serve as intermediates between other players in the market; and (iii) are very well connected with the other important players of the network, and therefore have the power to influence the other participants in the **PT Product + PT Participants** segment network. These three observations are supported, respectively, by the Degree, Betweenness, and Eigenvector centralities. The top 5 most central players were constantly from the **G16** and the **CCP** .

Same behavior was observed for the network drawn using the data set that followed the restrictions of the European Systemic Risk Board (**ESRB**) (Abad et al., 2016): **PT Products** segment.

The **Figure 11** shows the degree distribution of the **PT Product + PT Participants** segment in 28th December 2018. The majority (88%) of the counterparties interact with the maximum of five counterparties, and 54% with a single counterparty. Both percentages are slightly higher than the one reported by (Abad et al., 2016), which may be explained by the existence in our data set of reports with counterparties identified by the Client Code (**CLC**). Such highly heterogeneous networks (Gao, Liu, Li, & Havlin, 2015) are known to be very susceptible to target attacks, and as such events for which the highly central nodes might be more susceptible pose a high systemic risk to the entire system.

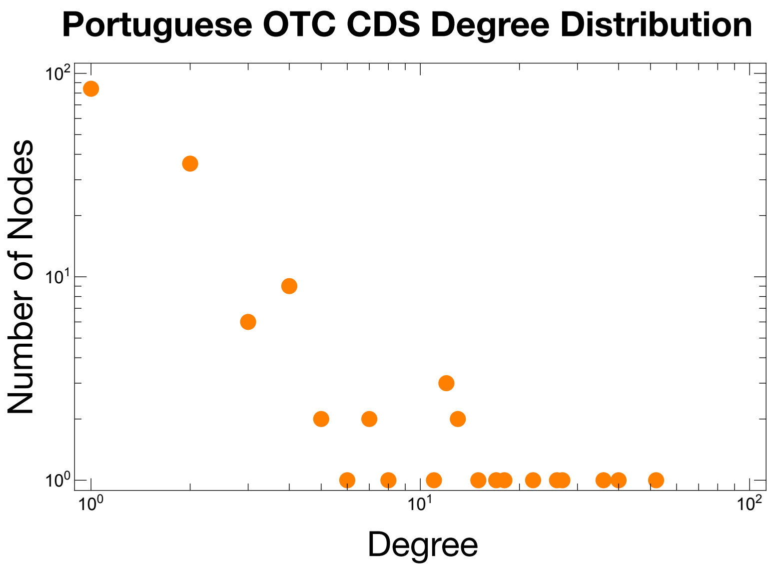

Figure 11– Degree distribution per number of counterparties

To explain, for the first time, the existing relationships in the **PT Product + PT Participants** segment it was drafted three graphic representation of the market – see **Figure 12** for the data set of the 28th December 2018.

The construction process of the network was based on the addition of a link between two nodes (representing the relationship between the counterparties in a transaction) as long as at least one transaction on a **CDS** contract was observed between them. The size of the nodes is proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*", whereas the thickness of the links is proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*" between the two counterparties. Self-loops (transactions where both sides of the transaction had the same *Legal Entity Identifier* **(LEI**) code were also excluded as it does not represent the same risk to the transaction chain.

Counterparties are colored to highlight their types: ((i) **G16** in bright green; (ii) **CCP** in red; (iii) Banks in magenta; (iv) Funds in orange; (v) Financial Counterparties (**FC**) in blue; (vi) Non-Financial Counterparties (**NFC**) in black; (vii) counterparties identified by **CLC** in grey and (viii) in light blue the Portuguese players irrespectively of their counterparty type.

In the **CDS** networks there is a *core* of larger nodes (i.e., having a higher number of links) that can be distinguished from the *peripheral* nodes, which are smaller and less linked to the other counterparties. In fact, with a few exceptions, peripheral nodes are mostly connected towards the core and much less to other peripheral nodes. The giant components of the networks are graphically represented in **Figure 12** (degree, betweenness and eigenvector centrality measures), and provide a good overview of some interesting features: the dominance and centrality of the **G16**[33]; the **CCPs** and a few banks that trade with peripheral entities and between each other, irrespectively of the centrality measured. For the complete network (giant and small components) please refer to **Figure 20** in **Section 7**. Despite not being equal, these findings are qualitatively similar to previous work by (Abad et al., 2016; Peltonen et al., 2014) and are in line with the more recent work of (D'Errico et al., 2018; Gross & Siklos, 2018). In the latter, the authors identified a sectoral clustering in the **CDS** network, with the center occupied by the financial institutions (**G16**, Banks, **FC**, Funds), and *Non-Financial Counterparties* (**NFC**) grouped around it.

It is noteworthy to mention that the giant component is qualitatively similar to one found and discussed in previous studies using **EMIR CDS** data (Abad et al., 2016). However, the **PT Product + PT Participants** segment has three smaller unconnected components: the largest components of the two has a **G16** player at its center working as the link between seven peripheral counterparties, all of which are funds; the mid-size component is comprised by 4 funds and 2 entities identified with the **CLC**, where the **CLCs** have a relationship (link) with all the funds; and the smaller components connects only two players, a Portuguese counterparty and a *Financial Counterparty* (**FC**).

The **PT Product + PT Participants** segment has six Portuguese players of which one is part of the smaller component with only two nodes. The remaining five Portuguese counterparties are part of the giant component where four are peripheral and only one (a Portuguese bank) serves as a connection between two central nodes.

[33] Includes all entities that belong to the G16 company, e.g., JP Morgan and JP Morgan Securities.

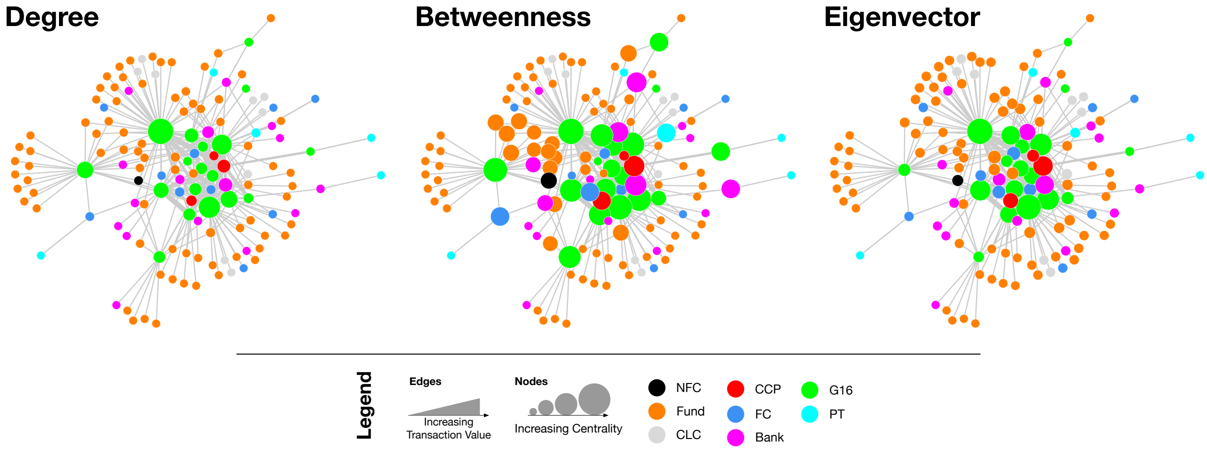

Figure 12- Undirected and **unweighted** network (**PT Product + PT Participants** segment) of counterparty-counterparty of gross notional amount (per **degree, betweenness, and eigenvector centrality**), highlighting the Portuguese counterparties within the network. The size of each of the 140 counterparties (nodes) is proportional to the transactions gross notional amount (in Euros), and the thickness of each of the 271 relationships (links) is proportional to the transactions gross notional.

The **Table 6** below provides a closer look to the top 5 counterparties per centrality measure, we observed that the most influence counterparty, e.g., a counterparty that if fails will have the most impact in the network is "4". This counterparty has the highest: (i) degree (highest number of links with other counterparties in the network), (ii) betweenness (serve as link between other counterparties in the network), and (iii) Eigenvector (high number of links with other counterparties well connected). It is noteworthy to mention the counterparty "1", which scope is more limited than the others within the degree top 5 as does not share the same level of links with the "very well connected" counterparties (eigenvector).

All counterparties in the top 5 per Degree centrality belong to the **G16** group.

Table 6 – Top 5 counterparties per Degree centrality and its placement regarding the other two centrality measures: Betweenness and Eigenvector for the **PT Product + PT Participants** segment. The place id identified in brackets after the value.

#	Counterparty ID	Degree	Betweenness	Eigenvector
1	4	52	3,466.01 (1)	1 (1)
2	12	40	2,361.43 (2)	0.95 (2)
3	3	36	2,012.37 (3)	0.79 (3)
4	10	27	1,699.21(5)	0.76 (4)
5	1	26	1,505.76 (4)	0.27 (18)

To unveil the ties between countries in which counterparties are hosted, a new network was built that focuses in the country of each counterparty involved in the **PT Product + PT Participants** segment. The construction process executed for the first network was replicated from the same initial data set, dated of 28th December 2018. A few minor albeit necessary adaptations were done, as the *country-country* network will be focused on the country of the counterparty rather than the counterparty itself. For that purpose, we cross referenced the *Legal Entity Identifier* (**LEI**) code of the fields "*Reporting Counterparty*" and "*Country of the other Counterparty"* with the information in the *Global Legal Entity Identifier Foundation* (**GLEIF**) data base and used the country reported in the field "*Country of the other Counterparty"* for those cases where no match was found in **GLEIF** data set.

Following the same process as above, the thickness of the links is proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*" between the countries where the counterparties involved in the transaction are based on. Self-loops (transactions where both sides of the transaction had the same **LEI** code) were also excluded as it does not represent the same risk to the transaction chain.

To facilitate the visual inspection of the network, and provide quicker information, nodes have been replaced by the flags of the country they represent. A black flag with double X was used to represent all reports where the "*Country of the other Counterparty*[34]" field shows "*XX*", which account for 8% of the total number of reports. The value "*XX"* is, according to the **ISO** 3166 Codes[35], acceptable to reference countries that have no country code as per this standard. Therefore, we kept in both the analysis and the graphical representation as long as meets the criteria pre-established to belong to the **PT Product + PT Participants** segment (see **Section 4.1** above). Reports where the counterparties used the "*EU*" in the "*Country of the other Counterparty*[36]" were also kept. Both acceptances pose constraints to an accurate assessment focused on the country of the network participants as: (i) the flag "*EU*" and/or the flag "*XX*" could have been used by a Portuguese counterparty which could have impact on the final graphical representation; and (ii) reports where the "*Other* Counterparty" is identified with the **LEI**, it is possible to cross reference with the **GLEIF** and track counterparty's country, however for those where the field is identified by the **CLC** that is not possible. We acknowledge the limitations of such decision as well as the potential impact in the overall picture but maintained these data as this work is a first glance on the Portuguese **OTC CDS** Derivatives Market.

The **Figure 13** represents the country network of each counterparty involved in the **PT Product + PT Participants** segment on the 28th December. The network below includes all those countries that are part of the transaction with a Portuguese counterparty or two foreign

[34] Field 5 of the RTS 2017/104 and the ITS 2017/105.
[35] https://www.iso.org/obp/ui/#search.
[36] Field 5 of the RTS 2017/104 and the ITS 2017/105.

counterparties executing a transaction in a Portuguese **OTC CDS** Derivatives. As reported in other articles on **CDS** under **EMIR**, the hegemony of the *United Kingdom* (**UK)** is clear. This can be justified as the **UK** has been historically the "home market" for the **OTC** transactions of such sub-asset class. In this sense, it can be concluded that the **PT Product + PT Participants** segment follows the tendency shown in (Abad et al., 2016) and the statistical report published by the European Securities and Markets Authority (European Securities and Markets Authority, 2018b).

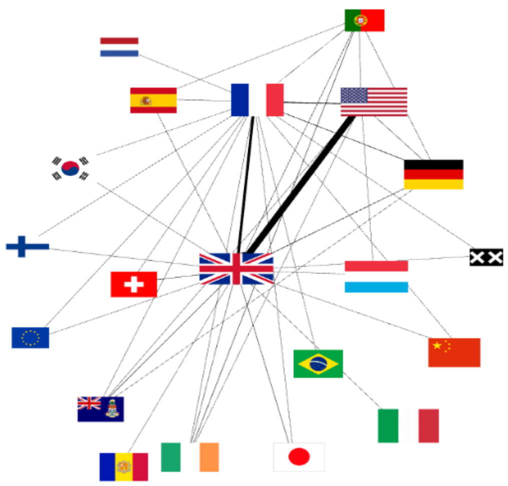

Figure 13 – **Undirected** and **unweighted** network of gross notional amount, per country. Each of the 18 nodes represent a country involved in the **PT Product + PT Participants** segment, and the thickness of each of the 271 relationships (links) is proportional to the aggregated transactions gross notional amount (in Euros) between the counterparties of the countries (based on the cleaned data set of the 28th December 2018).

Additionally, we provide in **Table 7** the top 5 country of counterparties per centrality measure. We observed that the influencer country, e.g., the country that if abandons the existing setting will have the most impact in the network is the United Kingdom - "**UK**", followed by France - "**FR**" and the United States of America - "**US**". The hegemony of **UK** is no news, considering that it has been in the center of the **OTC** Derivatives Market in Europe, not only for the **CDS**. These three countries have the highest: (i) degree (highest number of links with other countries in the network), (ii) betweenness (serve as link between other countries in the network), and (iii) Eigenvector (high number of links with other countries well connected). It is noteworthy to mention that contrary to the counterparty to counterparty network above, the top 5 share the same level of centralities.

Table 7 - Top 5 counterparties per Degree centrality and its placement regarding the other two centrality measures: betweenness and eigenvector for the **PT Product + PT Participants** segment. The ranking is identified in brackets after the value.

#	Counterparty country	Degree	Betweenness	Eigenvector
1	UK[37]	19	84 (1)	1 (1)
2	FR[38]	17	63.83 (2)	0.92 (2)
3	US[39]	8	7 (3)	0.61 (3)
4	PT[40]	6	1.92 (4)	0.534 (4)
5	DE[41]	5	0.25 (5)	0.49 (5)

4.2.2 PT Products segment (OTC CDS Derivatives)

This **Subsection** will provide details of the network analysis for the data set focused on the **Portuguese Product**, e.g., financial instruments identified with a Portuguese **ISIN** in the field "*Underlying Identification*[42]". For the analysis we will use the 12 monthly data sets obtained at the end of Step 13 as described in **Section 4.1**. The network inference and characterisation was performed for a single data set: 28th December 2018.

On average, there were 129 active counterparties on the **PT Products** segment in the year of 2018. Being the month of April the one that registered the lowest number of active counterparties (110), and July the highest (146). **Table 8**, summarises the main network metrics that characterise the networks for each monthly data set.

Table 8 – Network analysis metrics for the **PT Products** segment, including the number of nodes in the network (**N**), the average degree ($\langle \boldsymbol{k} \rangle$), the density of links, the maximum degree ($\boldsymbol{max(k)}$), the diameter of the network (**diam**), the average path length (**APL**), the Cluster Coefficient (**CC**), and the variance of the degree distribution ($\boldsymbol{var(k)}$)

	N	<k>	Density	max(k)	diam	APL	CC	var(k)
January	131	3.221	0.025	38	5	2.907	0.372	36.83
February	134	3.299	0.025	35	5	2.932	0.356	37.40
March	121	3.421	0.029	33	5	2.869	0.367	37.59
April	110	3.673	0.034	31	5	2.778	0.368	39.29
May	114	3.684	0.033	33	4	2.747	0.413	40.64
June	120	3.433	0.029	42	5	2.771	0.291	40.80
July	146	3.411	0.024	47	4	2.776	0.457	48.90
August	131	3.756	0.029	47	4	2.701	0.537	53.46
September	130	3.785	0.029	46	4	2.709	0.541	53.23

[37] United Kingdom.
[38] France.
[39] United States of America.
[40] Portugal.
[41] Germany.
[42] Field 8 (Section 2b) of the RTS 2017/104 and the ITS 2017/105.

October	140	3.900	0.028	46	4	2.793	0.429	53.83
November	141	3.929	0.028	48	4	2.801	0.429	54.65
December	133	3.970	0.03	49	5	2.835	0.46	53.04

The maximum shortest distance between two nodes in a network (number of links separating two nodes) – diameter of the network, in this case the longest path that a counterparty has to run to its furthest counterparty was lower than the network in **Subsection 4.2.1**: five for six data sets (January, February, March, April, June and December), and four for the remaining data sets (May, July, August, September, October and November).

The average degree of the **PT Products** segment did not have a steady ascendant movement as the previous network, but we can still conclude that all an all increased during the year of 2018, being December the month that registered the highest value (as the network in **Subsection 4.2.1**). This means that the number of counterparties for each participant active in the Market registered fluctuate during the year and ended with a slight increase. Such increase was mostly due to the increase of diversification in the relationships of the *Group of Sixteen* (**G16**). The maximum degree also increased along the year, which consolidated the previous statement. The **G16** players and the *Central Counterparty* (**CCP**) assumed the main roles in the network for the year of 2018.

Equally, the networks exhibit a very sparse connectivity structure, as only an average of approximately 3% of the possible links between counterparties exist. Such a low value indicates that the market might be highly susceptible to the existing relationships and be susceptible to the collapse of some of its central elements.

The average path length, which measures the average shortest path between all pair of nodes, was approximately three in all the data sets analysed.

The papers of (Abad et al., 2016; Kenny et al., 2016) highlighted that the main players of the **CDS** market are the **G16** and the **CCPs**, which is also the case here. Indeed, we observe that the **G16** players (i) have the highest number of relationships with other counterparties and between themselves; (ii) serve as intermediates between other players in the market; and (iii) they are very well connected with the other important players of the network, and therefore have the power to influence the other participants in the **PT Products** segment. These three observations are supported, respectively, by the centralities: Degree, Betweenness, and Eigenvector. The top 5 most central players were always from the **G16** and the **CCP.**

The **Figure 14** shows the degree distribution of the **PT Products** segment in 28th December 2018. The majority (86%) of the counterparties interact with the maximum of five counterparties, and 55% with a single counterparty. Both percentages are slightly higher than the one reported by (Abad et al., 2016). Such highly heterogeneous networks (Gao et al., 2015) are known to be very susceptible to target attacks, and as such events for which the highly central nodes might be more susceptible pose a high systemic risk to the entire system.

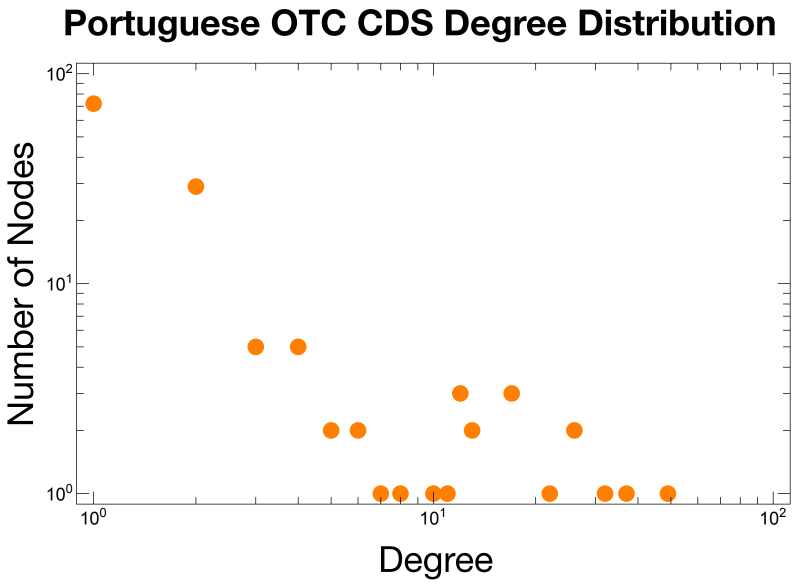

Figure 14– Degree distribution per number of counterparties for the **PT Products** segment

To explain, for the first time, the existing relationships in the **PT Products** segment we drafted three graphic representation of the market – see **Figure 15** using the data set of 28th December 2018.

The design process of the network was based on the addition of a link between two nodes (representing the relationship between the counterparties in a transaction) as long the product involved was a Portuguese **OTC CDS** (e.g. a **CDS** identified with a Portuguese **ISIN**) To be able to draw consideration regarding the other networks in **Subsections 4.2.1** and **4.2.3**, we used the same approach: (i) size of the nodes proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*", and (ii) the thickness of the links proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*" between the two counterparties. Self-loops (transactions where both sides of the transaction had the same *Legal Entity Identifier* (**LEI**) code were also excluded as it does not represent the same risk to the transaction chain.

Counterparties are colored using the same color scheme as in **Subsection 4.2.1**, except for the CLC that were not considered in the data set used (see Step 13 in **Section 4.1**), to highlight their type: ((i) **G16** in bright green; (ii) **CCP** in red; (iii) Banks in magenta; (iv) Funds in orange; (v) Financial Counterparties (**FC**) in blue; (vi) Non-Financial Counterparties (**NFC**) in black;

(vii) counterparties identified by the client code (**CLC**)[43] in grey and (viii) in bright blue the Portuguese players irrespectively of their counterparty type.

In the **CDS** networks there is a *core* of larger nodes (i.e., having a higher number of links) that can be distinguished from the *peripheral* nodes, which are smaller and less linked to the other counterparties. In fact, with a few exceptions, peripheral nodes are mostly connected towards the core and much less to other peripheral nodes. The networks are graphically represented in **Figure 15** (degree, betweenness, and eigenvector centrality measures), and provide a good overview of some interesting features: the dominance and centrality of the **G16**[44]; the **CCPs** and a few banks that trade with peripheral entities and between each other, irrespectively of the centrality measured. These findings are similar to previous work by (Abad et al., 2016; Peltonen et al., 2014) and are in line with the more recent work of (D'Errico et al., 2018; Gross & Siklos, 2018). In the latter, the authors identified a sectoral clustering in the **CDS** network, with the center occupied by the financial institutions (**G16**, Banks, **FC**, Funds), and non-financial entities (**NFC**) grouped around it.

It is noteworthy to mention that the network is similar to the one found in the *European Systemic Risk Board* **(ESRB)** paper (Abad et al., 2016).

The **PT Products** segment networks only have one giant component and none of the counterparties active in it is Portuguese.

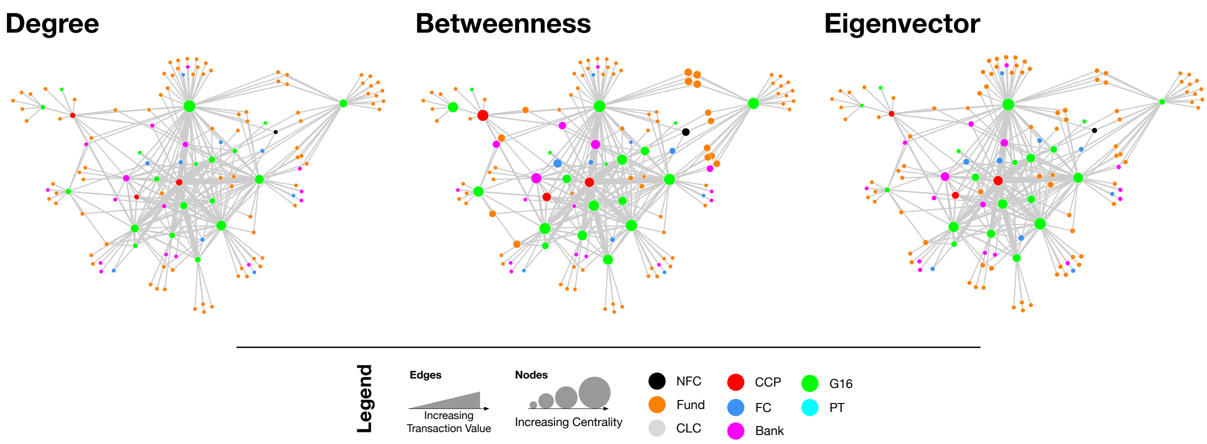

Figure 15 - Undirected and **unweighted** network (**PT Products** segment) of counterparty-counterparty of gross notional amount (per **degree**, **betweenness, and eigenvector centrality**), highlighting the Portuguese counterparties within the network. The size of each of the 133 counterparties (nodes) is proportional to the transactions gross notional amount (in Euros), and the thickness of each of the 264 relationships (links) is proportional to the transactions gross notional.

[43] Possible only for the non-reporting counterparty – field 4 of the RTS 2017/104 & ITS 2017/105.
[44] Includes all entities that belong to the G16 company, e.g.: JP Morgan and JP Morgan Securities.

The **Table 9** below provides a closer look to the top 5 counterparties per centrality measure, where we observe that the counterparty that if fails will have the most impact in the network is "4". This counterparty has the highest: (i) degree (highest number of links with other counterparties in the network), (ii) betweenness (serve as link between other counterparties in the network), and (iii) Eigenvector (high number of links with other counterparties well connected). It is noteworthy to mention the counterparty "23", has a more limited scope when compared with the others within the degree top 5 as does not share the same level of links with "other very well connected" counterparties (eigenvector). To be noted that counterparty "7" does not have the same linkage between other counterparties in the network as the remaining Top 5, which is obtained by the betweenness.

All counterparties in the top 5 per Degree centrality belong to the **G16** group.

Table 9 – Top 5 counterparties per Degree centrality and its placement regarding the other two centrality measures: betweenness and eigenvector (**PT Products** segment). The ranking is identified in brackets after the value.

#	Counterparty ID	Degree	Betweenness	Eigenvector
1	4	49	3,118.93 (1)	1 (1)
2	8	37	1,911.80 (2)	0.94 (2)
3	2	32	1,444.48 (4)	0.77 (3)
4	7	26	1,413.63 (6)	0.77 (4)
5	23	26	1,575.39 (3)	0.27 (19)

To unveil the ties between countries in which counterparties are hosted, a new network was built that focuses in the country of each counterparty involved in a Portuguese **OTC CDS** Derivatives. The process to build the first network was replicated but now focused on the countries of the counterparties active in the **PT Products** segment for the 28th December 2018. A few minor albeit necessary adaptations were done, as the *country-country* network will be focused on the country of the counterparty rather than the counterparty itself. For that purpose, we cross referenced the **LEI** code of the fields "*Reporting Counterparty*" and "*Country of the other Counterparty"* with the information in the *Global Legal Entity Identifier Foundation* (**GLEIF**) data base and used the country reported in the field*"* "*Country of the other Counterparty"* for those cases where no match was found in **GLEIF** data set.

Following the same process as in **Subsection 4.2.1**, the thickness of the links is proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*" between the countries where the counterparties involved in the transaction are based on. Self-loops (transactions where both sides of the transaction had the same **LEI** code) were also excluded as it does not represent the same risk to the transaction chain.

To facilitate the visual inspection of the network, and provide information with emphasis in the country, nodes have been replaced by the flags of the country they represent.

The **Figure 16** represents the country of each counterparty involved in a transaction of an **OTC CDS** identified with a Portuguese **ISIN** on the 28th December. As we saw in the country network of **Subsection 4.2.1**, and reported in other articles on **CDS** under **EMIR**, the hegemony of the *United Kingdom* (**UK)** is clear. This can be justified as the **UK** has been historically the "home market" for the **OTC** transactions of such sub-asset class. In this sense, it can be concluded that the **PT Products** segment network follows the tendency shown in (Abad et al., 2016) and the statistical report published by the European Securities and Markets Authority (European Securities and Markets Authority, 2018b). The absence of Portuguese counterparties in the counterparty to counterparty network is now confirmed as Portugal is not represented in the network below.

Figure 16 – **Undirected** and **unweighted** network of gross notional amount, per country. Each of the 17 nodes represent a country involved in the **PT Products** segment, and the thickness of each of the 264 relationships (links) is proportional to the aggregated transactions gross notional amount (in Euros) between the counterparties of the countries (based on the cleaned data set of the 28th December 2018).

Additionally, we provide in **Table 10** the top 5 country of counterparties per centrality measure. We observed that the influencer country, e.g., the country that if abandons the existing setting will have the most impact in the network is the United Kingdom - "**UK**", followed by France - "**FR**" and the United States of America - "**US**". The hegemony of **UK** is no news, considering that is has been the "home Market" for the **OTC** Derivatives Market in Europe, not only for the **CDS.** These three countries have the highest: (i) degree (highest number of links with other countries in the network), (ii) betweenness (serve as link between other countries in the network), and (iii) Eigenvector (high number of links with other countries well connected). Contrary to what we observed in the counterparty to counterparty network, the top 5 share the same level of centralities.

Such predominance may be closely followed in light of the changes towards the approach of the **UK** concerning Europe and the impact that the to be concluded **Brexit** may have in the activity in this Market, where the top players and **CCP** are based in the **UK**.

Table 10 – Top 5 counterparties per Degree centrality and its placement regarding the other two centrality measures: betweenness and eigenvector (**PT Products** segment). The ranking is identified in brackets after the value.

#	Counterparty country	Degree	Betweenness	Eigenvector
1	UK[45]	16	61.17 (1)	1 (1)
2	FR[46]	14	44.67 (2)	0.91 (2)
3	US[47]	7	7.17 (3)	0.61 (3)
4	DE[48]	4	0 (4)	0.48 (4)
5	KY[49]	4	0 (5)	0.48 (5)

4.2.3 PT Participants segment (Portuguese counterparties active in the OTC CDS Derivatives Markets)

In this **Subsection** we provide details of the network analysis for the data set focused on the **Portuguese Participants**, e.g., all Portuguese counterparties active in the **OTC CDS** Markets. For this purpose, we used the monthly data sets obtained at the end of Step 14 as described in **Section 4.1**, built only with transaction reports where at least one of the counterparties involved in such transaction is Portuguese. The network inference and characterisation was performed only for 28th December 2018.

The network is extremely small and very sparse, containing only 15 counterparties (nodes), 55 connections between them (links), and six components. Therefore, we will only highlight some of the metrics without running an exhaustive network metric analysis as we did in the previous **Subsections**. The dimension of the network can be justified mainly by two factors: (i) at least one of the counterparties of the transaction has to be Portuguese, and (ii) the level of specialisation associated to the **CDS**. The Portuguese financial market is small and went through a consolidation period post-crisis (Banco de Portugal (Eurosystem), 2018), which lead to a reduction in the number of entities with the capacity, willingness and the know how needed to participate in more complex Markets such as the **OTC CDS** Derivatives Markets.

In the European landscape the main players in the **OTC CDS** are the **G16**, Banks and *Financial Counterparties* (**FC**), all of which the Portuguese counterparties (Banks and **FC**) interacted as it can be observed below in **Figure 17**.

[45] United Kingdom.
[46] France.
[47] United States of America.
[48] Germany.
[49] Cayman Islands.

On average, there were 19 active counterparties on the **PT Participants** segment network in the year of 2018. Being the month of December the one that registered the lowest number of active counterparties (15), and January April and May the highest (22).

The diameter of the network, which represents the maximum shortest distance between two nodes in a network (number of links separating two nodes), in this case the longest path that a counterparty has to run to its furthest counterparty was constantly at two except in the months with the highest number of active counterparties (January, April and May): 4.

Contrary to what we saw for the previous networks, the average degree decreased during the year of 2018, being December the month that registered the lowest value. This means that the number of counterparties for each participant active in the Market decrease during the year. Such increase was mostly due to some players leaving the market, in particular those from the **G16** group.

It is noteworthy that all transactions in the data set are not-cleared and therefore we will not observe the same level of activity from the *Central Counterparties* (**CCPs**) as for the previous networks, making the **PT Participants** segment network substantially different from the **PT Products + PT Participants** and **PT Participants** segment networks (**Subsection 4.2.1** and **Subsection 4.2.2**, respectively).

To perceive, the existing activity of the **PT Participants** segment under **EMIR** it was also drafted three graphic representation (**Figure 17**) using the data set from the 28th December 2018.

The construction process did not deviate from the ones executed priory (**Subsection 4.2.1** and **Subsection 4.2.2**) hence we added a link between two nodes (representing the relationship between the counterparties in a transaction) as long as at least one transaction on a **CDS** contract was observed between them. The size of the nodes is proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*", whereas the thickness of the links is proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*" between the two counterparties. Self-loops (transactions where both sides of the transaction had the same *Legal Entity Identifier* (**LEI**) code were also excluded as it does not represent the same risk to the transaction chain.

For all nodes to be visible, we used a scale as per the **Figure 17** below. Additionally, counterparties are colored to highlight their types, following the same color pallet as before: (i) **G16** in bright green; (ii) **CCP** in red; (iii) Banks in magenta; (iv) Funds in orange; (v) Financial Counterparties (**FC**) in blue; (vi) Non-Financial Counterparties (**NFC**) in black; (vii) counterparties identified by the client code (**CLC**)[50] in grey and (viii) in light blue the Portuguese players irrespectively of their counterparty type.

The **Figure 17** below shows a very different scenery from the previous networks, hence providing a good overview of some interesting features: the dominance of the Portuguese players that are present in all components of the network.

The networks representing the **PT Participants** segment have six Portuguese players (belonging to the Bank and **FC** groups) of which five are part of each small component with only two nodes. The remaining Portuguese counterparty assumes a central role in the giant component, serving as the connection between the other four nodes (counterparties).

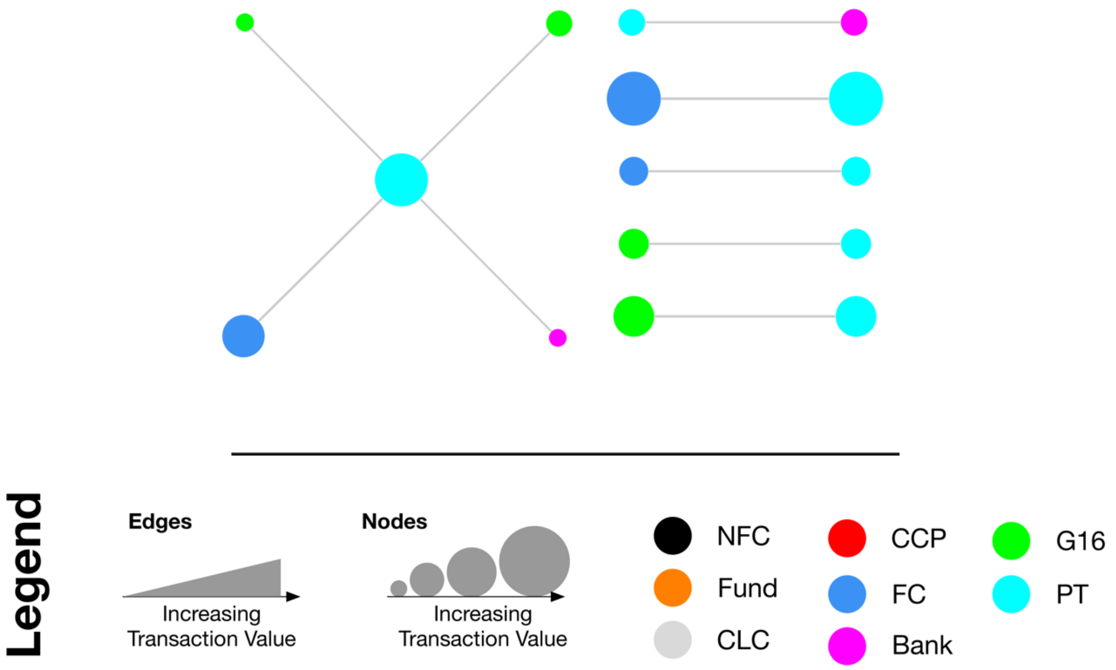

Figure 17 – **Undirected** and **unweighted** network (**PT Participants** segment) of counterparty-counterparty of gross notional amount, highlighting the Portuguese counterparties within the network. The size of each of the 15 counterparties (nodes) is proportional to the transactions gross notional amount (in Euros), and the thickness of each of the 9 relationships (links) is proportional to the transactions gross notional.

The **Table 11** below provides a closer look to the top 5 counterparties per centrality measure, we observed that the most influence counterparty, e.g., a counterparty that if fails will have the most impact in the network is "0". This counterparty has the highest: (i) degree (highest number of links with other counterparties in the network), (ii) betweenness (serve as link between other counterparties in the network), and (iii) Eigenvector (high number of links with other counterparties well connected).

[50] Possible only for the non-reporting counterparty – field 4 of the RTS 2017/104 & ITS 2017/105.

All counterparties in the top 5 per Degree centrality belong to the Bank, **FC**, and **G16** group, and only one is Portuguese.

Table 11 - Top 5 counterparties per Degree centrality and its placement regarding the other two centrality measures: betweenness and eigenvector (**PT Participants** segment). The place id identified in brackets after the value.

#	Counterparty ID	Degree	Betweenness	Eigenvector
1	0	4	6 (1)	1 (1)
2	9	1	0 (2)	0.50 (2)
3	1	1	0 (3)	0.50 (3)
4	2	1	0 (4)	0.50 (4)
5	3	1	0 (5)	0.50 (5)

To unveil the ties between countries in which counterparties are hosted, a new network was built that focuses in the country of each Portuguese counterparty involved in a transaction of a Portuguese **OTC CDS** Derivatives. The construction process executed for the first network was replicated from the same initial data set, dated of 28th December 2018. As performed in the previous **Subsections**, a few minor albeit necessary adaptations were done, as the *country-country* network will be focused on the country of the counterparty rather than the counterparty itself. For that purpose, we cross referenced the **LEI** code of the fields "*Reporting Counterparty*" and "*Country of the other Counterparty"* with the information in the *Global Legal Entity Identifier Foundation* (**GLEIF**) data base and used the country reported in the field*"* "*Country of the other Counterparty"* for those cases where no match was found in **GLEIF** data set.

Following the same process as above, the thickness of the links is proportional to the transactions gross notional amount (in Euros) – "*Gross Notional*" between the countries where the counterparties involved in the transaction are based on. Self-loops (transactions where both sides of the transaction had the same **LEI** code) were also excluded as it does not represent the same risk to the transaction chain.

To facilitate the visual inspection of the network, we replaced nodes have by the flags of the country they represent.

The **Figure 18** represents the country of each counterparty involved in a transaction on an **OTC CDS** Derivative for the **PT Participants** segment network. As it may be seen, Portugal assumes a non-usual central role in the network while confirming the leading placement of the centrality metrics of the counterparty to counterparty network above.

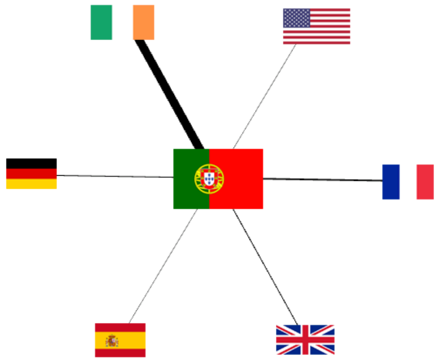

Figure 18 – **Undirected** and **unweighted** network of gross notional amount, per country. Each of the 7 nodes represent a country involved in the **PT Participants** segment network, and the thickness of each of the 9 relationships (links) is proportional to the aggregated transactions gross notional amount (in Euros) between the counterparties of the countries (based on the cleaned data set of the 28th December 2018).

Additionally, we provide in **Table 12** the country of counterparties per centrality measure. We observed that the influencer country, e.g., the country that if abandons the existing setting will have the most impact in the network is Portugal - "**PT**", which is justifiable considering the restrictions made to reach the final data set: a Portuguese counterparty shall always be involved in the transaction otherwise would be excluded. Portugal has the highest: (i) degree (highest number of links with other countries in the network), (ii) betweenness (serve as link between other countries in the network), and (iii) Eigenvector (high number of links with other countries well connected).

Table 12 - Top 5 counterparties per Degree centrality and its placement regarding the other two centrality measures: Betweenness and Eigenvector (**PT Participants** segment) The ranking is identified in brackets after the value.

#	Counterparty country	Degree	Betweenness	Eigenvector
1	PT[51]	6	15 (1)	1 (1)
2	IE[52]	1	0 (2)	0.41(2)
3	UK[53]	1	0 (3)	0.41 (3)
4	ES[54]	1	0 (4)	0.41 (4)
5	FR[55]	1	0 (5)	0.41 (5)

[51] Portugal.
[52] Ireland.
[53] United Kingdom.
[54] Spain.
[55] France.

5. CONCLUSIONS

In this work we have analysed the Portuguese **OTC CDS** Derivatives Markets from a network science perspective for the first time using the state report data set resulting from the transaction reporting obligation under *European Market Infrastructure Regulation* (**EMIR**) for the year of 2018.

We followed the practices already detailed in the existing literature. However, we have used the derivative state report under **EMIR** for the year of 2018 (after the revision of the requirements that took place in November 2017). As far as we know, this is the first work to explore the data under the new revision guidelines at domestic (Portugal) scale.

While our analysis suggests that so far, the data available is a breakthrough to understand the **OTC CDS** Derivatives activity in Europe, and show a strong potential to provide adequate improvements to supervision (measures, actions, controls, alerts), we also note the room for improvements regarding data quality.

During our analysis, and since we focused on the Portuguese **OTC CDS** Derivatives Market, we performed a multi-segment analysis considering the following segments:

(1) **PT Product + PT Participants** segment consisting of all reports where (i) at least one counterparty involved in the transaction is Portuguese; and (ii) non-Portuguese counterparties that entered into transactions in a **CDS** identified with a Portuguese *International Securities Identification Number* (**ISIN**) code. It is noteworthy to mention that in this data set we focused only on the **CDS** single names and included counterparties identified with a Client Code (**CLC**);

(2) **PT Product** segment consisting of all reports of transactions involving a Portuguese **OTC CDS** Derivative, e.g., a contract identified with a Portuguese **ISIN**, irrespectively of the country where the counterparty to the transaction was based on. To be noted that contrary to the previous data set, here we removed all reports where a counterparty was not identified with a valid **LEI**, e.g., excluding reports were the counterparty is identified by a **CLC**; and

(3) **PT Participants** segment consisting of all reports where one of the counterparties involved is Portuguese. Similarly, to the decision taken for the data set focused on the **PT Products** segment, we removed all reports where a counterparty was not identified with a valid **LEI**.

Despite the data quality issues found during the process, which are commonly acknowledge and reported in existing papers, articles and supervisors' official communications (European Securities and Markets Authority, 2019b), it was possible to observe that the Portuguese **OTC CDS** Derivatives Market, for the first two aforementioned segments: **PT Product + PT**

Participants, and **PT Products** segment the main counterparties are the **G16**, the **CCPs**, and the banks, that serve as the links with the other counterparties within the networks, where the United Kingdom assumes the central mediating role in each of these country networks. Such results follow the same tendency as the overall European **OTC CDS** Derivatives Market, and can be observed by the results of the betweenness centrality of these players, which measures the potential control of a few central players over the other players in the network. In particular, as the betweenness highlights entities have that more often intermediate the flow of information/capital between other entities.

The main difference between the **PT Products + PT Participants** segment, and **PT Products** segment is that the former exhibits more components (5, including the giant component), whereas the latter only shows one. The risk of failure of the central nodes in the **PT Products + PT Participants** segment is supplemented by those counterparties (nodes) belonging to the smaller components. We expect it to be less robust (not from the *Central Counterparty* (**CCP**), **G16** or major Banks), and thus more sensitive to random failures. In the **PT Products** segment such risk is concentrated in the **CCP**, **G16**, and Banks as it is the case in other European (**EU**) level papers, thus we expect it to be more sensitive to target failures.

In the **PT Participants** segment, we observed a completely different scenario with no presence from the **CCP**, being the risk assumed by the **G16** or Banks, the latter in its majority Portuguese who serve as the link to smaller counterparties in the network. Similarly, to the previous segments, these entities are also the ones that present a higher betweenness and therefore are those that control the information/capital flows of the system. Which, in case of a failure poses additional risk to a system that highly relies on those central players.

To be noted that in the **PT Products** segment network we do not identify the presence of any Portuguese counterparties, whereas in **PT Participants** segment network they dominate, e.g. are active but in non-**PT OTC CDS** Derivatives. Therefore, we concluded that foreigners are the players in the **PT Products** segment network while Portuguese counterparties prefer cross-border (non-domestic) **OTC CDS** Derivatives Markets.

Additionally, for each of the segments we performed an analysis of a meta-network, that aggregates data by country of the counterparties involved in the transactions on the **OTC CDS** Markets. For the **PT Products + PT Participants** segment, and **PT Products** segment, the United Kingdom (**UK**) assumes the leading role, with the highest betweenness centrality, which has also been reported in other available literature. Such leadership poses, in light of the recent shift in the **UK** towards Europe (**EU**) politics (**Brexit**), an additional concern to those already in place as the top players (in terms of access to other players in the network) are based in the

UK, and the main **CCPs** are also based in the **UK.** Hence the imminent Brexit may lead to regulatory arbitrage that could create disruption to the market with the loss of central players of the network, as well as unlevelled playing field. Such impact is real but still due to be assessed. On the contrary, the country network of the **PT Participants** segment is **PT**-center, where a Portuguese counterparty is involved even in the small components, always having a link with at least one Bank or a **G16** player that has scale and procedures in place to offer services to smaller (less scaled) entities as those in the Portuguese financial system.

These networks are resilient to random failures but largely susceptible to targeted failures of the few most central players in the network, which in case of failure can largely impair the function of the system and lead to the collapse of a large part of the network.

From the analysis performed, we concluded that albeit some gains, there is still room for improvements in terms of data quality and reporting requirements. We believe that an effort should be made through the implementation of enforcement measures directly to the counterparties and the *Trade Repositories* (**TRs**) to subscribe to the necessary data quality standards required for this short analysis. Both are responsible for the existing data flaws, which are in breach with the European Regulation: **EMIR**. Furthermore, the activity(ies) that exist in these less opaque environments (**OTC** Derivatives Markets) and that could endanger the market, should be flagged for further investigation by the supervisors and policy makers.

Overall, **EMIR** transaction reporting data is a useful and powerful tool that regulators in Europe should continue to use and continue to explore fields to improve and include into their daily and specific supervisory actions or plans.

The modelling of such data allowed us to map the Portuguese **OTC CDS** Derivatives Market participants while identifying those that may be considered as a soft spot, e.g., those that present more of a risk as in case of failure are more susceptible to impact the network.

We conclude this working paper with a brief mention to the Challenges and Limitations faced in the execution of this work, and an overview of Future Work opportunities following the methodology.

5.1. CHALLENGES AND LIMITATIONS

Past works exploring **EMIR** data, but also **ESMA** on its *Supervision – 2018 Annual Report and 2019 Work Programme on Credit rating agencies, trade repositories, third country central counterparties, and third country central security depositories* (European Securities and Markets Authority, 2019a), and most recently the final report on the peer review made to six

European competent authorities of the most significant derivatives markets in the European Union regarding the supervision made using the EMIR data (European Securities and Markets Authority, 2019c), recognise the effort being developed by the industry to improve the **EMIR** data quality. However, and more importantly, they also identified issues with the quality of existing data and the potential room for improvement in that respect.

The **EMIR** reporting data sets available for the studied timeframe included: (i) daily transaction reporting that includes all changes to the transactions since they are open, up until their close, and (ii) state reports snap shots of the transactions in a specific date. Hence deciding which data set was best for the ensuing analysis that we report here, involved a tradeoff between the large volumes of daily raw data that contained all the information of each transaction (open or close of a position, modifications, cancelations) or rely on the state reports. The latter although a smaller data set (reduction of the data volume) only provide daily snap shots of the market and arguably introduce some information loss.

Data quality and reporting issues faced during our study boiled down to three main reasons:

i. Entity fault - counterparties to the transaction that misreported at least one field;
ii. Trade Repositories fault - the first layer of data validation accepted reports with data flaws, shared them with **ESMA**, who then reshared it with the competent authorities alongside with accurate reports; and
iii. Requirements (mandatory vs optional) fault – the optionality of some of the fields to be reported, should be revisited as some of those deem to have an important role in accessing the exposure and respective risk of each counterparty.

We choose to work with the state report as it should be a snapshot of the market in a given day, and hooped it would reduce the data issues broadly reported. However, we still faced some inconsistencies that had a relevant impact in the cleaning process, caused delays, and posed challenges to an accurate mapping of the Portuguese **OTC** activity in **CDS**. Below a non-exhaustive list of fields of the state report to which we considered there is room for reporting improvement and thus help in market supervision:

- Maturity date, should not be allowed to be blank as an empty field misleads if the transaction should still be considered or has been terminated/closed;
- There should be consistency between the field for the "*ID of the other Counterparty*[56]" and "*Type of ID of the other Counterparty*[57]" as mismatching happens (e.g. the first field

[56] Field 4 of ITS 2017/105.
[57] Field 3 of ITS 2017/105.

has a valid **LEI** whereas the other indicates that the counterparty is identified with a **CLC**);

- Contract type, should be mandatory as its reporting may allow to cross reference for the clearing obligation as well as to adequately analyse the distinct products within each asset class; and
- Rethink the reporting of baskets as a whole and the **CDS** in particular as with the existing free text field is not feasible to link the **CDS** baskets to a specific competent authority.

5.2. FUTURE WORK

Both 2019 and 2020 will be years of transformation in the **EMIR** landscape as (i) all industry players are pushing for an improvement in the reporting data quality; (ii) the **EMIR** has just been revised (**EMIR Refit**[58] or **EMIR 2.2** (European Comission, 2019)); and (iii) the United Kingdom is negotiating an exit from the European Union (so called **Brexit**[59]). Hence, we foresee the potential benefits of further exploration and analysis of this data from a network perspective.

At first glance, **EMIR Refit** will bring changes to the reporting obligations (e.g. introduction of a new type of counterparty – *Small Financial Counterparties* (**SFC**); removal of obligation to report transactions within the same group, national competent authorities may now decide what information to receive from the **TR**s, among others), and therefore a whole new potential for the **EMIR** transaction reporting data.

Additionally, it may be equally interesting to widen the scope of the analysis:

- Through the inclusion of the remaining asset classes subject to the EMIR: Interest Rate Derivatives (**IRD**); Foreign Exchange Derivatives (**FX**), Commodity Derivatives, and Equity Derivatives or any of its sub-asset classes;
- By comparison with the full Portuguese Derivatives Market (e.g. include the transactions on Stock Exchanges);
- Broaden the data by using the transactions report (daily files with all the transactions to be reported).

We believe that further studies could take advantage of the methodology basics herewith but with a focus on the diversification of the analysis, either:

[58] Entry into force: 17 June 2019.
[59] There is still a lot of uncertainty regarding the date for the United Kingdom to leave the European Union as well as the terms of the agreement; or even if there will be an "exit agreement".

- Event specific: like an analysis of the impact of Brexit in the Portuguese **OTC** Derivatives Market;
- Regulation driven: considering the extensive range of European Regulations on different topics of the financial markets, this work may serve as a basis to seek a better understanding of other European or national data driven regulatory requirements. Or even to cross reference the transactions reported in compliance with different European Regulations (e.g. Stock Exchange Derivative transactions reported under the **EMIR** versus Stock Exchange Derivative transactions reported under the *Market in Financial Instruments Regulation* (**MiFIR)**);
- Link current metrics used by supervisors to assess the risk of failure of different players with their position in the network in an attempt to detect ahead of time potential systemic problems to the financial system.

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7. ANNEX

7.1. LIST OF EXISTING TRADE REPOSITORIES (TR)[60]

Table 13 – Trade repositories approved by ESMA per asset class and date

Trade Repository	Asset class	Effective date
DTCC Derivatives Repository Plc (DDRL, previously DTCC Derivatives Repository Ltd.)	All asset classes	14 November 2013
Krajowy Depozyt Papierów Wartosciowych S.A. (KDPW)	All asset classes	14 November 2013
Regis-TR S.A.	All asset classes	14 November 2013
UnaVista Limited	All asset classes	14 November 2013
CME Trade Repository Ltd. (CME TR)	All asset classes	05 December 2013
ICE Trade Vault Europe Ltd. (ICE TVEL)	Commodities, credit, equities, interest rates	05 December 2013
	Foreign exchange	04 June 2015
NEX Abide Trade Repository AB	All asset classes	24 November 2017
DTCC Data Repository (Ireland) Plc	All asset classes	1 March 2019
UnaVista TRADEcho B.V. (The Netherlands)	All asset classes	25 March 2019

7.2. VARIABLES DESCRIPTION

The descriptions below were taken from the Commission Delegated Regulation (EU) 2017/104[61] of 19 October, supplementing **EMIR**:

Table 14 – Variables selected from the original data set

Field	Description
Reporting Counterparty ID	Unique code identifying the reporting counterparty of the contract.
ID of the other Counterparty	Unique code identifying the other counterparty of the contract. This field shall be filled from the perspective of the reporting counterparty. In case of a private individual a client code shall be used in a consistent manner.
Country of the other Counterparty	The code of country where the registered office of the other counterparty is located or country of residence in case that the other counterparty is a natural person.
Type of ID of the other Counterparty	Type of the code to identify the other counterparty.
Report submitting entity ID	In the case where the reporting counterparty has delegated the submission of the report to a third party or to the other counterparty, this entity has to be identified in this field by a unique code. Otherwise this field shall be left blank.
Clearing member ID	In the case where the derivative contract is cleared and the reporting counterparty is not a clearing member itself, the clearing member through which the derivative contract is cleared shall be identified in this field by a unique code.

[60] https://www.esma.europa.eu/supervision/trade-repositories/list-registered-trade-repositories.
[61] (RTS 2017/104) with regards to regulatory technical standards on the minimum details of the data to be reported to trade repositories.

Beneficiary ID	The party subject to the rights and obligations arising from the contract. Where the transaction is executed via a structure, such as a trust or fund, representing a number of beneficiaries, the beneficiary should be identified as that structure. Where the beneficiary of the contract is not a counterparty to this contract, the reporting counterparty has to identify this beneficiary by a unique code or, in case of a private individual, by a client code used in a consistent manner as assigned by the legal entity used by the private individual.
Counterparty side	Identifies whether the reporting counterparty is a buyer or a seller.
Value of contract	Mark to market valuation of the contract, or mark to model valuation where applicable under Article 11(2) of Regulation (EU) No 648/2012 (**EMIR**). The **CCP**'s valuation to be used for a cleared trade.
Contract type	Each reported contract shall be classified according to its type.
Asset class	Each reported contract shall be classified according to the asset class it is based on.
Product identification type	The type of relevant product identification.
Product identification	The product shall be identified through **ISIN** or **AII**[62]. AII shall be used if a product is traded in a trading venue classified as **AII** in the register published on ESMA's website and set up on the basis of information provided by competent authorities pursuant to Article 13(2) of Commission Regulation (EC) No 1287/2006. **AII** shall only be used until the date of application of the delegated act adopted by the Commission pursuant to Article 27(3) of Regulation (EU) No 600/2014 of the European Parliament and of the Council (**MiFIR**).
Underlying identification type	The type of relevant underlying identifier.
Underlying identification	The direct underlying shall be identified by using a unique identification for this underlying based on its type. AII shall only be used until the date of application of the delegated act adopted by the Commission pursuant to Article 27(3) of Regulation (EU) No 600/2014 (**MiFIR**). For Credit Default Swaps, the **ISIN** of the reference obligation should be provided. In case of baskets composed, among others, of financial instruments traded in a trading venue, only financial instruments traded in a trading venue shall be specified.
Trade ID	Until global UTI is available, a Unique Trade ID agreed with the other counterparty.
Venue of execution	The venue of execution of the derivative contract shall be identified by a unique code for this venue. Where a contract was concluded OTC and the respective instrument is admitted to trading or traded on a trading venue, MIC code “XOFF” shall be used. Where a contract was concluded OTC and the respective instrument is not admitted to trading or traded on a trading venue, MIC code “XXXX” shall be used.
Notional	The reference amount from which contractual payments are determined. In case of partial terminations, amortisations and in case of contracts where the notional, due to the characteristics of the contract, varies over time, it shall reflect the remaining notional after the change took place.
Execution timestamp	Date and time when the contract was executed.
Maturity date	Original date of expiry of the reported contract. An early termination shall not be reported in this field.
Confirmation timestamp	Date and time of the confirmation, as set out in Article 12 of Commission Delegated Regulation (EU) N. º 149/2013.
Cleared	Indicates, whether clearing has taken place.
CCP	In the case of a contract that has been cleared, the unique code for the CCP that has cleared the contract.
Intragroup	Indicates whether the contract was entered into as an intragroup transaction, defined in Article 3 of Regulation (EU) No 648/2012 (**EMIR**).

[62] *Alternative Instrument identifier* - composed of six elements, and they collectively constitute the Alternative Instrument Identifier for an instrument.

Table 15 – Example of the variable's outcome of the data set

Variable Nr.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Extra1	Extra2	Extra3
Variable Name	Reporting Counterparty ID	ID of the other Counterparty	Country of the other counterparty	Type of ID of the other counterparty	Report submitting entity ID	Clearing member ID	Beneficiary ID	Counterparty side	Value of contract	Contract type	Asset class	Product identification type	Product identification	Underlying identification type	Underlying identification	Trade ID	Venue of execution	Notional	Execution timestamp	Maturity Date	Confirm timestamp	Cleared	CCP	Intragroup	Gross_Notional	Country of the Reporting Counterpart ID	Product_Country
Example1	156	16	GB	LEI	156	2552	156	B	-6785,94	SW	CR	A	EZ37X7R50	I	KEZPKKKM10(	AZERTYWSDE	XXXX	3 000 000	17/12/2017	23/01/2024	17/12/2017	Y	CCP1	N	3 000 000	UK	UK
Example2	2	112	PT	LEI	2	11150	5568A	S	13 785	SW	CR	I	X7R576605	I	(KOTEALK101:	KKJYTHG1	XXXX	2 250 000	03/05/2016	18/12/2028	03/05/2016	N		N	2 250 000	DE	PT

7.3. LEI STATUS

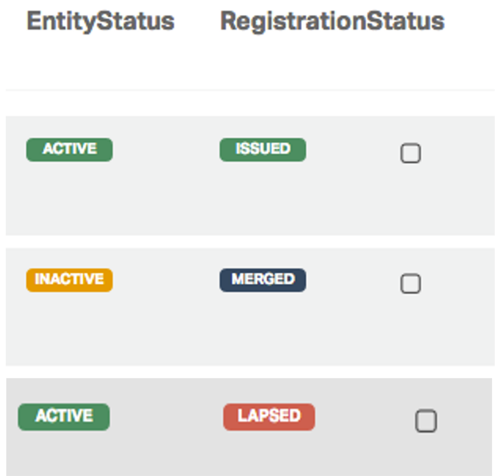

Figure 19 - LEI status

7.4. COMPLETE NETWORK – *PT PRODUCTS + PT PARTICIPANTS*

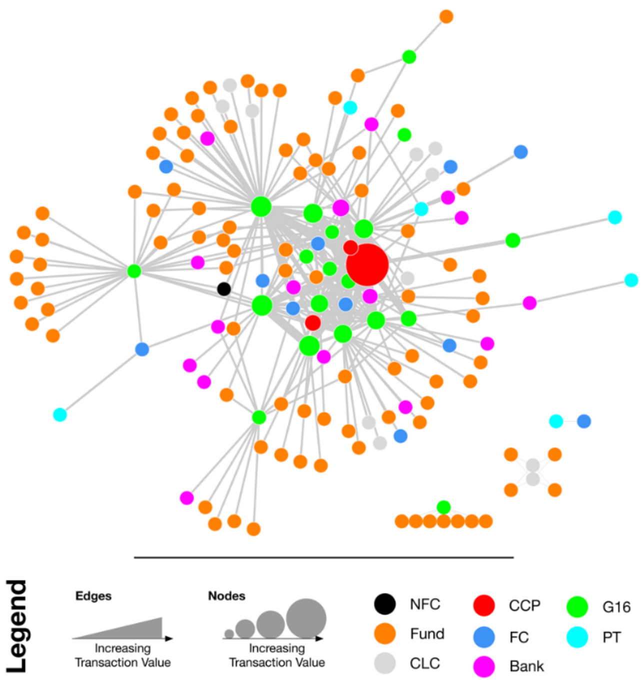

Figure 20 - Undirected and **unweighted** network of counterparty-counterparty of gross notional amount (per **degree centrality**), highlighting the Portuguese counterparties within the network. The size of each of the 156 counterparties (nodes) is proportional to the transactions gross notional amount (in Euros), and the thickness of each of the relationships (links) is proportional to the transactions gross notional