Università
Ca'Foscari
Venezia

Master's
Degree

in Economia
e Finanza

curriculum

Finance

Final Thesis

Pricing models and empirical evidence for a CDO-type instrument: the Collateralized Loan Obligation

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Academic Year
2019 / 2020

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Introduction

The history of recent decades has made clearer the crucial role the banking system has assumed in the economic cycle. The lending system makes possible for the real economy to complete its life cycle. As soon as access to credit becomes more difficult or the banking system goes through troubles, the consequences for the real economy are immediate.

Since the 1990s, there have been several major shocks in the banking system, which have damaged the economies of different countries. Most of these crises are accumulated by the same triggering factors, which essentially can be identified in the lack of diversification of credit portfolios and in an overly permissive lending policy. These crises, which have had heavy consequences for diverse world economies, have focused the attention of the banking and academic world on concepts related to risk management, and in particular credit risk management. The strong interest in credit risk pushed the growth of new forms of measurement. The management and control of these aspects are studied from three points of view: the study of models with the aim of determining the risk associated with credit exposures or a credit portfolio, the creation of various financial instruments that allow the transfer of credit risk and regulatory review by supervisors.

As regards the risk associated with credit exposures, different banking institutions have developed their own procedures with the intent of measuring the credit risk associated with a certain credit exposure or a given credit portfolio. In essence, the ultimate goal of these models is to extend the idea of "Value at Risk" (VaR), which was originally designed for market risk, to credit risk and to allow its determination. At the beginning, credit derivatives did not exist. In the past, banks, once the loan was granted, had no alternative but to wait for the repayment, in the hope that the financed entity would not default; with the diffusion of credit derivatives, banks may now trade the risk linked to the non-repayment of the financing as if it were a commodity.

It should be stressed that there has also been a continuing evolution from a regulatory point of view, which has seen the introduction of new prudential rules to avoid challenging situations for financial institutions. The several Basel Accords proposed and continuously revised seek to take greater account of the risks associated with banking and financial activities. As crises occurred in the past few years, the regulatory examination

is still at work to produce piece of law more and more detailed to guarantee a less risky banking system.

Within financial assets, different types of risk to which the holder is exposed can be identified; the following is a short list:

- credit risk
- market risk
- country risk
- liquidity risk
- exchange rate risk

For credit banking business, credit risk is the most relevant and critical aspect to be managed. The approach used by banks has changed considerably over time. We have moved from a traditional approach that is limited to following loan-by-loan philosophy aimed at identifying and cancelling the risk of the individual loan, to a management of this risk factor as a variable to be measured and controlled using techniques based on portfolio approaches.

The reasons that led the introduction of Credit Risk Management areas within banks, in addition to the criticality of credit risk for financial institutions, are the possibility of creating value for shareholders by efficiently allocating the bank's capital. The aspects that characterize the credit-risk management process consists in the attempt to measure credit risk associated with financial activities through methodologies that are objective and not discretionary. Banks must be able to identify and estimate the different risk components and to establish the maximum loss they can bear, all through the internal development of rating systems that are fundamental to credit risk management.

The consequence was the development of particular financial operations such as securitization, and the creation of secondary markets for bank loans with subsequent study and design of derivative instruments for more effective credit risk management. Loans are intrinsically illiquid securities, so the development of a secondary market allows a continuous monitoring of their value. It also makes it possible for banks to free up assets in order to diversify their business, thus making active management of the credit portfolio possible.

In this thesis, we study the market and the pricing models of a loan-related financial instrument belonging to the family of the Collateralized Debt Obligations (CDOs): the Collateralized Loan Obligation (CLO). Such highly structured products are becoming increasingly popular and well established among investors because of their historical safety and their substantial return. The issue of CLOs is very high profile given the exponential growth in recent years and the dangerous similarities with the subprime CDO market that triggered the 2008 crisis. Even institutional bodies such as the Bank for International Settlements (BIS) are paying attention to this market. In their quarterly report of September 2019, in the article "Structured finance then and now: a comparison of CDOs and CLOs" by Aramonte & Avalos, they show having a close eye on this subject and expressing considerable concern about the significant risk exposure that banks are facing to CLO products.

In the first chapter, we briefly overview credit risk and securitisation in the banking system environment. In particular, we analyse the relation between credit risk, securitisation and derivatives. The link that joins them together are derivative products, such as CDOs and CLOs.

In the second chapter, we review some pricing models for CDO-type instruments. We first define these derivatives and explain how the various types are designed. Then, we examine the models used to price and assess their risk

In the third chapter, we deepen the study of CLOs. We first analyse how the outbreak of Covid-19 has affected the CLO market by influencing high-yield bonds and leveraged loan markets. Then, we present a comparison between the CDO market in 2008, which led the Global Financial Crisis, and the CLO market today. Finally, we carry out an empirical analysis where we study the relation between CLO market indicators, such as indices of CLOs prices and Leveraged loans, and the CDS spreads of banks.

1. Credit risk and Securitisation

1.1. Credit risk

Since the end of the 1980s, and more recently following the subprime mortgage crisis, the Supervisory Authorities themselves have initiated a continuous process of reform of existing agreements in order to induce banks to better allocate equity capital with respect to the risks to which they are actually exposed (prudential regulation).

Before proceeding with the analysis of credit risk, it is necessary to give its definition. Credit risk is the possibility that a financial institution, which has opened a credit position with another party, experiences a deterioration in the market value of the credit position due to an unexpected change in the borrower's creditworthiness. Thus, as stated in the definition of credit risk, it should not be interpreted only as the likelihood that the counterparty will default, but credit deterioration should also be taken into account.

Further aspects must be pointed out. Another fundamental point is that the change in creditworthiness must be unexpected, so in order to actually speak of risk it is necessary that the deterioration of the credit is not foreseen and consequently not taken into account during the credit period and when determining the interest rate to be applied. The risk lies in the possibility that the assessments made with the counterparty may be incorrect a posteriori, since the events taken into consideration, even if they can be estimated, may still be unexpected.

The definition of credit risk refers, as a logical consequence of the deterioration in creditworthiness, to a change in the market value of the credit exposure. At this point, it must be considered that, for a banking institution, the majority of the credit exposures held are linked to illiquid assets, for which there is no well-developed and sufficiently liquid secondary market. The market value of such assets cannot be identified on the basis of prices derived from the secondary market, but must be determined through appropriate models built in-house by the financial institution that capture changes in economic value of banking assets.

1.1.1. Sources of credit risk

Once credit risk has been defined, a classification of the sources of this risk category, i.e. the causes that expose the financial institution to this uncertainty, can be made.

The most evident concept is the risk of default of the counterparty to which the bank has a credit exposure; in the event of default, the bank would incur an economic loss equal to the failure to repay the principal and collect interest. In addition, there would be further negative effects on the profit and loss account due to the costs incurred by the bank in initiating credit recovery procedures and the collection of collateral.

The risk of deterioration in creditworthiness (credit migration risk) must also be considered, which is usually followed by the downgrading of the debtor's rating class by the credit rating agencies (e.g. Moody's or Standard & Poor's) or by internal analysts.

Generally speaking, a deterioration in creditworthiness does not result in an instantaneous economic loss unless it results from an asset traded in a liquid secondary market that will no longer be readily and economically marketable (e.g. in the case of a corporate bond). Nevertheless, credit institutions cannot overlook this event, especially as the counterparty's bankruptcy often does not occur suddenly, but is preceded by a constant deterioration in creditworthiness. It follows that credit risk, precisely because of its complexity, could not be analysed by referring exclusively to a binomial distribution (default/non-default), even though there are models that do not actually consider migration risk, but using a multinomial distribution in which the counterparty's insolvency is only the final event that can be realised.

1.2. Securitisation

The regulatory and ideological/philosophical change at the basis of the great financial innovation, and consequently of derivatives, is represented by the financial deregulation started in the 70s and 80s. It developed, before spreading throughout the world, in the USA under the Reagan government, where it replaced the Glass-Steagall regulation system devised in the mid-1930s. It abolished the separation of the activities of commercial banks from investment banks. This and other factors such as the integration of financial markets, privatisation, the liberalisation of brokerage activities and capital movements, contributed to the birth of the so-called New Financial Architecture. The NFA is a global and integrated financial system with low capital regulation, based on the conviction that the free market always offers a fair allocation of risk as long as decisions are not distorted by regulation imposed by governments. Consequently, if economic agents know the exact allocation of risk, they will not be induced to hold less or more risk than optimal (the practical implementation of this concept makes use of complex

mathematical models). The theory that supports this belief is called "Theory of efficient markets". One of its cornerstones, as said, is the idea of the correct allocation of risks specific to the financial system, which has contributed to the creation and development of new derivative products because they allow (given their construction) to diversify risk more easily by making the allocation of resources in the markets more efficient.

At the heart of this new financial system is the development of securitisation or securitisation process. Securitization is "the process by which one or more illiquid financial assets, capable of generating cash flows, such as a bank's loans, are transformed into tradable securities, i.e. bonds called Asset Backed Securities (ABS)". The result of this operation consists of derivative instruments because the financial asset at the origination of the process becomes the underlying of the instrument. Depending on the type of underlying, derivative instruments can be divided into the following:

- MBS (Mortgage Backed Securities), derivative instruments that have as their underlying mortgage loans
- CDO (Collateralized Debt Obligation) derivative instruments that have as their underlying public or private bonds
- CLO (Collateralised Loan Obligation) derivative instruments that have as their underlying loans, especially leveraged loans
- ABCP (Asset Backed Commercial Paper), derivative instruments that have as their underlying short or very short-term loans

The advent of securitization revolutionizes the classic role of the bank as a financial intermediary between depositors and borrowers. On one hand the depositors confer the funds and on the other hand the bank allocate them to the borrowers after an analysis of the creditworthiness of the latter and wait for the maturity of the loans. Historically, in fact, the balance sheet of a bank is composed of the assets made up of the provided loans and the liabilities made up of the conveyed deposits. Through securitization, at the same time, the assets involved in this process are sold (thus leaving the bank's balance sheet) to ad hoc companies, often owned by the bank itself, called Special Purpose Vehicles (SPVs), which have the task of selling the ABSs (called MBSs in the case of mortgage-loans), resulting from securitization, to investors.

Economic theory believes that the legitimate motivation behind the securitisation process is the removal of the risk of an asset (e.g. the mortgage) from a single agent (the bank) by

sharing its risk to a wider range of entities (the investors buying the ABS). However, the great development of this type of derivatives in the pre-crisis period was not determined by the above-mentioned motivation, but was driven by the banks' desire to circumvent the minimum capital requirement rules laid down in the "Basel Accords".

Securitisation makes possible to reinvest the proceeds from the sale of the assets by subscribing other loans, which are then securitised and subsequently re-invested throughout the process. In this way, deposits do not finance the loans made the bank as in the traditional depositor-bank-borrower system. This creates a clear discrepancy between the amount of deposits and the amount of loans. As noted by Acharya and Richardson in 2009, total deposits in America amounted to US$ 7 trillion while the sum of mortgages and loans of various nature exceeded US$ 15 trillion.

In order to facilitate MBSs' placement, the bank provides guarantees on financial instruments that facilitate the obtaining of higher ratings, thereby simplifying the sale. One of the forms of guarantees used by banks is to retain lower-rated tranches as a good indicator of the quality of the underlying loan (thus taking on the task of absorbing losses in the event of partial or total default). In this way, greater assurance is given to the investor that the product purchased is safe. The Special Purpose Vehicles and all non-banking institutions involved in the securitisation process of the NFA form the so-called "shadow banking system". Since they are not subject to capital restriction rules, this system has contributed to the creation of increasingly complex securitised derivatives that have increased information asymmetries with (non-professional) buyers. An example of additional complexity is given by the additional securitisation levels, i.e. the creation of derivatives that have as their underlying the MBS of the first level of securitization instead of the starting loan (e.g. CDO-squared). Clearly, the complex construction of MBSs entails an objective difficulty in assigning an appropriate level of risk to them, mainly due to the amount of original loans underlying them. In fact, the greater the number of loans in the starting pool, the greater the possible combinations of default of the derivative. Consequently, the risk associated with the instrument becomes more difficult to be assessed correctly even with the use of sophisticated mathematical models. Moreover, the risk becomes exponentially more difficult to determine if subsequent levels of securitization are added. In conclusion, a further obstacle to the risk assessment process is the relative short history of this type of derivatives, which is unable to provide sufficient qualitative and quantitative historical data on their performance.

2. Pricing models for CDO-type instruments

The models we will soon see refer to the wide CDO family. Recall that CDOs are part of ABS (Asset Backed Security) group. The CDOs are so denominated because they have in their underlying any type of debt. The CLOs, which will be the core of the next chapter, are simply one kind of CDO. While in their generic form CDOs have any type of underlying debt, CLOs have in its underlying loans. The particular type of CLOs we will speak about, which gained futher attentions in today financial world, have in their underlying Leveraged Loans. Therefore, the pricing models for CDOs that we will soon see, their pros and cons, are the same models that have assessed the risk for both CDOs in the Great Financial Crisis and CLOs today.

2.1. Collateralized Debt Obligation

Before we discuss the methods for assessing CDOs' risk, we first define what these products are. A collateralized debt obligation (CDO) is a type of asset-backed security (ABS). An asset-backed security (ABS) is an investment security, a bond or note, which is collateralized by a pool of assets, such as loans, leases, credit card debt, royalties, or receivables. Therefore, a CDO is a structured financial product backed by a pool of loans when a retail or commercial bank approves loans such as mortgages, auto loans or credit cards to individuals or businesses, these loans are then sold to a Special Purpose Entity (SPES). SPEs are usually bankruptcy-remote, meaning they are delinked from the credit risk of the bank arranger (also known as the originator). The bank arranger can earn servicing fees, administration fees, and hedging fees from the SPE, but otherwise has no claim on the cash flows of the assets in the SPE. The SPV (Special Purpose Vehicle, synonym of SPE) repackage these loans to form an investment product called CDO, which is then sold to investors. The principal and interest payments made on the loans are redirected to the investors in the pool. The promise repayment of the loan in the pool is the collateral that gives the CDO value, here the term collateralized. If the underlying loans go bad, the bank transfers much of the risk to the investors, which will typically be a large pension fund or hedge fund. As the result, banks slice the CDO into various risk levels, or tranches. Senior tranches are the safest because they have the first claim on assets if the underlying loans default, junior tranches are riskier and therefore offer interest rates to attract investors.

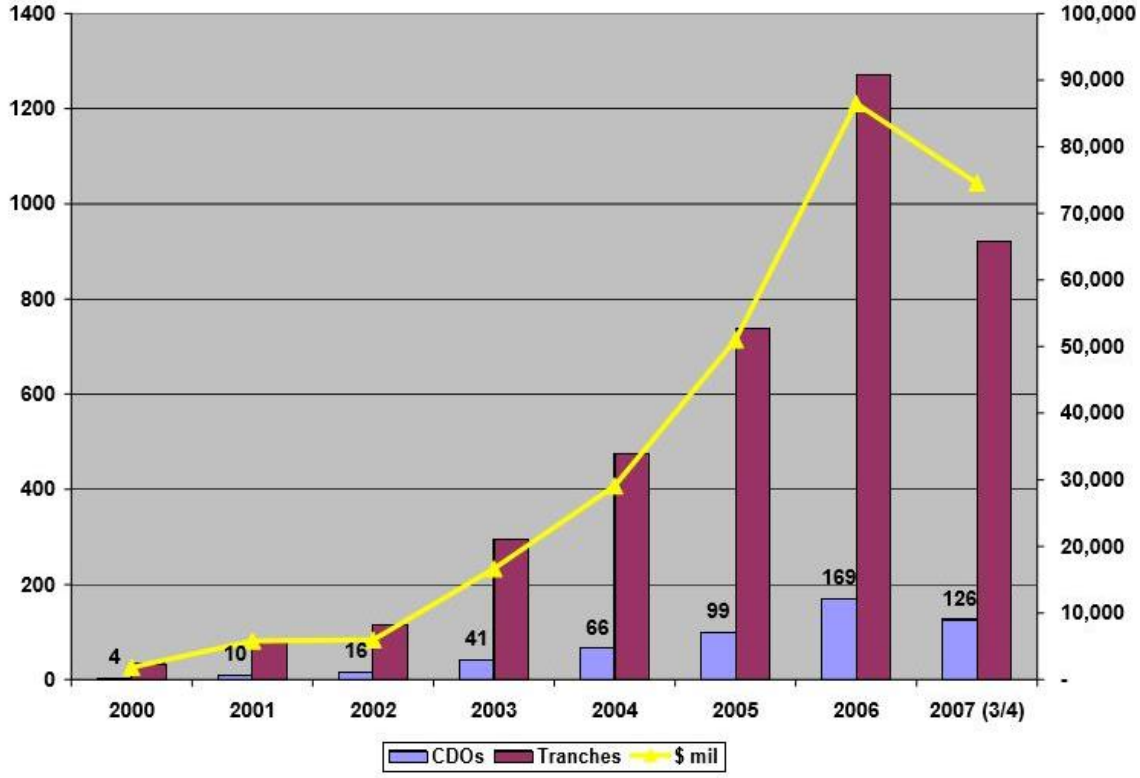
Usually banks sell CDOs to investor for two main reasons, which, nonetheless, are linked. First, via the funds they receive selling these products they are able to make new loans to their customers. Secondly, they relief their balance sheet from capital constraints imposed by the legislation, since each commercial bank that makes a loan has to keep on-the-side part of its capital in case the loan defaults. CDOs permits to move credit risk from bank to investors. It is based on the originate-to-distribute model, rather than keeping assets they originated on their balance sheets, the credit risk is passed on to investors.

While the first CDOs were created in the 1980s, global issuance remained low, under $100 billion annually, until the mid-1990. During 1990-2002 most CDO were a backed by a diverse group of loans which limited the risk of default and gave the extra reputation for stability, but around 2003 the housing boom led a number of banks to use subprime mortgages as the main source of collateral. With the popularity of CDOs skyrocketing, home lenders received the steady stream of cash and, thus, as a result they often extended credit to high-risk borrowers (so-called subprime mortgages). When the real estate market stalled and mortgage default start to rise, CDO issuers and their investors suffer enormous losses.

From 2002 to 2007, CDOs have been the fastest growing sector of the asset-backed securities market. In the United States, CDOs issuance reached a new high of $312 billion, an increase of 102 per cent on 2005 (itself a record year). In 2006 CDOs represented the second largest asset-backed securities (ABS) sector in the United States, second only to home equity ABS (the total ABS market size in 2006 was $1.2 trillion; home equity ABS accounted for $630 billion of that).[1]

[1] http://www.globalsecuritisation.com/07_intro/DB07_008_014_DB_CDO.pdf

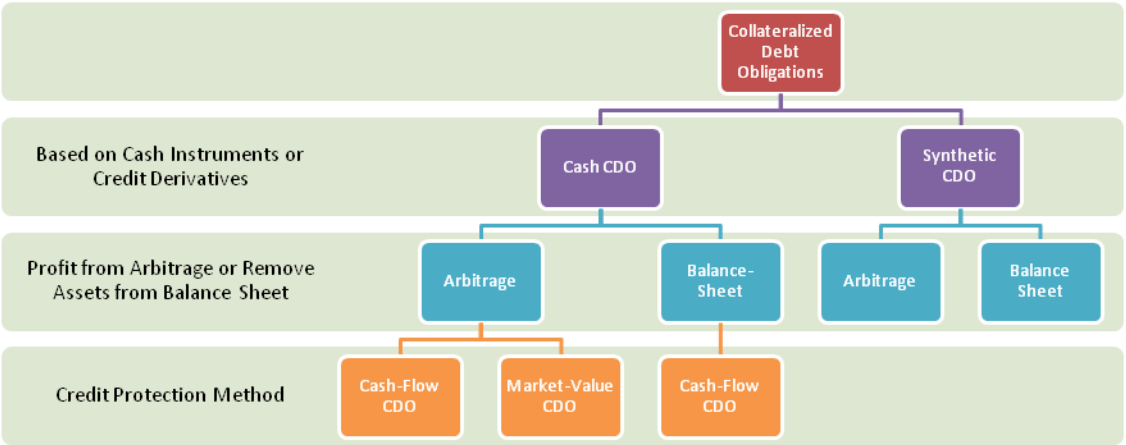
Figure 2.1 (1): CDO issuance by year



While CDOs offer the possibility for attractive fixed returns, the fallout from the financial crisis led to greater scrutiny regarding the assets that serve as their collateral.

2.2. Types of CDO structure

Figure 2.2 (1): Types of CDO structure



As we have already seen, CDOs can be classified according to their underlying debt. There are other ways to classify CDOs structures. The first classification is by leverage

structure or, simply, by source of funds for principal and interest payments. In this classification, CDOs can be dividend in:

- *cash flow CDOs*
- *market value CDOs*

Cash flow CDOs pay interest and principal to tranche holders using the cash flows produced by the CDO's assets. It represents a structured finance product that pool and repackage a diversified pool of assets in order redistribute their risk into different classes of risk (the tranches we already mentioned above). The securities are issued and placed into capital markets and bought by investors. The returns are constructed based on the cash flows generated by the underlying assets. The entire structure is built such that the proceeds coming from the asset-side collateral (underlying pool) fully pay off the entire liability-side obligations (interest and principal payments). Cash flow CDO procedure spans over three periods: (1) the ramp-up period of assembling transaction's portfolio; (2) the reinvestment period when principal proceeds are reinvested into new collaterals; c) the winding-up period, once the collateral pool matures, when the procedure is terminated and the entire debt obligations are fully repaid to CDO investors, according to cash flow waterfall rules.

Market-value CDOs are similar to cash flow CDOs except the amount of liabilities the CDO can issue is determined by advance rates for each asset in the pool and collateral is marked-to-market frequently. When the liabilities outstanding exceed the advance rates, the manager must sell collateral and pay down notes until compliance is restored.

Market value CDOs have the same structure and hold the same risk-return profile and the procedure consists in same three periods as the cash flow CDOs. The way in which the market value CDOs are different is that, in order to enhance investors returns, CDO manager attempt to realize capital gains on the assets in the CDO's portfolio through a frequent trading and profitable sale of collateral assets. CDO managers periodically mark-to-market the CDO's portfolio. The performance of this kind of CDOs is highly dependent to CDO managers' ability to buy, sell and trade securities within the transaction's collateral portfolio. While the main duty in cash flow CDOs of common CDO managers are managing the credit quality of the underlying portfolio, in market

value CDOs context, CDO managers mostly care about volatilities of collaterals' prices and liquidity levels.

There are two fundamental motivations why a CDO are created; these are so-called balance sheet and arbitrage purposes.

Balance-sheet CDOs are principally motivated by financial institutions' desire to achieve regulatory capital requirements relief or to free up capital for lending purposes. Another main reason would be offloading banks' balance sheets from credit risk. Balance-sheet issuers are typically lending institutions.

Arbitrage transactions are usually financed by investments bank that acquire assets from lending institutions and packages them into a CDO to earn management fees on the deal.

However, the most relevant classification in which CDOs are sorted is by form of funding for interest and payments. This core difference change the perspective on how credit ratings have to price and weight credit risk of these products.

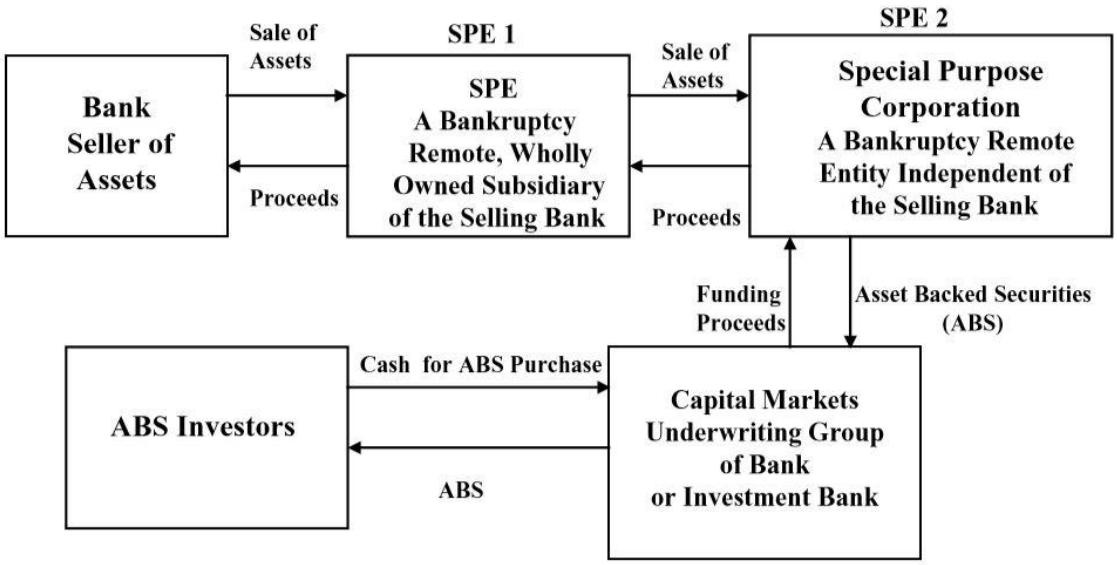
2.2.1. Cash CDO

Cash CDOs are the most common and plainest CDO used in the market. In a cash CDO, the SPV buys the collateral assets such as loans, credit card debt and other different liability from a bank so it becomes the owner of these assets. To be able to buy this liabilities, the SPV, which is not owned by the bank itself, issues CDO's tranches and sell them on the capital markets where are acquired from institutional investors. As interest and principal are generated by the underlying collateral, proceeds are distributed to the CDO investors in a pre-specified way, in order of seniority. The risk of loss on the assets is divided among tranches in reverse order of seniority. In reality, the procedure is more complicated since actually there are two SPVs to be established. The first SPE is a wholly owned, bankruptcy-remote subsidiary of the originator/seller, and the SPE buys the assets in a true sale[2]. The assets are now beyond the reach of both the creditors of the originator/seller and the originator/seller. The second SPE is the issuer of the debt (or asset-backed security (ABS)) and is entirely independent of the originator/seller. It is a bankruptcy-remote entity. The second SPE buys the assets of the first SPE as a true sale

[2] A true sale provides the issuer's creditors with assurances that in the event the company defaults or becomes bankrupt or insolvent its creditors will not have access to the assets sold to the issuer.

for accounting purposes, and a financing for tax purposes[3]. To understand better the whole structure look at the figure below. CDO issuance exceeded $400 billion in 2006.

Figure 2.2.1 (1): Cash CDO structure



2.2.2. Synthetic CDO

In contrast, synthetic CDOs obtain their credit exposure through derivatives contracts instead of assets purchases. Synthetic CDOs do not own cash assets like bonds or loans. Instead, synthetic CDOs gain credit exposure to a portfolio of fixed income assets without owning those assets via using of credit default swaps[4]. A synthetic CDO issues notes to investors, invests the proceeds in risk-free securities, and enters into a series of credit default swaps (selling protection). As a cash CDO, the risk of loss on the CDO's portfolio is divided into tranches. Investors in a synthetic CDO receive periodic payments from swap premiums. Since SPV enters into a swap agreement, where the insured products are the very assets of the bank (such as loans, etc.) if there is a credit event in the reference portfolio, the SPV, hence the investors that bought its obligations, has to cover up this exposure.

In the synthetic CDO structure, however, because the premiums payments by the s ponsoring bank cannot fully compensate all the costs that the SPV paid to the investors,

[3] For example, two entities are required for Italian securitizations. The first entity can be onshore and purchases the assets. The onshore entity cannot issue bonds, or it will attract heavy Italian taxes. The second entity is offshore and issues the bonds.

[4] Under such contract, as an insurance, the credit protection seller, in this case the SPE, receives periodic cash payments, called premiums, in exchange for agreeing to assume the risk of loss on a specific asset in the event that asset experiences a default or other credit event.

another funding source is needed. To make up for the shortfall, the SPE invests its proceeds from the notes by issuing in high-grade assets, AAA-rated products, which are then employed as both collateral for the obligations towards the sponsoring banks and the excess of the coupon payments promised by the notes. If no default occur, at the maturity date of CDO notes, the CDS is terminated and the SPE then liquidates the collateral to repay investor's principles thoroughly. In case of defaults, CDO investors have to absorb all the defaulted relative loss. When a credit event occurs, and thus a pay-out to the swap counterparty is required, the payment comes from the reserve account that holds the liquid investments.

The buyer of protection pays a predetermined annual premium (known as a spread) on the outstanding tranche principal and is compensated for losses that are in the relevant range. In the case of the equity tranche, the arrangement is slightly different: the buyer of protection pays a certain percentage of the tranche principal upfront and then 500 basis points on the outstanding tranche principal per year. As in the market practice, the protection buyer of an equity tranche needs to pay not only a fixed payment but also an upfront payment. The initial coupon spread on each tranche is held fixed over time (but applied to the remaining notional amount within each tranche).

In contrast with the junior tranches that require upfront fees, senior tranches are usually unfunded as the risk of loss is much lower. Unlike a cash CDO, investors in a senior tranche receive periodic payments but do not allocate any capital in the CDO when entering into the investment. Alternatively, the investors retain continuing funding exposure and may have to make a payment to the CDO in case the portfolio's losses climb to the senior tranche. The figure below provides a glimpse of synthetic CDO design.

Figure 2.2.2 (1): Synthetic CDO structure

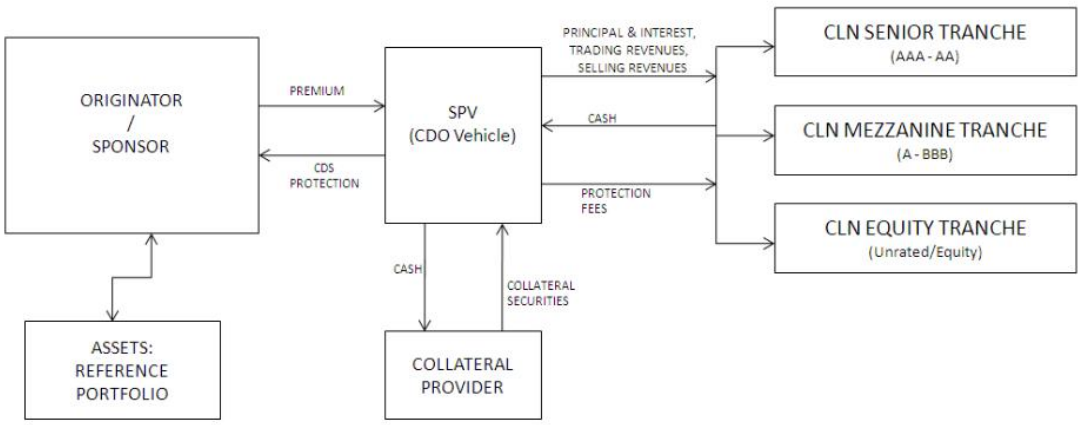


Table 2.2.2 (2): Summary cash CDO vs synthetic CDO

FEATURES	CASH CDO	SYNTHETIC CDO
Motivation	Transfer of credit risk and funding Both true-sale and synthetic securitizations enable the same volume of credit risks to be transferred to the CDO investors	Transfer of credit risk and funding (just in case of funded and partially funded transactions). Both true-sale and synthetic securitizations enable the same volume of credit risks to be transferred to the CDO investors
Underlying assets and related risks management	Assets are sold to the SPV and all related risks are thus transferred to the SPV. The SPV becomes assets' owner	Only credit risks are transferred through credit derivatives to the SPV. Originator continues to be asset's owner
Underlying assets status	Assets go off-balance sheet from originator bank	Assets remain on-balance sheet in originator bank
Carrying out transaction objectives	Originator acts as seller of the on-balance sheet assets	Originator acts as protection buyer for the on-balance sheet assets
Aim of transaction	Balance sheet frame and arbitrage situation	Balance sheet frame and arbitrage situation
Securitization technique	True-sale	Synthetic
Source of funds for principal and interest payments	Cash-flow structures; market-value structures	Cash-flow structures; market-value structures
Funding technology (liabilities distribution)	Cash-based (true sale)	Synthetic (credit derivatives based): fully-funded, partially-funded, fully-unfunded
Collaterals management style	Actively managed (dynamic); passively managed (static)	Actively managed (dynamic); passively managed (static)

2.2.3. Hybrid CDO

Hybrid CDOs have a portfolio embodying both cash assets, like cash CDOs, and swaps that give the CDO credit exposure to additional assets, like a synthetic CDO. Part of the proceeds from the funded tranches is invested in cash assets and the residuum is held in reserve accounts in order to cover payments that may be required under the credit default swaps. The CDO receives payments in three ways: the return from the cash assets, the reserve account investments and the CDO premiums. This type of CDO is less common than the cash CDO and synthetic CDO abovementioned.

2.3. CDO-related features

So far, we have abruptly introduced the CDO features. Our goal is to be able to assess the riskiness of these products in order to determine their price. Before we specifically introduce the tools and formulas used to determine the riskiness of CDOs, we first need to look at some other features involved in the process that we have not yet explained. In addition, we deepen into details about other technical components of CDOs to explain better their function and their importance within the pricing models.

In today's global economy the average rating corporate debt is BBB, whereas the average risk appetite of fixed-income investors in aggregate is much lower. Generally, most fixed-income investors, which also consist of many ultra-risk averse investors such as central banks, demand a high degree of safety of principal. Yet the basket of AA and AAA rated individual corporate bonds is quite modest. The fixed-income investors with risk averse appetite seeking for AA and AAA rated securities with equity-like returns (say 10 percent) have little choice. CDO market has risen substantially in order to match this need with the accessible profile of fixed-income assets. The result is that by issuing CDOs from portfolios of A and BBB grade bonds, financial institutions like investment banks may create a larger pool of AAA rated securities to be sold to those investors.

2.3.1. Credit enhancement

The presence of considerable sources of credit enhancement in CDO structures supports the origination of investment grade securities backed by speculative grade assets. Credit enhancement is a set of strategies employed to improve credit risk profile of a structured financial transaction. Typically, it is used to obtain better terms for repaying the debt and

so reducing the risks to investors of certain structured financial products. These are the most common methods used in structured finance.

Subordination or tranching: by creating multiple tranches, cash flows generated by assets are allocated with different priorities to classes of varying seniorities. Such protection comes under a waterfall structure (it will be explained deeper further in the chapter). Priority for cash flow comes from the top, while distribution of losses rises from the bottom. If an asset in the pool defaults, the losses incurred are distributed from the bottom up (from junior to the most senior tranche). The senior tranche remains unaffected, unless the amount of the losses exceeds the amount in the subordinated tranches.

Overcollateralization: the aggregate face value of the underlying assets in the portfolio assets sold, for example, by the commercial bank to the SPV, is larger than the value of the securities, backed by those assets, issued to investors. Even if a portion of payments for the underlying loans are late or in default, principal and interest payments on the asset-backed security can still be performed.

Excess spread: normally, the weighted average spread on CDO's assets exceeds the weighted average spread on its liabilities. The excess spread is the difference between the interest rate received on the underlying collateral and the coupon on the issued security. Even if some of the underlying loan payments are late or default, the coupon payment can still be made.

Reserve account: issuers may deposit cash in a reserve account or a trust account and these funds can be used to meet principal and interest payments when needed. Excess spread may also be preserved in a reserve account.

We recall that CDO's portfolio pool together all the cash flows from the underlying assets. This pool is partitioned into rated tranches. Each tranche has a debt rating given by a credit rating agency. Due to information asymmetries between the originator and the investors concerning the quality of the underlying portfolio, the tranches need to be rated by an external rating agency[5].

[5] Nonetheless, after the subprime crisis it has been claimed that between credit rating agencies and CDOs' issuers (i.e. investment banks) conflict of interests took place since the latter financed with huge fees credit rating agencies in order to give high ratings to their CDOs' tranches. We overlook this topic, as it is not focus of this paper.

These ratings reflect assessments of the tranches' default probability (Standard & Poor's and Fitch) or expected default losses (Moody's), and are used by investors as an indicator of the tranche's quality. A key feature is the division of the liabilities into tranches of different seniorities: payments are made first to the senior tranches, then to the mezzanine tranches, and finally to the junior tranches. This prioritization scheme causes the tranches to exhibit different default probabilities and different expected losses.

In the table below, an example of different levels of tranches displayed as percentages is shown.

Table 2.3.1 (1): Example of the most common CDS index used to price synthetic CDOs

Reference Portfolio	Tranche level	Tranche name	Attachment point	Detachment point
DJ iTraxx Europe: Portfolio of 125 CDS	1	Equity	0%	3%
	2	Junior Mezzanine	3%	6%
	3	Senior Mezzanine	6%	9%
	4	Senior	9%	12%
	5	Super Senior	12%	22%

The starting point and the ending point of each tranche level are denominated attachment point and detachment point, respectively. Notice that on each level, the detachment point overlaps with next level's attachment point.

For instance in a synthetic CDO, for a given tranche level investors purchase, they have to pay off all losses (defaults) that are greater than the related attachment point and less than the corresponding detachment point of the notional amount of the assets portfolio. In exchange of protection, the protection buyers (i.e. commercial bank) also pay premiums proportional to the remaining notional amount of reference assets at the time of payment. The premiums pass through the SPV that collects them. At this point, the SPV distribute the collected cash to investors proportionally to the risk they bear. For

example, the riskiest tranche, equity tranche, might receive 5000 basis point on the notional per annum; the senior mezzanine, which is safer, could receive 2500 basis point on the notional per annum and so on. This system works as long as there are no defaults on reference portfolio. Losses occur when defaults in reference portfolio take place. For example, we assume the tranches of a synthetic CDO to be partitioned as in the table above. In this case, the equity tranche has to bear all the losses until they reach 3% of the total notional of the reference portfolio of assets. If the total loss exceeds 3%, the next tranche in our structure, Junior Mezzanine has to absorb the rest of losses until they reach 6% of total notional reference portfolio of assets. Senior Mezzanine would be pledged in case the losses in the total notional come up to 6% but do not overpass 9% and so on and so forth. Commonly, junior tranches are quite thin compared to senior tranches which are larger the seniority increase.

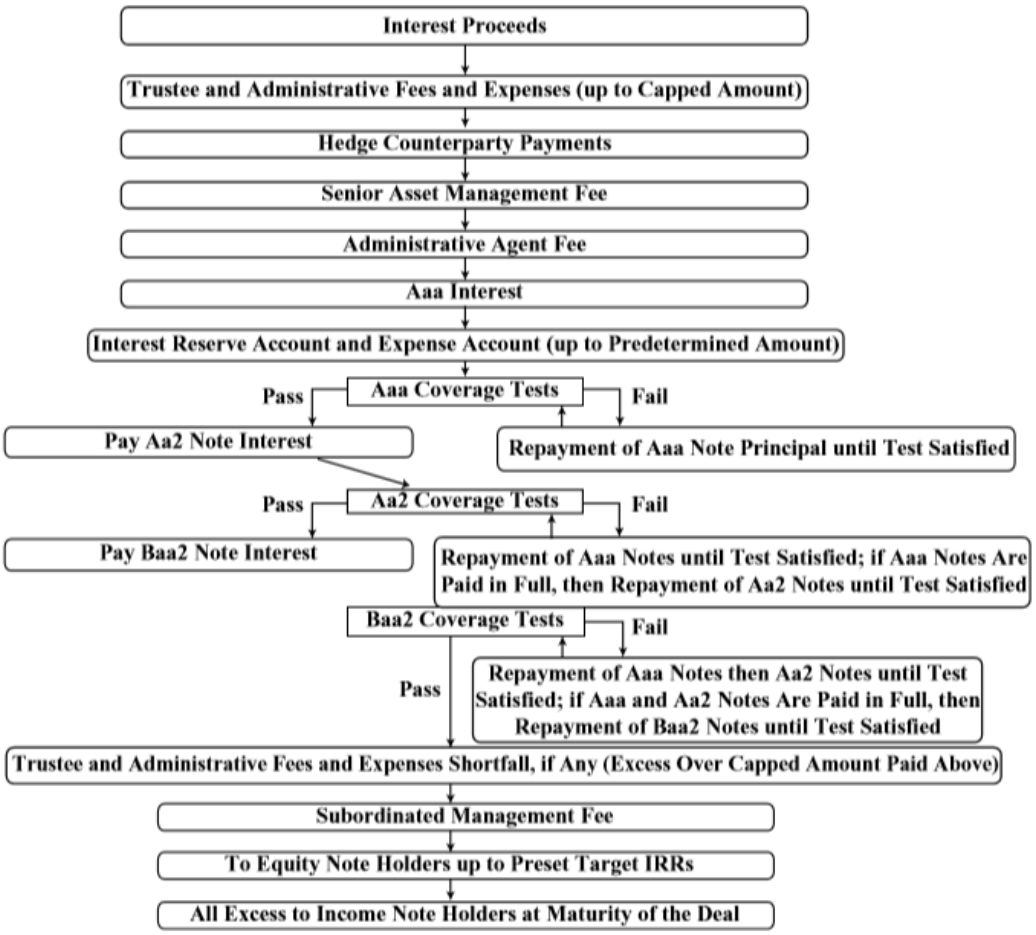
2.3.2. Waterfall scheme

Now we consider a cash CDO. The practice for allocating cash flows from the underlying assets to tranches are defined by what is known as a "waterfall scheme". The interest payments stipulated to tranches normally decrease with seniority. When SPV collects all the interest payments coming from the underlying assets, these are allocated to tranches in order of seniority so that the AAA-rated tranches get promised interest payments on their outstanding principal first; after that, the AA-rated tranches get their promised interest payments on their outstanding principal; and so on.

Waterfall scheme is not a fixed rule. Depending on the type of the CDO and depending on the underlying asset, waterfall scheme may be performed in different ways. We need to differentiate whether the proceeds are interest or principal. Interest proceeds for the cash CDO include all interest received on the underlying assets plus interest earned on any cash in reserve accounts. All payments from hedge counterparties are also treated as interest proceeds. A small reserve account is financed and replenished from future interest proceeds, if necessary. The aim of the reserve account is to guarantee that the notes above the equity tranche receive timely interest payments. In a cash CDO, principal proceeds include all principal prepayments from the assets' portfolio, payments at maturity and all principal inflow derived from asset sales or realized trading gains. In particular, trading gains from asset sales and all the recoveries on default assets are treated as principal

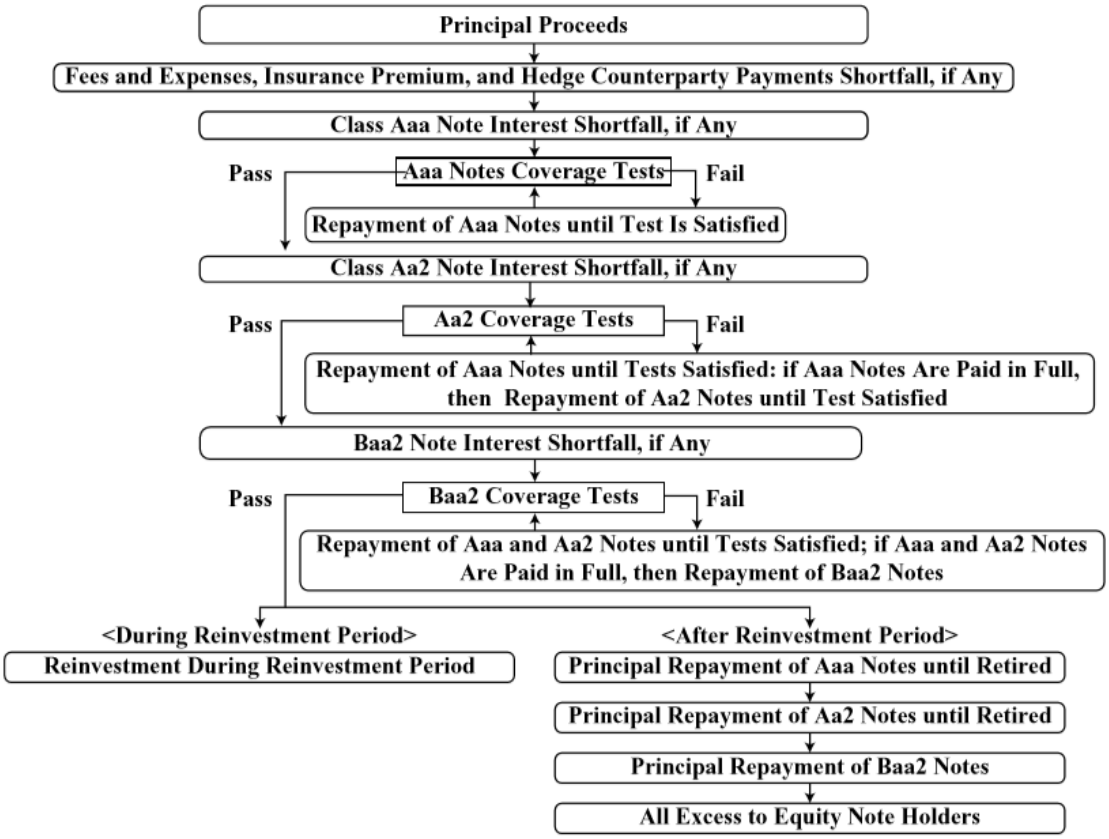
proceeds. Figure 3 gives a simplified representation of waterfall distribution of interest proceeds.

Figure 2.3.2 (1): Interest proceeds waterfall scheme in cash CDOs



Yet the principal proceeds, in a cash CDO, is slightly different.

Figure 2.3.2 (2): Principal proceeds waterfall scheme in cash CDOs



In both structures, fees are the first to be distributed when interest and principal amounts are collected from the portfolio assets via SPV. Various and multiple fees are paid first and then the cash flow flows through investors' tranches in order of seniority. The most senior tranche is paid first, then the second most senior and so on until the equity tranche. To check whether the most senior tranche has been paid off a coverage test is run. If the coverage tests pass, meaning if the tranche has been fully paid, the cash stream move on and the next most senior tranche start to be paid. Before the cash flow pass over the next tranche, a coverage test must be run and shall pass. The structure becomes intricated when the number of defaults from the underlying assets starts to rise. In certain types of CDO, for instance, when mortgages compose assets portfolio, a different technique is adopted.

Coverage tests are employed to ensure that sufficient collateralization or interest coverage levels are preserved to secure a CDO's rated debt tranches. These tests usually consist of par values (or collateralization tests) and interest coverage tests. A par value test typically aims to maintain a minimum ratio of collateral portfolio amount to the par amount of CDO debt tranches. An interest coverage test generally seeks to control the ratio of interest proceeds from the collateral portfolio to the coupon payable on debt tranches. As

we can see from the interest waterfall for our cash deal, when the coverage tests are violated, interest is not paid on the subsequent tranches, and principal on the senior tranches is paid down instead. This continues until the coverage tests are satisfied. Principal is diverted to pay down senior tranches, even during the reinvestment period, if coverage tests are violated.

2.4. CDO risk assessment

Up to this point, we discussed the CDO deals in their technical parts. We explained what a CDO is and how it is designed by explaining its various types, processes and surrounding figures. We will now go into the details of our study by investigating how the risk of credit for this product is assessed and what methods are used to determine its risk.

The losses on the asset's portfolio due to the default of underlying firms depend on the likelihood to default of each firm and the losses derived from each default (loss given default). In addition, the intensity of dependence between the firms' default probability, defined as default correlation, plays an important role on the timing of the firms' default (in case they are inclined to cluster or if they are independent) and, as a result, on the distribution of losses. We have already mentioned that a CDO consists on trancing and giving away the credit risk of the underlying assets. Naturally, the tranche holders need to be recompensed for bearing these risks. Their compensation consists in periodic fee, called premium, which they receive until the maturity of the CDO.

Here lies the core of our study, determine the price of CDO premiums. Since tranche holders need to be compensated for the expected losses they will undergo and, thus, they depend on the distribution of the portfolio losses, which again depend on the underlying firms' default probabilities (that we have mentioned before), default correlation and losses given default. These are the main ingredients. We have to produce the formula we need to evaluate the riskiness of CDOs' tranches.

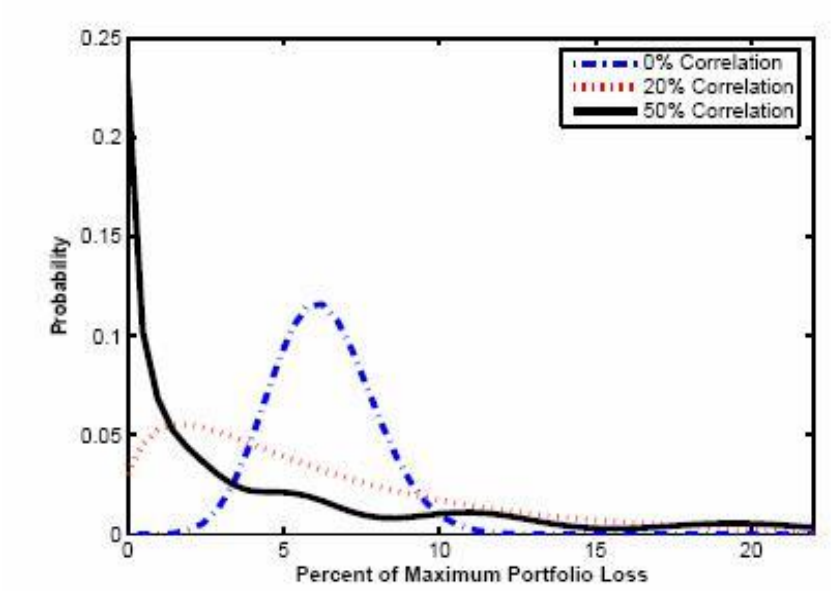
However, among the three ingredients (underlying firms' default probabilities, default correlation and losses given default) pointed out in order to derive the final formula to describe CDOs' riskiness, default correlation leads to greater problems. In fact, if all the underlying assets of the CDO were independent the modelling would be trivial: assess the default distribution of each individual asset separately and multiply them together to produce the joint distribution. Unfortunately, in reality this does not happen. The

underlyings, even if fully diversified, are never entirely independent. Despite that estimating the correlation between two assets would not be easy, in case of a CDO, you need to consider $n(n-1)/2$ correlations of n underlyings, considering that the task is even more difficult since most obligors are idiosyncratic with restricted data available such as mortgages.

Different default correlations may originate various shapes of loss distribution and so leading to various forms of distribution functions. For instance, higher defaults correlation, which may occur, for example, during a crisis, tends to produce a fatter tail in loss distribution. Fatter tail implies that both low level and high level of defaults are more probably to occur than the average default level. On the other hand, a low default correlation conduce to a skinnier tail in loss distribution.

Figure 2.4 (1): Influences of default correlations on the portfolio loss distribution

(Source: Dominique and Julien 2005)



Therefore, the modelling of default correlation architecture contribute significantly in determine the loss distribution function, and thus pricing the CDO tranche. Consider that inside the CDO pricing framework, we may consider, apart from the joint defaults, also the timing of defaults because premium payments rely on the outstanding notional amount, which could be reduced over the lifespan of the contract if any debtor defaults.

2.5. Risk models

Various models for deriving CDO's risk were advanced in late 20th century. However, all of them were articulate and not easy to perform. Data were often limited or unavailable and so most of the models proposed were inefficient. In short, there was not a unique model used to price such products among financial institutions. Yet in 1999, a Chinese quant in Canada, David Li, published a paper proposing a straightforward, ductile and simple to parameterise model for dependent defaults, used by actuaries to solve the broken heart syndrome. The Gaussian copula model. Suddenly, all the practioners quickly adopted this model due to its simplicity. This is one of the reason for which CDOs were issued to a higher pace in early 2000s leading this products to spread easily all over the world. At the beginning of 2000, when Li's article started to circulate the total issuance of CDOs was worth less than $70 billion. By 2006 and 2007, at the height of the CDO bubble, global issuance had grown to over $500 billion per year.

In literature, we may identify essentially two different paths for measuring credit risk:

- Model-based approaches
- Traditional approaches that rely on historical data of defaults

Among model-based approaches, we may recognize structural models and reduced-form models; both are considered to be the highest level of models to model credit risks.

In order to valuate CDO tranches, we have to model the expected defaults in the underlying asset pool, because each default has a repercussion on CDO payments. Especially, the default correlation between the different assets is very important for the estimation of fair tranche prices. Practically, there are two main approaches for pricing CDO tranches:

- Bottom-up models: The default of every single underlying asset is designed at lowest level under consideration of a determined dependence structure between the single assets. By gathering the single defaults, the simulated tranche loss distribution is predicted.
- Top-down models: These approaches consider the asset pool as a whole. The cumulative portfolio loss is modelled by a counting process with a determined portfolio intensity. An inspection of the single underlying assets is not under consideration.

Copula models belongs to bottom-up approach for pricing CDOs where, unlike the top-down approach, tranche premiums depend on the individual credit risk in the underlying assets portfolio and the dependence design between default times. Li's copula became industry standard approach due to its fair absence of major complications. However, before his copula intuition, the prior CDO pricing models were based on Vasicek's analytical KMV and J.P.Morgan's Monte Carlo CreditMetrics. Both lacked of functionality. The fundamental for pricing such credit derivatives is the dependence between assets' default in the underlying debt pool. From a mathematical point of view, the key is the dependence structure between multiple random variables entirely defined by their joint distribution function. Hence, the marginal default distributions of the single entities in the portfolio and their default dependency need to be used in order to estimate the joint loss distribution of the underlying debt pool. Li's solution was to adopt copulas to build a bridge between the marginal default distributions and the joint default distribution. The bridge would link together (in fact copula means connecting two objects) the factors by determine the dependence structure. This permits the dependence structure to be carved independently from the marginal distributions.

The aim of the next paragraph is to display the standard default correlation model and mandatory argument, which are fundamental to recover the loss distribution in a CDO pricing framework.

Before we begin, remind that default correlation, by definition, measures, in probability terms, whether one asset (i.e. firms, loans, etc.) defaulting on its debt is affected by whether or not another obligor has defaulted on its debt. It measures the likelihood that two assets are expected to default simultaneously or separately.

2.5.1. Introduction of copula rationale and Li's Gaussian copula model

A copula is a mapping from univariate marginal to their multivariate distribution. As Li defines it: for n uniform random variables $U_i, \ldots, U_n$, the joint distribution function C, defined as

$$C(u_1, \ldots, u_n, \rho) = P(U_1 \leq u_1, \ldots, U_n \leq u_n)$$

In a copula function, thanks to an important property called Sklar's Theorem, it is shown that any multivariate distribution function may be written as in the form of a copula

function. Thus, the theory displays that copula can link the marginal probability into a joint distribution.

The abovementioned Sklar's Theorem states: if $F(x_1, x_2, \dots, x_n)$ is a joint multivariate distribution function with univariate marginal distribution functions $F(x_1), F(x_2), \dots, F(x_n)$, then there exists a copula function such that $F(x_1, x_2, \dots, x_n) = C(F(x_1), F(x_2), \dots, F(x_n))$.

From a model's prospective, there are two types of default correlation models proposed: structural and reduced form models. Duffie and Singleton (1999) and Merton's (1974) already proposed their models, which are quite computationally intricated when they are applied to price structured products. Li's model principal underlied is such to exploit copula function's property to use the factor copula created by the joint probability distribution for the times to default of obligors to be built from multiple marginal distributions.

The Gaussian copula definition is: Let Φ be the distribution function of the one-dimensional standard normal distribution and Φ_{Σ}^{n} the distribution function of the n-dimensional standard normal distribution with positive definite correlation matrix Σ. Then the n-dimensional Gaussian copula C_{Σ}^{Φ} is defined as follows:

$$C_{\Sigma}^{\Phi}(u_1, u_2, \dots, u_n) = \Phi_{\Sigma}^{n}\,(\Phi - 1(u_1), \dots, \Phi - 1(u_n))$$

Consider a portfolio of N obligors and assume that the marginal probabilities of defaults are known for each obligor. Consider:

- t_i : The time of default for the ith obligor
- $Q_i(t)$: The cumulative default probability function obligor i will default before time t ; that is, $P\,(t_i \leq t)$ i.e. the cumulative distribution function of t_i

To originate a one factor standard copula model[6], we determine a random variable x_i $(1 \leq i \leq N)$.

$$x_i = \rho_i Y + \sqrt{1 - \rho^2} \cdot \varepsilon$$

[6] The standard one factor model is the common copula model groundwork we use to design the default correlation. All the other copula models, as well as the Gaussian copula model, are constructed based on this framework.

Where the variable X_i is considered to be the default indicator variable for the ith obligor: the lower X_i is, the earlier a default is expected to arise. Every X_i has two stochastic elements. Y is a systematic risk factor, which describes market risk, universal to all companies. ε introduces idiosyncratic risk factors, which are specific for each obligor/company. Both factors have independent zero-mean and unit-variance distributions. The correlation with the markets is expressed by ρ_i . One of the fundamental assumptions of this model is that the correlation between each pair of obligors is flat due to the homogeneity of the asset pool. This means that ρ is equal for each pair of assets. One of the core assumptions of this model is the flat correlation between each pair of companies due to the homogeneity of the asset pool. This leads to one value ρ for the correlation of every pair of assets.

If the Y's and the ε's follow standard normal distributions, it produces a Gaussian copula. It follows that each choice of distribution leads to a different factor copula to describe the default correlation structure and hence it follow in different approaches to determine loss distribution function in order to price CDO tranches. The section of the copula models sets the shape of the default dependence structure.

Having the following parameters:

- F_i: cumulative density function (CDF) of x_i
- H : cumulative density function of ε_i (assuming that the ε_i is identically distributed)

Thus, generally, $x_i = x$ is mapped to $t_i = t$ where

$x = F_i^{-1}[Q_i\,(t)]$

Or equally

$$t = Q_i^{-1}[F_i\,(x)]$$

To build the default correlation structure, we do not need to define the correlation structure between the variables t_i 's by adopting the structural models or the reduced form models which both leads to major computational complexity. Through the factor copula model, we apply a technique to map significant variables such t_i's into more governable variables as x_i 's and consequently determine the default correlation structure among those workable variables.

The current benchmark, the one-factor Gaussian copula model, is explained as follow.

Consider a portfolio of reference assets composed by N obligors. Recall that it is called Gaussian copula only if the Y's and the ε's follow a standard normal distributions. In the model, x_i is defined as

$$x_i = \rho_i Y + \sqrt{1-\rho^2} \cdot \varepsilon$$

where x_i is a latent random variable that follow a standard normal distribution[7].

The other parameters are described as before.

Considering the default time $t_i, i = 1, 2, \dots, N$ are modelled from the Gaussian vector X[8], the default times are given by $t = Q_i^{-1}[F_i(x)]$. However, in the case of Gaussian copula we have

$$t = Q_i^{-1}[\Phi_i(x)]$$

with Q_i be the CDF of t_i and $\Phi_i$be the cumulative distribution function of x_i; Q_i^{-1} is the inverse function of Q_i. Therefore, x_i is given by

$$x = \Phi_i^{-1}[\mathrm{Q}_i(x)]$$

The cumulative probability of the ith default by time t, conditional on the common factor Y is

$$P(t_i < t \mid Y = y) = P(x_i < x \mid Y = y)$$

$$= P(\varepsilon < \frac{x - \rho Y}{\sqrt{1-\rho^2}} | Y = y)$$

$$= \Phi[\frac{\Phi_{-1}[Q(t)] - \rho Y}{\sqrt{1-\rho^2}}]$$

$$= p_i(y)$$

In order to proceed we need to address the main assumption Li's model is based on.

First, the model assumes that the same default intensities for all the underlying reference entities over the time period of interest. Second, the model assumes the same pairwise

[7] specifically, $x_i \sim N(0,1);\ i = 1, 2, \dots, N$

[8] $X = (x_1, x_2, \dots, x_N)$, following multivariate normal distribution, namely, $X \sim N_N(0, \Sigma)$

correlations. Furthermore, it assumes that each entity represented in the portfolio result in an equal share of the very portfolio, simply we say that homogenous portfolio is equally weighted.

2.5.2. Li's Gaussian model limitations and drawbacks

Li's model suffers from two major problems that now we will study over. In first place, the implied correlation assumed to estimate CDO tranche price is inconsistent. Secondly, the model lacks of efficiency since it fails to consider extreme events due to the missing tail dependence.

<u>Inconsistency in implied default correlation evaluation</u>

Gaussian factor copula became industry standard despite the fact that its assumptions, on which it is heavily built, are quite strong. For instance, one of the assumption, as we already mentioned, is that the correlation parameter with the market, defined as compound implied correlation, $\rho_i = \rho$ works for all obligors. Another example follows: the model assumes that recovery rates on asset's default are constant (usually at 40%). These assumptions tend to misprice tranche spreads and, consequently, they do not match market values.

Since the model assumes that ρ is constant whatsoever, a flat correlation structure is outlined. Yet a flat correlation structure is not satisfactory to reflect the variety of the underlying assets. In fact, a constant correlation cannot describe accurately the complicated connection between default times of various assets.

Mashal et al. (2004) specify the implied correlation (ρ) of a tranche as *the uniform asset correlation number that makes the fair or theoretical value of a tranche equal to its market quote*. In other terms, Hull and White (2004) for instance identify the implied correlation for a tranche as *the correlation that causes the value of the tranche to be zero*.

There are two measures to estimate implied correlation: compound correlation and base correlation.

The first approach, compound correlation, is very much alike to the implied volatility approach. In this approach, each tranche is treated singularly and is priced applying a single correlation parameter as input. Through an iteration process, the compound correlation can be determined as the input correlation number, which provide a spread that equal the market quote. The one-factor Gaussian model utilizes only one correlation

value (ρ) for all tranches to specify the loss distribution and the price, for such reason you should obtain equal correlation values for each tranche by the compound correlation method. However, this is the very problem since this technique does not generate a unique solution for all tranches because the compound correlation is a function of the two together, attachment point and detachment point. Moreover, certain tranche spreads, as can be shown empirically, are not monotonic in correlation. As a result, the estimation of the stable correlation parameter may deliver two different results that turn to the same market spread.

Table 2.5.2 (1): Implied correlations from Gaussian copula

Tranche	**[0,3]**	**[3,6]**	**[6,9]**	**[9,12]**
Market quote	**27.6%**	**1.68%**	**0.7%**	**0.43%**
Gauss ρ =21.9%	27.6%	2.95%	1.05%	0.42%
Gauss ρ =4.2%	43.1%	1.68%	0.1%	0.005%
Gauss ρ =87.9%	-------	1.68%	1.35%	1.14%
Gauss ρ 14.8%	33.2%	2.68%	0.7%	0.2%
Gauss ρ =22.3%	27.3%	2.96%	1.07%	0.43%
Gauss ρ =30.5%	21.6%	3.05%	1.35%	0.67%

The table above shows that the correlation parameter ρ exists in all tranches and yet is not unique. For example, if we consider the tranche [3,6], ρ =4.2% and ρ =87.9% leads in the same market quote premium 1.68%.

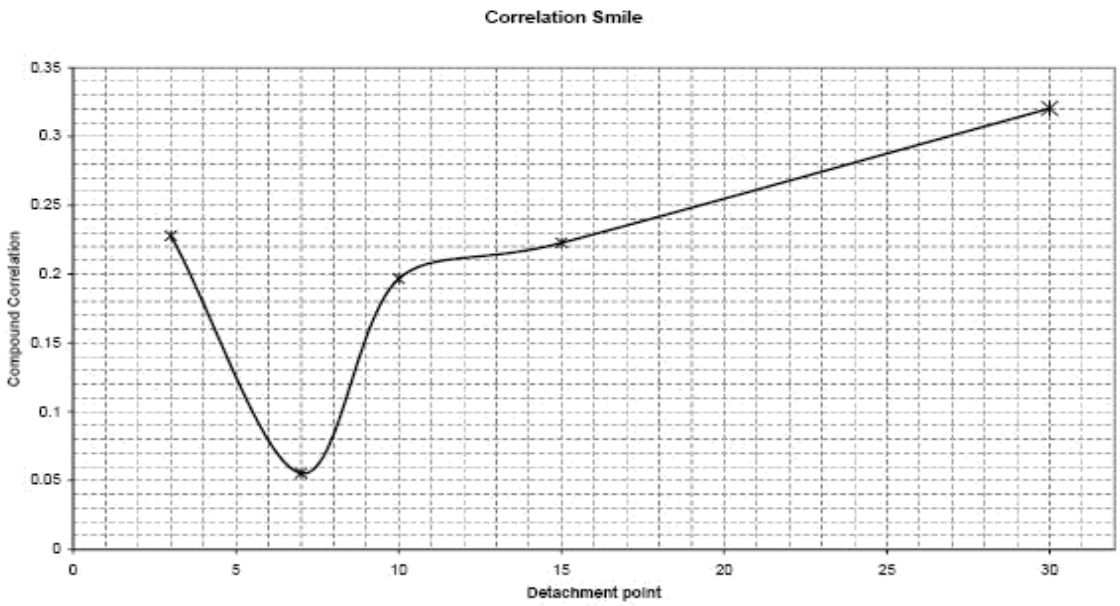
As time passes, CDOs market spreads became more and more available and operators in the market or simply researchers may calibrate their model parameters to the real market ones. Under the chosen model, via a correlation matrix, we can estimate the spreads for each tranche. Thus, through these spreads, the implied correlation obtained. Real market quotations shows that different tranches on the same underlying portfolio trade at

different implied default correlations, which seems a smile skew and for this is reason is called correlation smile. Nevertheless, in the standard Gaussian model things are different since the compound correlation must be equal for each tranche so that Gaussian copula model leads to a flat structure instead of a smile skew. Another important observation can be made; the implied default correlations for each tranche are not the same. These flaws occur due to the simplifying assumptions to the model such that correlations, recovery rates and CDS spreads are kept constant and equal for all obligors.

The correlation smile in the figure below illustrates how in mezzanine tranche we observe a lower default time correlation compared to the equity and senior tranches. Thus, we may say that the degree of default clustering assumed by the market seems to be higher for the equity and senior tranches. The real market quotations shows that different tranches on the same underlying portfolio trade at different implied default correlations. This is one of the reason why the Gaussian copula model miss to reflect accurately the joint distribution of default times.

Figure 2.5.2 (2):

Compound Correlations plotted against the detachment level of the tranches. Quotes on standard tranches on the DJ CDX basket are used from the 18th of October 2004. (Source: Van der Voort, M., 2005)

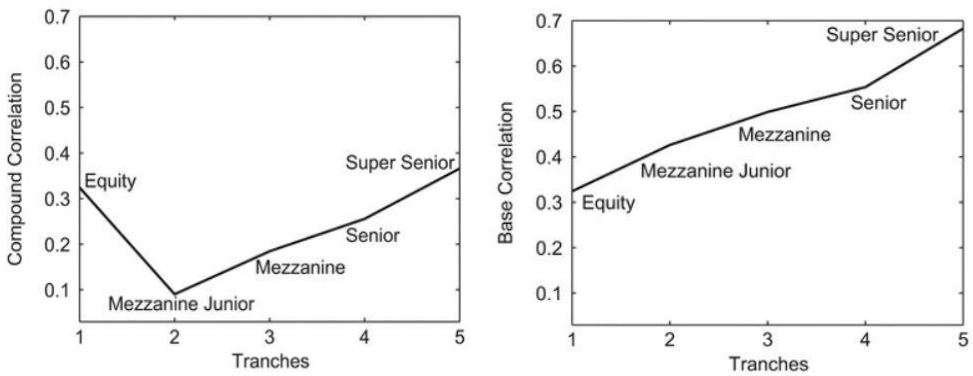


On the other hand, the main idea behind base correlation is that each tranche may be decomposed into two first loss tranches, which imply that tranches with lower attachment point zero are valued. It is an approach proposed by JP Morgan. In contrast to compound

correlations, base correlations examine the value of different tranches together by employing a bootstrapping technique. For instance, in order to reproduce a long position in a tranche with attachment point a_i and detachment point d_i and a short position in a first-loss-tranche with detachment point a_i. Through the bootstrapping process, all base correlations may be calculated progressively. The idea of base correlations solve a number of limitations of the compound correlations. For example, it offers a unique implied default correlation for fixed attachment points and a broader variety of tranche spreads may be reversed into a base correlation attribute.

However, base correlation have some flaws. The issue of different correlation parameters for each tranche holds and further there might be still situations where you cannot scale the correlations to market spreads. In addition, another issue emerge; the expected tranche loss could turn negative under some market conditions, which violates the primary no-arbitrage restrictions.

Figure 2.5.2 (3): Compound and base correlation



There are multiple reason why the compound correlation has a smile skew. The first possible reason is that distinct bunch of investors (protection sellers as hedge funds for equity tranches or banks for mezzanine tranches) retain different perspectives over the correlations throughout tranches. Another probable interpretation lies on the fact that there is quite an uncertainty over the selection of a proper model to assess credit risk. The correlation smile could be the reflection of this uncertainty of the market participants. Besides, the process of demand and supply on the market might motivate its smile shape since usually mezzanine tranches are the most requested within investors. In conclusion, we can assert that applying a single value of default correlation among the obligors in the standard market model would cause a misprice when pricing CDOs' premiums. In order

to solve this problem, researchers are constantly studying to implement the standard model in order to improve its predictability over market quotes.

Tail dependence failure

Although there are many types of copulas that could be used in CDO modelling, not all of them are suitable for the purpose. The copulas used to study for independent or perfectly correlated variables are clearly not the one researchers were looking for CDO modelling.

Multivariate normal distributions of credit risk, namely Gaussian copula, fail to capture default clustering, as for instance during crisis periods where if one obligor defaults it is more probable that another obligor will shortly default. The tail behaviour of a copula may be investigated by means of its tail dependence. However, the Gaussian copula standardly applied is tail independent. In credit risk framework, if Gaussian copula is applied, it means that an obligor defaults independently as the magnitude of the number of defaults increases. This is an assumption too strong to be realistic. Considering that the widely used Gaussian copula method is not able to design tail dependence, the contingency of extreme events in the upper and lower tail of the joint distribution of numerous random variables is significantly underestimated. This is dangerous especially in case of extreme events like financial crisis when a number of assets in the underlying portfolio goes default simultaneously and they cannot be included properly in the model. This cause a huge mispricing in structured products, such as CDO tranches, due to the underestimation of default correlations among the underlying assets.

2.6. Suitable copulas

Student-t approach

The Student-t copula is a mere expansion of the Gaussian copula. The spontaneous replacement would be the Student-t copula being alike to the Gaussian but having positive tail dependence. Nevertheless, it includes another parameter to be estimated, the degrees of freedom v. This might be a benefit in risk management context because as v increases the Student-t get closer to the Gaussian[9]. For this reason, one may launch a high v and lower it to monitor the impact of fattening tails. However, it becomes more challenging to fit to data. Moreover, the Student-t copula is symmetric. This implies that it includes

[9] When the degrees of freedom go to infinity, the model becomes a Gaussian copula.

both upper and lower tail dependence. This property is not sustainable in our framework since, in the real world, we expect wide negative co-movements to be of greater likelihood than large negative co-movements. Therefore, it is important to examine copulas having only lower tail dependence.

In the Student-t approach, the vector V follow a Student-t distribution with v degrees of freedom. We examine the symmetric case in which we have $V_i = \sqrt{Z}X_i$ and $X_i = \rho V + \sqrt{1-\rho^2}\bar{V}$ where:

- V ,$\bar{V}$ are independent Gaussian random variables
- Z is independent from $(X_{1,\dots,} X_n)$ and follows an inverse Gamma distribution with parameters equal to $\frac{v}{2}$
- $Cov(V_i, V_j) = \frac{v}{v-2}\rho^2$ for $v > 2$

We then also indicate by t_v the distribution function of the standard univariate Student t that is the univariate CDF of the V_i's. Then, we take $\tau = F_i^{-1}(t_v(V_i))$. It may be seen that conditionally on (V, Z) default times are independent and:

$$p_i^{i|V,W} = \Phi\left(\frac{-\rho V + Z^{-\frac{1}{2}} t_v^{-1}\big(F_i(t)\big)}{\sqrt{1-\rho^2}}\right)$$

Therefore, we cope with a two-factor model. The Student-t copula, as we mentioned before, has upper and lower tail dependence with equal coefficients equal to

$$2t_{v+1}\left(-\sqrt{v+1} \times \sqrt{\frac{1-\rho^2}{1+\rho^2}}\right)$$

It is important to note that in case of $\rho = 0$, we still have tail dependence. Indeed, we still have tail dependence whatever ρ and v value they take.

Double t copula

This model represents another plain extension of the one-factor Gaussian copula. Hull and White (2004) were the first ones to employ heavy-tailed distributions, such as the Student-t copula we have just described, in a one-factor copula model. They discovered that double t copula model fits well the market data in CDO pricing.

Define a latent random vector $(V_{1,\dots,} V_n)$, which modelled the default times. The latent variables are such that:

$$V_i = \rho(\frac{v-2}{v})^{\frac{1}{2}} V + \sqrt{1-\rho^2}(\frac{\bar{v}-2}{\bar{v}})^{\frac{1}{2}} \overline{V_i}$$

where:

- $V, \overline{V_i}$ are independent random variables following t student distribtuions with v and $\bar{v}$ degrees of freedom
- $\rho \geq 0$

It is noted that Student t distributions are not stable under convolution, while two main factors V and $\overline{V_i}$ both follow t-distribution, V_i's do not. Hence, the copula associated with $(V_1, \dots, V_n)$ is not a student copula, which differentiate itself from student t copula model previously explained.

The default times are given by:

$$\tau_i = F_i^{-1}(H_i(V_i))$$

for $i = 1, \dots, n$ where H_i is the distribution function of V_i[10]. Subsequently:

$$p_i^{i|V} = t_v(\left(\frac{\bar{v}}{\bar{v}-2}\right)^{\frac{1}{2}} \frac{H_i^{-1}\left(F_i(t)\right) - \rho\left(\frac{v}{v-2}\right)^{\frac{1}{2}} V}{\sqrt{1-\rho^2}})$$

If $v > \bar{v}$, then the tail factor (V) is smaller than the tail of the idiosyncratic risk $(\overline{V_i})$ and there is no tail dependence between the default times. We underline that we may have no tail dependence between default times even if the factor has fat tails.

Clayton copula

Define a random variable V, which follows a standard Gamma distribution with shape parameter $\frac{1}{\theta}$ where $\theta > 0$, namely $V \sim \Gamma(\frac{1}{\theta})$.

The probability density function (PDF) of V is given by:

$$f(x) = \frac{1}{\Gamma(\frac{1}{\theta})} e^{-x} x^{\frac{1-\theta}{\theta}}$$

for $x > 0$.

[10] H_i depends upon ρ.

We indicate ψ the Laplce transformation of f and so we obtain:

$$\psi(s) = \int_0^\infty f(x)e^{-sx}\,dx = (1+s)^{-\frac{1}{\theta}}$$

The Clayton factor model is presented as:

$$V_i = \psi\left(-\frac{lnU_i}{V}\right),$$

Where $U_i, \dots, U_n$ are independent uniform random variables yet independent from V. Lastly, the default times are such that:

$$\tau_i = F_i^{-1}(V_i) \quad i = 1, \dots, n$$

The conditional default probabilities may be displayed as:

$$p_i^{i|V} = \exp(V\left(1 - F_i(t)^{-\theta}\right))$$

It is important to observe that the V_i's have uniform marginal distributions. Being the default times increasing functions of the V_i's, the copula of the default times is the joint distribution of the V_i's. The distribution of the V_i's is called Clayton copula.

Stochastic correlation

Another extension, one of the simplest, of the Gaussian copula is the stochastic correlation, modelled to match "correlation smiles" in the CDO market.

Define latent variables as:

$$V_i = B_i\left(\rho V + \sqrt{1-\rho^2}\,\bar{V}_i\right) + (1-B_i)\left(\beta V + \sqrt{1-\beta^2}\bar{V}_i\right)$$

for $i = 1, \dots, n$, where:

- B_i are Bernoulli random variables
- $V, \bar{V}_i$ are standard Gaussian random variables, all these are jointly independent
- ρ, β are some correlation parameters such that: $0 \le \beta \le \rho \le 1$

The model displayed above is a convex sum of one-factor Gaussians copulas, involving a mixing distribution over factor exposure. We can rewrite the equation above as:

$$V_i = (B_i\rho + (1-B_i)\beta)V + \sqrt{1-(B_i\rho + (1-B_i)\beta)^2}\bar{V}_i,$$

That clearly states that we cope with a stochastic correlation copula model. We obtain a factor exposure ρ with probability p and β with probability $1-p$. Simply, we are able to verify that the marginal distributions of the V_i's. The default dates are defined as:

$$\tau_i = F_i^{-1}(\Phi(V_i)) \quad i = 1, \dots, n$$

Default times are independent conditionally on V and we can type the conditional default probabilities as:

$$p_i^{i|V} = p\Phi\left(\frac{-\rho V + \Phi^{-1}\big(F_i(t)\big)}{\sqrt{1-\rho^2}}\right) + (1-p)\Phi\left(\frac{-\beta V + \Phi^{-1}\big(F_i(t)\big)}{\sqrt{1-\beta^2}}\right)$$

As a result, the former model could be observed as a mixture of Gaussian copulas, including al combinations of correlations. The tail dependence coefficient is equal to zero if $\beta \leq \rho < 1$, to p^2 if $\beta < \rho = 1$ and to 1 if $\beta = \rho = 1$.

Marshall-Olkin copula

This is considered a "shock model". We provide the most basic representation of the model related to a sole fatal shock.

Define some latent variable $V_i = \min(V, \overline{V_i})$, $i = 1, \dots, n$ where:

- $(V, \overline{V_i})$, $i = 1, \dots, n$ are independent and normally distributed random variables with parameters $\alpha, 1-\alpha, \alpha \in]0,1[$

The corresponding survival copula is part of the Marshall-Olkin family and may be expressed as:

$$\widehat{C}(u_1, \dots, u_n) = \min(u_1^\alpha, \dots, u_n^\alpha) \prod_{i=1}^{n} u_i^{1-\alpha}$$

The default times are identified as:

$$\tau_i = S_i^{-1}(\exp(-min(V, \overline{V_i})))$$

Given that $t \to S_i^{-1}(\exp(-t))$ are increasing functions, the copula of default times is equal to the copula of $\min(V, \overline{V_i})$. Furthermore, we may observe that the survival function τ_i is simply S_i. We may also see, via the definition of default times, that the default times are conditionally independent upon V and the conditional survival probabilities are determined by:

$$q_i^{i|V} = 1_{V>-lnS_i(t)} S_i(t)^{1-\alpha}$$

We observe upper and lower tail dependence with the same coefficient equal to α. $\alpha = 0$ relates to the independence, while $\alpha = 1$ implies that $\tau_i = S_i^{-1}(V)$,namely the default dates, are comonotonic. If we examine the case of equal marginal distributions of default times, the model permits simultaneous defaults with positive probability. There is evidence that when α increases, the dependence between default dates increases.

The discussion over the diverse models proposed is not over yet. We add last two models, which are not less important than the others we have just discussed but we introduce them briefer and without passing through their mathematical explanations.

Normal Inverse Gaussian model and Random Factor Loading (RFL) model

Normal inverse Gaussian (NIG henceforth) distribution is a special example of the group of generalized hyperbolic distributions. In specific conditions, they are stable under convolution[11]. All the probability density function (PDF), the cumulative density function (CDF) and the inverse distribution are quite simple to be computed. Kalemanova et al (2005)[12] showed in their work that NIG models applied to CDO pricing provide a decent fit to market data. The NIG distribution is a mixture of normal and inverse Gaussian distributions.

Andersen and Sidenius (2004) first proposed the Random factor loading (RFL) model. It is based on the idea of making factor loading, found on the factor models, being functions of the system/common factors themselves. The model is set up interpreting the systematic factor as the status of the market with its value being high in a bear market and low in a bull market. The model also well imitate the empirical effect that equity (and thus asset) correlations are higher in a good time economy rather than in a bad time economy.

[11] In mathematics, convolution is a mathematical operation on two functions that produces a third function expressing how the shape of one is modified by the other. The term convolution refers to both the result function and to the process of computing it. It is defined as the integral of the product of the two functions after one is reversed and shifted. Moreover, the integral is evaluated for all values of shift, producing the convolution function.

[12] Through their work they also used other models, such double t copula model, to rebut to Hull and White (2004), which claimed that the double t copula model fits market data when the parameter ν (the degrees of freedom) is 4. Kalemanova et al declared that the double t copula model fits market data better when ν = 3 than ν = 4.

The general model is quite flexible, differing in the functional relationship between systematic factors and loading and in the selection of distribution for factors and residuals. For instance, we consider the specific case building on the Gaussian copula model. If we adopt the Gaussian copula with the RFL model, we do not only simulate the empirical dependence of correlation on the general market, but also we produce a base correlation skew that we have already studied. To expand the idea, think from the point of view of a senior tranche investor. From its position, he will only undergo losses when a certain companies/obligors will default simultaneously. Broadly, high values of correlation parameters/factor loading have a tendency to result in fatter tails of distribution, which means the extreme loss outcomes. For example, the systematic factor might be low, and then the factor loadings would be high make it seem to senior investor that the correlation is high.

2.7. Default leg and premium leg

Before we begin the model comparison, we introduce the discussion on default leg and premium leg over CDO tranches, which we have not examined yet.

If we start increasing the correlation parameter ρ within Gaussian double t and Student-t copula, increasing the parameters ρ, β or p in the stochastic correlation model, increasing the parameter θ in Clayton copula model, or increasing the parameter α (representing the relative magnitude of the common shock) in Marshall-Olkin copula, all lead to an increase in dependence among default times. Therefore, it may be demonstrated that CDO tranche premiums of equity or senior class, whether with an attachment point being equal to zero or a detachment point being equal to 100%, are monotonic with respect to the dependence parameter. Thenceforth we will focus on equity tranches, also known as first loss tranches, which are generally related to the base correlation approach.

To simplify, we may consider the common Gaussian copula case, while the outcome may be extended freely to the other models we have listed. We can show that equity tranche premiums decrease with regard to the correlation parameter. This is an important consideration because it ensures the singularity of base correlations irrespective to the maturity of the CDO or the marginal distributions of default times.

The expected loss on the reference portfolio is the sum of the expected losses on the obligors and is constant with regard to the correlation structure.

The expected loss for a base tranche with detachment point K or, alternatively called, "base expected loss" is:

$$E[\min(K, L(t))]$$

where:

- K is the detachment point of the tranche
- $L(t)$ is the aggregate loss for time t

We might assert that the base expected loss decreases with the correlation parameter ρ (assuming deterministic recovery rates). Given that the present value of the default leg of an equity tranche involves a discounted average of such expectations[13], we may affirm that the value of the default leg of an equity tranche decreases when the correlation parameter increase.

In order to finalize the analysis, we shall take into account the effect of the premium leg of a CDO tranche with respect to the dependence parameter. We remember that the premium paid is commensurated to the outstanding nominal of the CDO tranche. We end up that the value for the premium leg increases with correlation parameter. Considering that, concurrently, the value of the default leg decreases, the value of the buy protection (in case of a synthetic CDO) on an equity tranche decreases when the correlation parameter increases. If we apply the same logic, the conclusions we have just ended with hold similarly for the stochastic correlation, Student-t, Clayton and Marshall-Olkin copulas with respect to the related dependence parameters.

Consider that $0 \leq \rho \leq \rho' \Rightarrow E[\left(K - L_{\rho}(t)\right)] \leq E[\left(K - L_{\rho'}(t)\right)]$, the value of the default of a senior tranche with attachment point K always increases with the correlation parameter. The premium paid on the senior tranche is proportional to the outstanding nominal of the tranche, which is more complex than for an equity tranche.

Let us examine a [30%-100%] tranche on the portfolio of 100 obligors. At origination, the protection buyer may suppose a maximum payout of 70%. Hence, the corresponding premium is based on the outstanding nominal. We take an example assuming that the first default is pain-free. For example, the Initech subordinated debt is associated to a recovery rate of 100%. Following the first default, the maximum loss equals 99% and so the

[13] see Laurent and Gregory (2005)

maximum payout of the most secured tranche is now equal to 69%. Reasonably, the premium payment should be proportional to the maximum payout.

Consequently, the premium leg's value of a senior tranche decreases with the correlation parameter. Thus, the value of a buy protection senior tranche always increases when the correlation parameter increases. Eventually, results on CDO tranches show somewhat of monotonicity with respect to the copula dependence parameter.

2.8. Comparison of CDO tranche premium and correlation under various models

In our final paragraph, we compare the different models we have described so far among themselves and compare them to market quotes.

In order to understand better the comparison between the models among themselves, we set a practical example. We take 100 obligors, set constant recovery rate 40%, and consider credit spreads all equal to 100bps assuming they are constant until CDO's maturity. Tranches' attachment point are set at 3% and 10% and CDO maturity is equal to five-year lifespan. The default free rates are given.

We take into consideration in our analysis equity, mezzanine and senior tranches[14] for different models. Being the Gaussian model the market standard, we compute the margins with regard of its correlation parameter (ρ^2). The results indicate a robust negative dependence of the equity tranche with respect to the correlation parameter, a positive dependence of the senior tranche and thumped curve for the mezzanine tranche, which is not so sensitive to the correlation parameter.

Before comparing the different premiums in mezzanine and senior tranches, we need to set the dependence parameters of the other different models to get firstly the same equity tranche premiums. Once we have calibrated the different parameter for each model in order to get the same equity tranche premium, we can compute the different premiums for both mezzanine and senior tranches with respect to the different models.

[14] Equivalent to (0-3%), (3-10%) and (10-100%) tranches.

Table 2.8 (1): Mezzanine tranche premiums (bps) calculated within number of models for different levels of Gaussian copula correlation

ρ	0%	10%	30%	50%	70%	100%
Gaussian	560	633	612	539	443	167
Clayton	560	637	628	560	464	167
Student (6)			637	550	447	167
Student (12)			621	543	445	167
$t(4)$-$t(4)$	560	527	435	369	313	167
$t(5)$-$t(4)$	560	545	454	385	323	167
$t(4)$-$t(5)$	560	538	451	385	326	167
$t(3)$-$t(4)$	560	495	397	339	316	167
$t(4)$-$t(3)$	560	508	406	342	291	167
MO	560	284	144	125	134	167

Table 2.8 (2): Senior tranche premiums (bps) calculated within number of models for different levels of Gaussian copula correlation

ρ	0%	10%	30%	50%	70%	100%
Gaussian	0.03	4.6	20	36	52	91
Clayton	0.03	4.0	18	33	50	91
Student (6)			17	34	51	91
Student (12)			19	35	52	91
$t(4)$-$t(4)$	0.03	11	30	45	60	91
$t(5)$-$t(4)$	0.03	10	29	45	59	91
$t(4)$-$t(5)$	0.03	10	29	44	59	91
$t(3)$-$t(4)$	0.03	12	32	47	71	91

t(4)-*t*(3)	0.03	12	32	47	61	91
MO	0.03	25	49	62	73	91

Looking at the tables above, we can observe some intriguing results. The first peculiarity to be noticed is how close Clayton and Student-t values compared to the Gaussian model are. For example, in senior tranche premium with Gaussian correlation of 50%, we obtain 36 bps under the Gaussian assumption while we get 33 bps under the Clayton assumption and 35 bps under a Student-t with 12 degrees of freedom. The values among these three models are similar in both mezzanine and senior tranches premiums. On the other hand, it stands out how different are the values under Gaussian, Clayton and Student-t assumption compared to Marshall-Olkin model. Under MO assumption, values at the same level of Gaussian correlation change dramatically.

2.9. Comparison between market and model CDO tranche premiums

We now compare the market quotes of Dow Jones iTraxx Europe index to the models we have studied. We consider the CDO maturity of five years. 3%, 6%, 9%, 12% and 22% match the attachment detachment points of the conventional iTraxx CDO tranches. The index is based on 125 companies. In order to facilitate the comparison, credit spreads and default free rates are given. The results for tranches as quoted in the market are provided in the table below.

Table 2.9 (1): iTraxx CDO tranche premiums (bps) using market and model quotes

Tranches	Market	Gaussian	Clayton	Student (12)	*t*(4)-*t*(4)	Stoch.	MO
[0-3%]	916	916	916	916	916	916	916
[3-6%]	101	163	163	164	82	122	14
[6-9%]	33	48	47	47	34	53	11
[9-12%]	16	17	16	15	22	29	11
[12-22%]	9	3	2	2	13	8	11

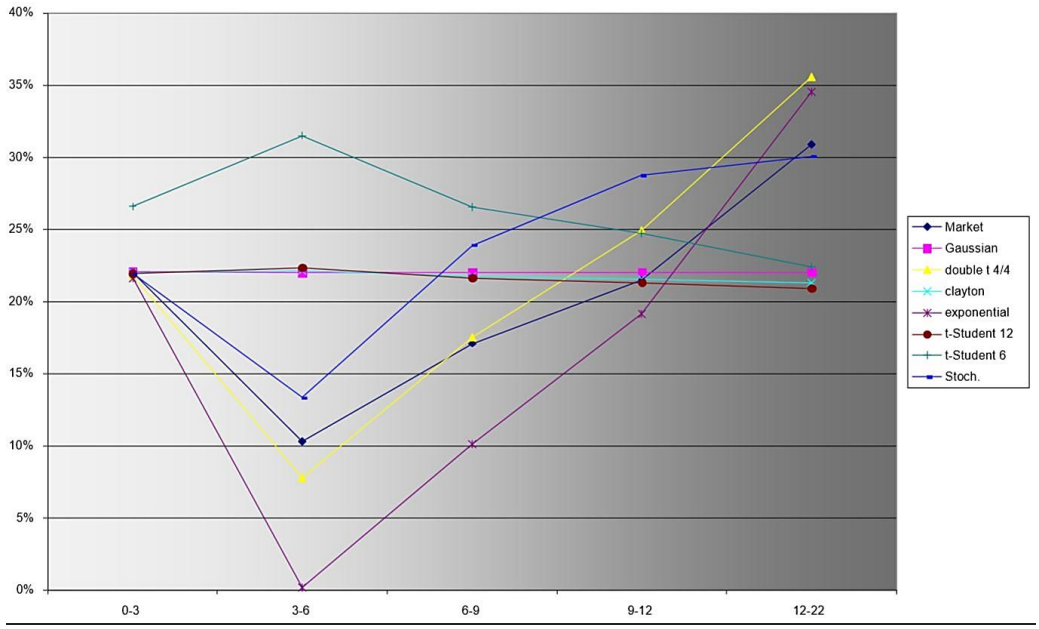
Nonetheless, the most interesting features regarding the comparison among market and models results are captured through the results about correlation. As before, this time we

take as reference the market standard meaning the Gaussian copula model. As we already explained previously in the chapter, it gained its status due to its computational simplicity. In fact, it assumes a flat correlation structure over the reference portfolio. However, Gaussian copula model fails to capture the presence of the correlation skew (i.e. "correlation smile") in iTraxx tranches meaning it is not reliable in CDO valuation due to lack of tail dependence.

Table 2.9 (2): Implied compound correlation for iTraxx tranches

Tranches	Market	Gaussian	Clayton	Student (12)	*t*(4)-*t*(4)	Stoch.	MO
[0-3%]	22%	22%	22%	22%	22%	22%	22%
[3-6%]	10%	22%	22%	22%	8%	13%	0%
[6-9%]	17%	22%	22%	22%	18%	24%	10%
[9-12%]	22%	22%	23%	21%	25%	29%	19%
[12-22%]	31%	22%	21%	21%	36%	30%	35%

Figure 2.9 (3): Implied compound correlations of various models



If Gaussian misses to price consistently CDO tranche premiums, we may address the same problem to Clayton and Student-t having similar values to Gaussian (they do not reproduce the correlation smile either). The Marshall-Olkin model underestimates

mezzanine tranches' prices and overestimates the super senior. The stochastic correlation model provides a good fit compared to market prices, especially the equity and junior super senior but it overestimates the mezzanine tranche. In any case, it provides a reasonable skew, close to the observed market levels. The double-t copula from White and Hull (2004) deserves a distinct remark. It has been shown that double-t distribution copula, where both the market factor and the idiosyncratic factor have student-t distribution/heavy tails, they offer a good fit to iTraxx and CDX market data. However, it has been observed that its instability under certain conditions causes a dramatic grow in mathematical computations makes it difficult to apply practically. Kalemanova et al suggested the Normal Inverse Gaussian (NIG) copula model. It has higher tail dependence than Gaussian distribution and it is more stable than double-t copula. This model leads to considerable progress in computation time and elasticity over the modelling of the dependence of default structure. Copula models with random recovery rate (RR) and random factor loadings (RFL) match better the correlation smile than the Gaussian flat correlation. However, random RR it is not fully reliable due to its lack in generating a significant skew in tranche values. Factor loadings method perform much better and is able to produce a correlation smile very close to the observed market data.

To sum up, we have seen several models studied by practitioners and academics used in CDO valuation context. We highlighted their characteristics, strengths and weaknesses. Clayton and Student-t copula models produce similar results to the market standard Gaussian copula. Double-t model, random factor loadings and stochastic correlation copula, despite their flaws, provide the best fit to market data reaching the required level of correlation skew.

The industry standard is far to be reliable in CDO pricing framework. However, apart from the lack of tail dependence, other issues arise in CDO evaluation as for example that there is no secured formula in order to define the recovery rates. It seems that the models proposed do not live up the expectations of being a suitable replacement for the Gaussian copula either. Some studies indicates that we still have not enough data to produce reliable models. Until a worthy model is found, the best the companies can do is to select or build the model that best suit their specific requirement and situations.

3. An empirical analysis on the CLO market

The current situation we are experiencing, intra and post Covid-19, has had a great impact on the whole world. A large part of the system that has been disrupted by the virus has been the economic sector. Finance, in particular, has suffered and will perhaps suffer even more from the impact of the virus. In the second half of March 2020, we observed a breakdown in financial markets, following the advance of the virus and threats of lockdowns, and market fears began to rise, leading world stock exchanges to plummet. All the major financial indicators have dropped all together, leading to severe concern among insiders.

Our focus will be on structured finance, in particular the world of CLOs and CDOs. In the first chapter we introduced them and in the second chapter we saw how to assess their risk. In this chapter, we ask ourselves whether those who sell, trade and buy these products were more careful than they were a dozen years ago, when the latest global financial crisis occurred. To better highlight the potential danger caused by the "underworld" of CDOs and CLOs, we will show how this system did not stop or slow down after 2008 just because it caused the latest big financial crisis, but rather increased from year to year. Although CLO market has been monitored and bound by increasingly stringent regulations, it has continued to creep in, fuelling the danger and making the itself more fragile. That is why the virus is nothing more than the unexpected, the black swan, which could again upset the balance and spit out another monster from the mouth of the finance sector.

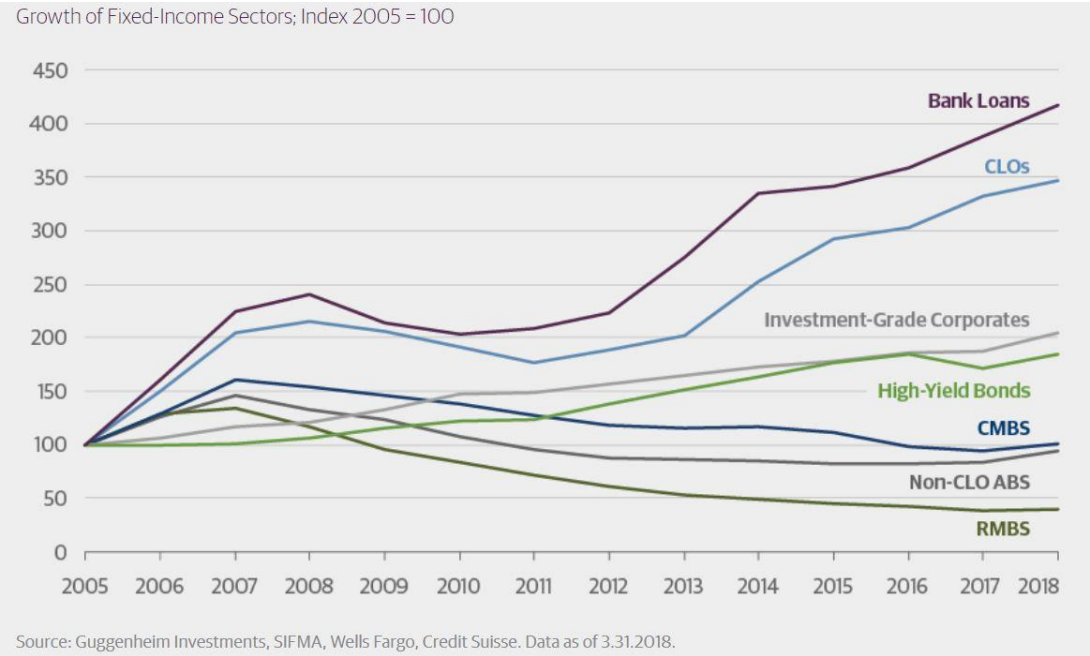
What we are going to investigate in the following is whether there are similarities between the current crisis in the financial sector and the Great Financial Crisis (GFC) of 2008. We study several different indicators and compare them in the two reference periods, i.e., the months around September 2008 and the latest months.

3.1. CLO market overview

The structured credit marketplace has evolved significantly since the financial crisis. If we look at the US market, the CLO market grew from a post-crisis of $263 billion to $590 billion as of January 2019, according to Wells Fargo research. The strong historical credit performance and attractive floating-rate coupon attracted many new investors. Prior to the GFC, investor sponsorship was largely dominated by hedge funds, structured

investment vehicles (SIVs) and Wall Street trading desks. However, post-crisis regulation has all but eliminated these highly leveraged investor types. Today's investor base is primarily composed of money center banks, large institutional asset managers and insurance companies. These real-money investors do not employ the high leveraged strategies of the pre-crisis investor base.

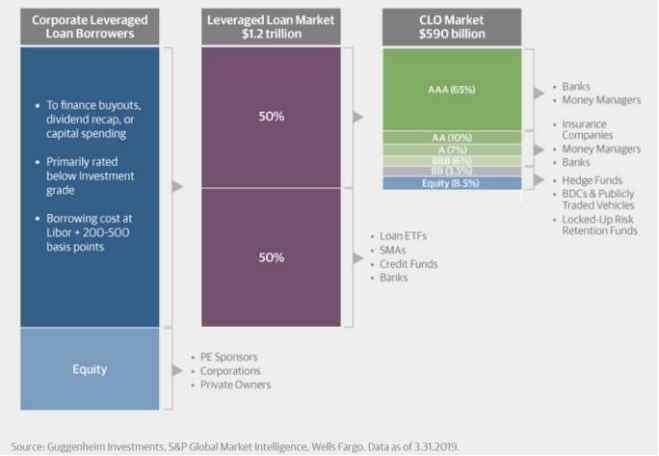
Graph 3.1(1): CLOs and Bank Loans Outpace Growth of Other Fixed-Income Sectors



At $590 billion, CLOs represent half of the total $1.2 trillion U.S. leveraged loan[15] market. About 65 percent of CLO market debt is AAA-rated and is typically held by banks and money managers. A further 23 percent of the market is made up of AA, A, and BBB-rated debt, tranches that are typically held by banks, money managers, and insurance companies. The riskier tranches, BB and equity, round out the remaining 12 percent and tend to attract hedge funds, business development companies, publicly traded vehicles, or pension funds. Borrowers rated below investment grade typically pay a premium of 200–500 basis points over Libor to service their debt.

[15] A leveraged loan is a type of loan that is extended to companies or individuals that already have considerable amounts of debt or poor credit history. It refers to speculative-grade loans based on their credit rating or credit quality ratios, such as net-debt-to-earnings, debt-to-assets, or debt-to-equity ratio. Leveraged loans are predominately syndicated, that is, several (a syndicate of) lenders participate in the issuance of a loan.

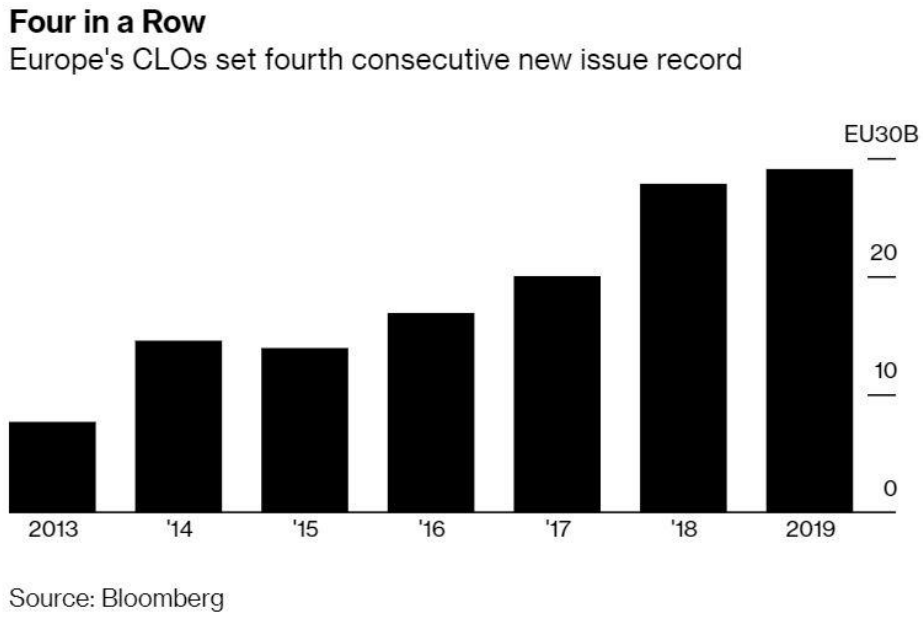
Graph 3.1 (2): Leveraged Loan and CLO Markets Capital Flow



As we stated earlier, we are comparing not only two different historical periods but also two different products: CDOs and CLOs. In fact, one, the CLO, is the subclass of the other one, the CDO. The CLO is nothing more than a CDO that, however, has as its underlying only loans, mostly leveraged. We will also attempt to differentiate between the US and EU markets and we will try to review the dynamics within various banks according to the two different markets that play a decisive role within the analysis.

The number of CLO issued in the market by investment banks has grown steadily in recent years. This seems to be the particular case for the European CLO market. Bloomberg shows us how the number of CLO emissions in the European market has grown consistently year on year.

Graph 3.1 (3): number of EU's CLOs issuance by year



The CLO market has not only boosted in Europe but worldwide. However, these products often hide pitfalls as they depend on their underlying parts. Although the awareness of these products has grown significantly since the last financial crisis, they remain potentially dangerous. In order to tackle their dangerous nature and not encourage those who "create" them to use them recklessly, the supervisory authorities have introduced more and stricter laws and constraints to make their use safer. The banks are in fact the main architects of such products. As they had a central function within the 2008 financial breakdown, they are still the focus of this market today.

The vast majority of the debt holds an intact, triple-A rating, which has allowed these securities to be drawn in a large group of risk-averse investors that might otherwise be intimidated from the hazardous loan market underpinning CLOs. Protections have also been built in, ensuring money is redirected to pay investors in the highest rated tranches of debt first, should the underlying loan market come under severe stress. Those protections are now being put to test. While the history is encouraging, some investors warn that the current crisis, as well as the state of the loan market, is far different from anything that has come before. Rather than a crisis originating in one corner, such as consumer debt in 2007, the global shutdown is suppressing earnings across sectors. Furthermore, the quality of the underlying loans held by CLOs has sharply deteriorated over the past decade. Moody's noted that financial covenant protections for investors were at their worst on record just before the coronavirus hit. The average number of lower-rated, single-B loans held by CLOs was also at a high point. As the coronavirus has spread, compelling economies into lockdown and devastating corporate revenues, rating agencies have swiftly begun downgrading loans even further. More than 12 percent of the loans held by CLOs are now rated triple C, often indicative of a company on the brink of collapse, according to S&P Global. Analysts stated that the number of loans downgraded in both US and Europe has been large and severe, unlike to what we have seen in the past.

One of the reasons why CLOs have grown at such a speed despite the distrust following the 2008 economic crisis is their proven security. In fact, CLOs have had a very low default rate in recent years. Let us now analyse the CLO market in the US and the EU separately.

3.1.1. US CLO market

The combination of conservative collateral and sound securitization structure has resulted in strong credit performance. In fact, AAA and AA-rated CLO tranches have only experienced one default since 1994. CLOs' historically low default rate holds true across the ratings range (see table below).

While CLOs exhibited strong and resilient credit performance during the financial crisis, post-crisis CLOs feature numerous additional credit improvements compared to their pre-crisis counterparts. First, rating agencies now require that CLOs substantially feature more credit enhancement to each rated debt tranche compared to their pre-crisis counterparts. Second, where pre-crisis CLOs were able to make investments in subordinated bonds and other CLO debt instruments, post-crisis CLOs are collateralized primarily by senior secured bank loans. Third, post-crisis CLOs' documentation is much more investor-friendly, shortening the trading period during which the manager is able to actively manage the loan portfolio, and limiting extension risk for CLO securities. Thus far among CLO 2.0, 43 post-crisis tranches have been downgraded by S&P or Moody's since 2012, and more than 70 percent of those downgraded tranches are 2014 vintages with most of the balance from 2013. Over half of the tranches were originally rated single B with no downgrades of CLO 2.0 AAA or AA tranches.

Figure 3.1.1 (1): CLO tranches defaults in US CLO market

	CLO 1.0 (Issued 1994-2009)		CLO 2.0 (Issued 2010-Present)		Total (CLO 1.0 + CLO 2.0)	
Original Rating	Tranches Rated	Defaulted	Tranches Rated	Defaulted	Tranches Rated	Defaulted
AAA	1540	0	1801	0	3341	0
AA	616	1	1388	0	2004	1
A	790	5	1179	0	1969	5
BBB	783	9	1007	0	1790	9
BB	565	20	903	0	1468	20
B	28	3	294	0	322	3
Total:	4322	38	6572	0	10894	38

Source: Guggenheim Investments, S&P Global Ratings. Data as of 4.10.2019.

3.1.2. EU CLO market

Although coronavirus was already in the news at the end of February, the economic situation in the leveraged loan sector was still viewed positively. European CLOs issued

before 2013, or CLOs 1.0, had almost fully terminated, with a 1.3% default rate in 20 years. At the same time, CLOs 2.0, those issued from 2013 onward, displayed very stable performance, with only one tranche downgraded among European transactions in their history. The 12-month trailing speculative-grade default rate for corporates in Europe, at 2.4% as of March 2020, continued to be minimal and lower than the historical average.

Figure 3.1.2 (1): CLO tranches defaults in EU CLO market

As of April 30, 2020

	CLO 1.0			CLO 2.0		
Rating	No. of original ratings	No. of defaults	Currently rated	No. of original ratings	No. of defaults	Currently rated
AAA	472	0	0	293	0	158
AA	225	0	0	326	0	225
A	239	0	0	250	0	199
BBB	290	4	1	203	0	130
BB	205	17	1	191	0	135
B	11	1	0	170	0	136
Total	1,442	22	2	1,433	0	983

Source: S&P Global Ratings Research.

3.2. The "big alchemy" explained

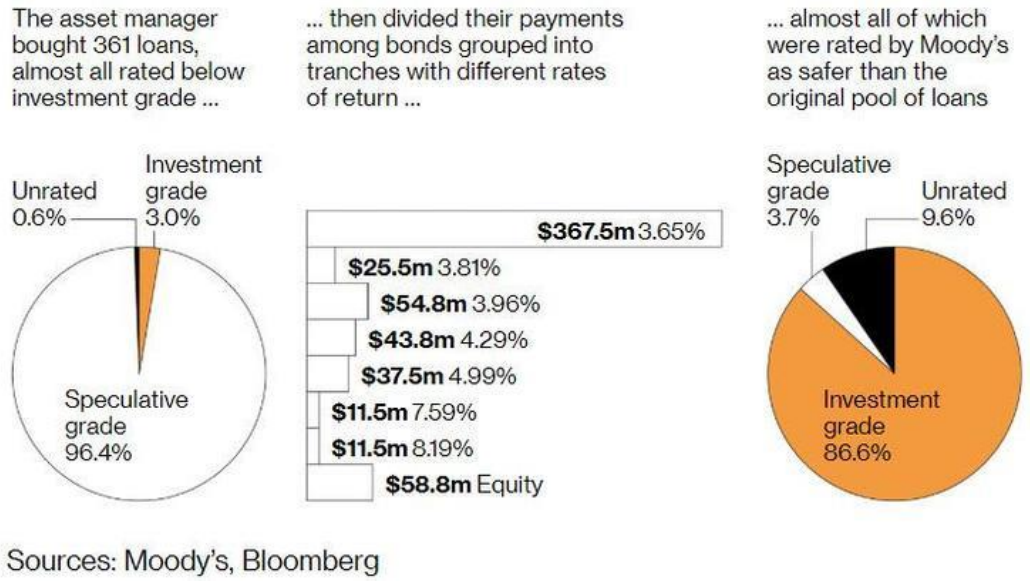
Several factors alert practitioners to a possible collapse in the structured derivatives market. Now, as a follow-up to the virus, attention to the dangerousness of these products has increased. CLOs are simply tradable securities backed by loans. These loans were issued by commercial and non-commercial banks, both to individuals and companies. However, we will concentrate on CLOs backed by Leveraged loans since they are most under stress. Once issued, the bank "sells" them, in order not to bear the relative credit risk, to an investment bank. The latter after "buying" a set of loans leaves them in a warehouse. The process ends, as we have explained in previous chapters, with the creation of CLO tranches to be sold to investors. For a long time the system had therefore been expanding with the production of CLOs constantly increasing as investors demand for these products has been very high. In fact, the investors were in continuous search of products that offered a return to their needs given the negative rates of sovereign bonds. Therefore, investment banks had an incentive to produce CLOs since demand was at roof. Even small commercial banks had incentives to provide loans because they knew they

could easily "resell" the credit risk to investment banks. At the same time, households and firms also had incentives to borrow as interest rates were generally very low. This vicious circle was disturbed by Covid-19 arrival. The virus slowed down the current economic cycle. The economy has faltered, causing to brake it violently. Stock markets have plummeted and consumption has stopped. This has meant that all those products, such as CLOs, which had a value and a guarantee of the underlying in loans to individuals and especially troubled businesses, have been downsized and put in danger. Several ratings for companies, loans to companies and related marketable securities (i.e. CLOs) have been downgraded. This created a downward spiral that was unwelcomed by investors who had invested in such products and by central banks who saw the danger of systemic risk again.

One of the aspects that cause concern is the so-called "great alchemy". By alchemy, we mean the operation through which big banks and big financial operators transform a product made up of 90% of junk loans into an investment grade bond portfolio. In practice, this system makes it possible to mask the risks, which remain low during a period of calm in the markets. However, in the event of a destabilizing and unexpected event, as in our case Covid-19, it may lead to an exponential increase in risks that can spread at great speed.

For banks in order to attract customers, i.e. investors, a double hook is needed: a good return and guarantees of relative protection. The first is achieved by handling large layers of securities with a low rating. A logic of normal risk premium. On the other hand, it is more difficult to offer the precautionary principle of calculated risk. Those who pack and sell CLOs give priority in the securitization process to the tranches of higher-rated loans, putting them higher and more prominently and then offering to scale up in terms of security and resulting in higher returns. In short, the first and most numerous (and safest) AAA tranches are offered, then AA and so on up to the most profitable but riskiest equity tranches. The result is a scheme that clearly explains the concept of alchemy. The scheme shown below was adopted by Long Point Park to create its CLO, consisting of 361 initial loans with a purchase price of $610 million.

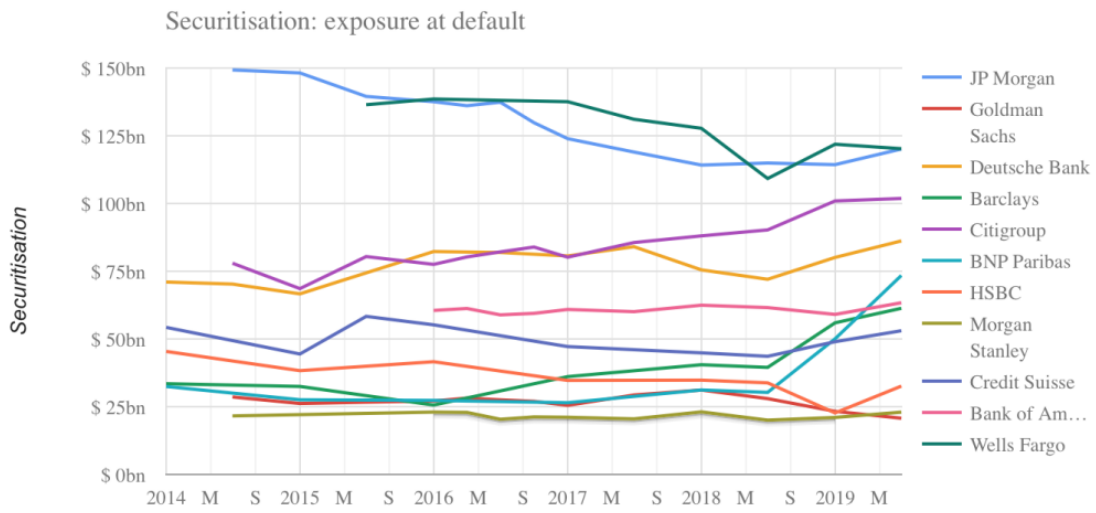
Figure 3.2 (1): the "big alchemy" explained



Within the initial pool, 96.4% were junk rated loans, almost all of them. Following the alchemy of turning loans into pool of bonds according to maturity and payments, the final result offered to investors is a set of hybrid bonds composed of 87% investment grade rated securities and only 3.7% junk rating. The method by which this process succeeds is called diversification. However, as we have said before, an unexpected event of great impact can disrupt a system that is already at risk in its normal course. As the number of these products issued on the market increases, so does the investor's apprehension. The problem triggered by Covid-19 turns into liquidity crisis that is affecting the system. The rating agencies have started to lower the rating of the loans that support the CLOs and therefore to lower the rating of the CLOs themselves. This change was rapid. The other major problem is that banks are full of these products. The number of downgrades since the beginning of the year has grown considerably, leading the banks themselves to resell the loans, which they had just bought and left in the warehouses, even before packing them. To give an idea, such loans may have been bought at 100 to be packaged and resold at 200, because of the downgrades, were resold at 20 before they even went through the securitization process.

A further factor that alarms the ECB is the great exposure of European banks to these products. In particular, banks such as BNP Paribas and Deutsche Bank have invested heavily in securitisation in recent times, thus exposing themselves to great risk. The ECB monitors the situation closely and once again, the solution may be to pump liquidity into the coffers of the most exposed banks to prevent their junk products to let them sink.

Figure 3.2 (2): Securitisation: exposure at default



3.3. An unstable situation

Usually, CLOs are allowed, under their own rules, to hold up to a certain percentage of their assets in triple-C-rated debt (typically, in case of CLOs, the percentage is around 7.5%). If they stay within the threshold, then CLOs managers can treat the loans they own as if they are worth 100 cents on the dollar. This is because when a CLO is designed, the underlying portfolio of loans is larger than managers need to pay off debt investors. This is known as over-collateralization (we explained it in the prior chapter). So as long as the number of loans that are near to defaulting remains below the 7.5 percent threshold, the portfolio is treated as though there will be enough money left at the end to pay investors. However, if a CLO exceeds its triple-C bucket, as many now have, then the lowest priced loans above the threshold are required to be valued at a market price. In a crisis, with loan prices having fallen steeply, this lowers the overall value of the portfolio of loans reported by the CLO. That may influence how investors are being paid. If, for instance, the value of excess collateral drops by more than a few percentage points, managers commonly first cut off 50 percent of any interest payments on the underlying loans that would have gone to equity holders and use it to buy more loans, with the goal of increasing the value of the portfolio and filling the gap. But if the value of the underlying loans falls further, then all money is cut off to equity investors. That money is then used not only to pay interest to debt investors but also to start paying back the principal of the debt, starting from the triple-A-rated bonds.

The test used to check the cash flow system is self-correcting, reducing a CLO's debt so that the loans it holds can more easily cover the remaining debt payments to maturity. However, the mechanism is not guaranteed to work. More than 100 CLOs were failing by escalating triple-C loans, according to April data compiled by Barclays, with 40 failing tests for their triple-B-rated tranche or higher, debt that is regarded as investment grade. Even few AA-rated tranche failed their tests. As the quality of loans held by CLOs has progressively deteriorated, it has pushed rating agencies to start considering downgrading the debt sold by CLO managers, as the prospect that they will be unable to pay back their investors grows. The rumours suggest that approximately a third of all triple-B-rated CLO bonds are now on review for a downgrade. Historically, it has been very rare for the debt of CLOs not to be able to be paid back. The investors, which are whether risk-averse or holds higher rated tranches of CLOs, are much more susceptible to rating downgrades. They prefer to hold only the tranches of highest quality. So if investors are tied to ratings and downgrades begin to affect the bonds they are holding, they may start thinking to quickly sell those assets.

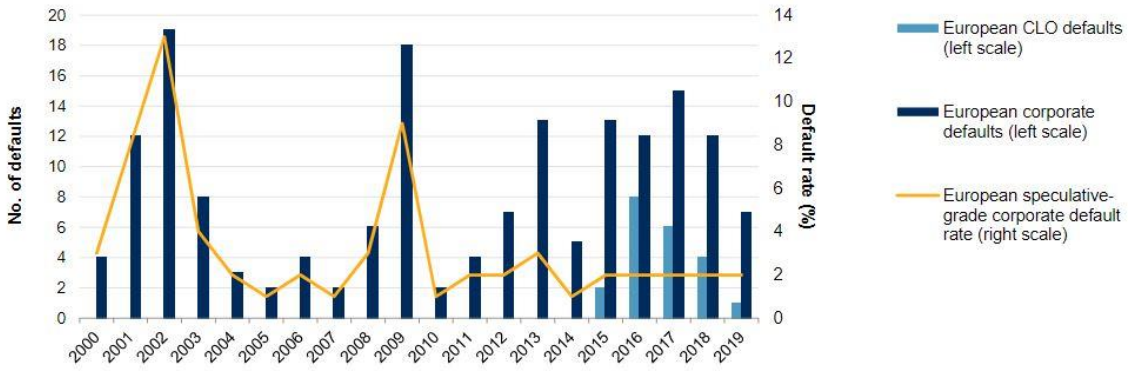
3.4. Covid-19 outbreak impact on CLO market

CLO has been a reliable investment having historically performed well for the last 20 years. Despite the 2008 turmoil, CLOs have behaved in a satisfactory way helped by remarkable low default rates, rating constancy and broadly regular high returns for investors. Before Covid-19 break, there was a favourable interest rate environment in which corporate defaults were rare and liquidity filled in the market. These conditions contributed in favour of rating stability of CLOs, especially in Europe. However, as the size of leveraged loans continued to increase, we have seen market participants express their apprehension about underwriting standards and loose loan documentation.

CLOs are ordered in their most general way in 1.0 and 2.0. CLOs 1.0 were issued from 1994 until approximately 2008. CLOs 2.0 are the most recent ones, related to about the last ten years. Although both have performed well in terms of returns and low default rates, the latter seem to be designed to be more risky. CLO 2.0s are based on lighter documentation of both the underlying loans and have more flexible documentation regarding the coverage tests and covenants to which they are bound. These types of CLOs are also called COV-lite because they have a more agile coverage test imposition system and more discretion over covenants.

European CLOs issued before 2010s, or CLOs 1.0, had almost fully terminated, with a 1.3% default rate in 20 years. At the same time, CLOs 2.0, those issued from 2010 onward, show very stable performance, with only one tranche downgraded among European transactions in their history.

Graph 3.4 (1): European CLO defaults and speculative-grade corporate default rate

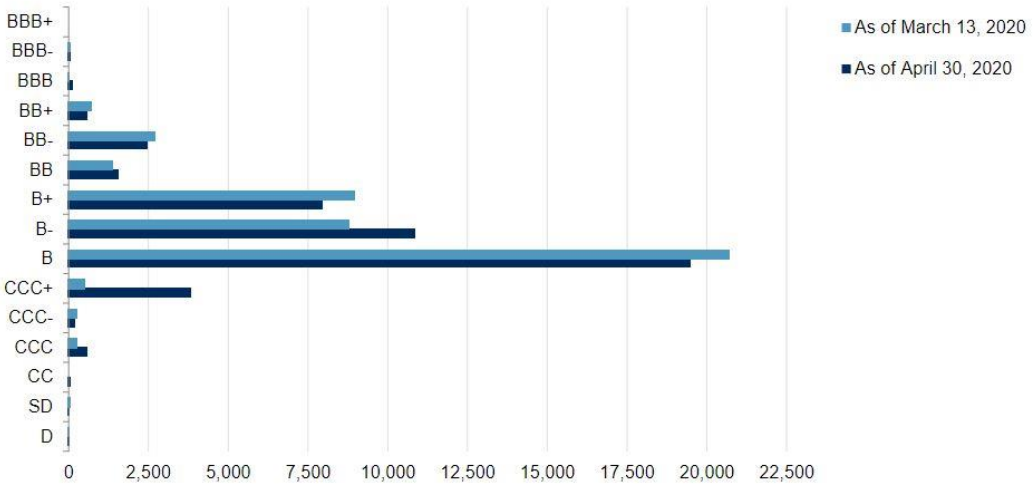


Source: S&P Global Ratings.

After Covid-19 outbreak, rating agencies immediately took negative rating actions placing on negative outlook the corporates that globally they deemed to be strongly influenced by the virus. Standard & Poors took actions at the end of February. They placed on their watch-list or downgraded 21 firms and sovereigns. At the same time, the crash in global oil prices lead the overall number of speculative-grade companies to increase more than three time so far in 2020, rising to 442 from 128 in December 2019. The number increased to 1,774 at the end of April 2020. The wave of negative rating actions has affected several sectors, geographies, and products.

From March to April, the rating breakdown for corporate loans contained in European CLO portfolios evolved in this way:

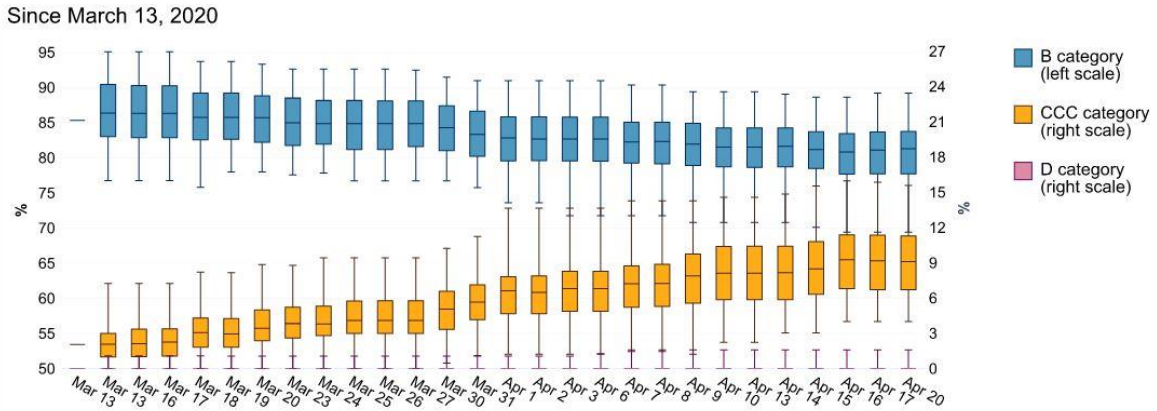
Graph 3.4 (2): European CLO exposure by rating category



Source: S&P Global Ratings.

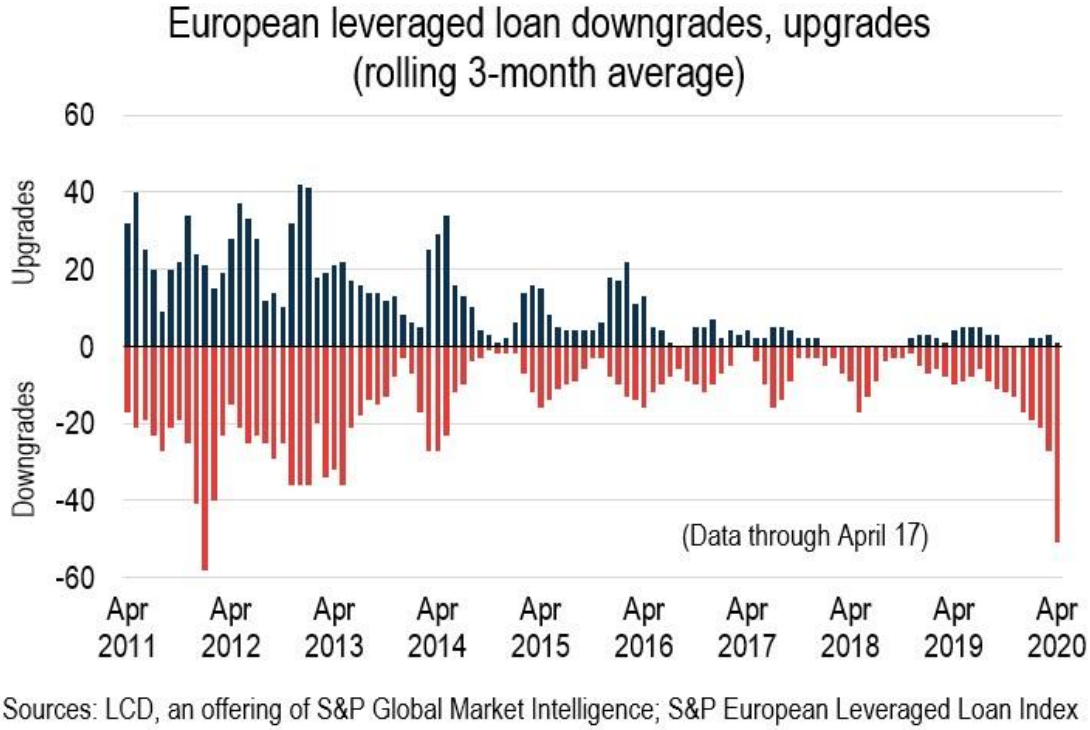
The rating agencies' downgrade was sudden enough to be flashy. The rating agencies have gradually but in a few days downgraded the ratings of various companies that have been affected by the pandemic. This process, unusual for this sort of market, has alarmed the insiders. As can be seen in the chart below, European CLO tranches have been downgraded, thereby lowering their quality in favour of greater risk.

Graph 3.4 (3): European CLO exposure by rating category



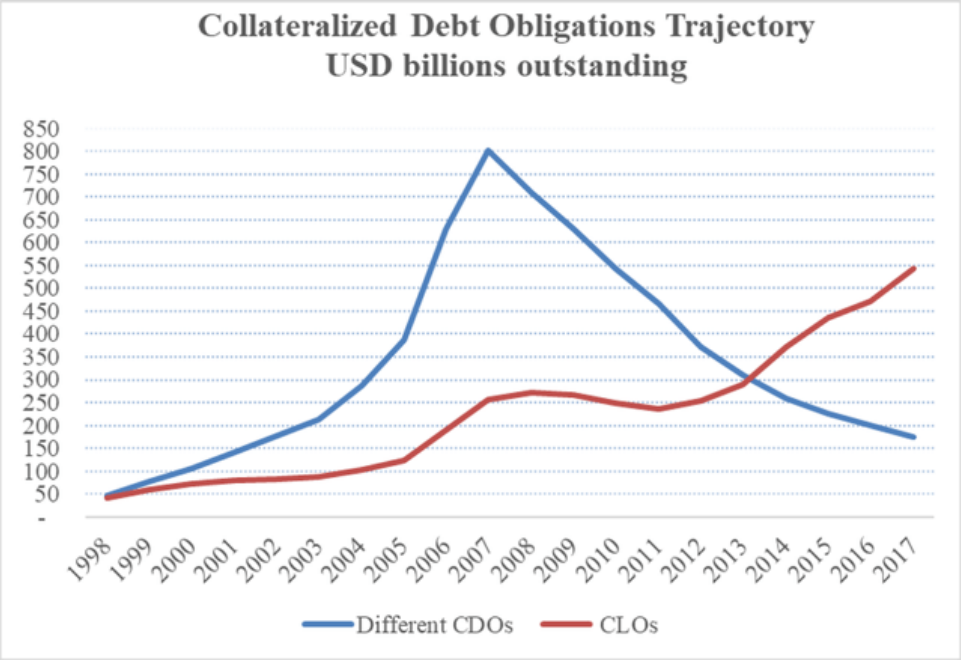
Source: S&P Global Ratings.

Graph 3.4 (4): number of European leveraged loans downgraded and upgraded



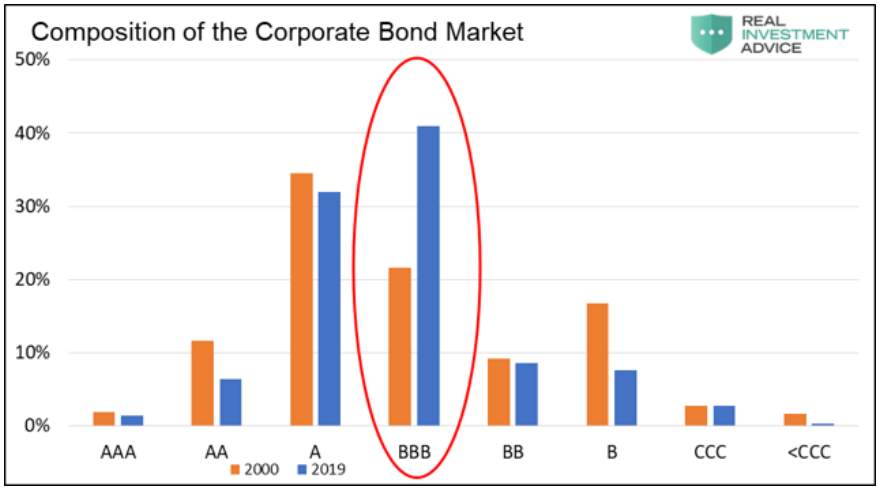
In 2008, CDO got the news by reaching his peak of $800 billion. At the time, CDOs were mortgage based and turned out badly when housing prices and mortgage prices dropped. Over the past decade, from the latest financial crisis, corporate debt has been rising progressively, resulting in a decline in corporate credit quality. The current situation is different from 2008. If we move forward to today, we do not have much of mortgage-backed CDOs but we have shifted to CLOs. The US CLO market reached $600 billion at the end of 2019, large enough to be systemically significant. While EU CLOs volume stops at roughly €160 billion.

Graph 3.4 (5): CDO vs CLO billions outstanding from 1998 to 2017



Since CLOs are mostly corporate credit backed, in order to better assess their rating we need to examine corporate bond yields. From 2000 to 2019, the majority of corporate bonds have been rerated to BBB corporate bonds. That might be a premonition of the deterioration of the leveraged loan market.

Graph 3.4 (6): CDO vs CLO billions outstanding from 1998 to 2017



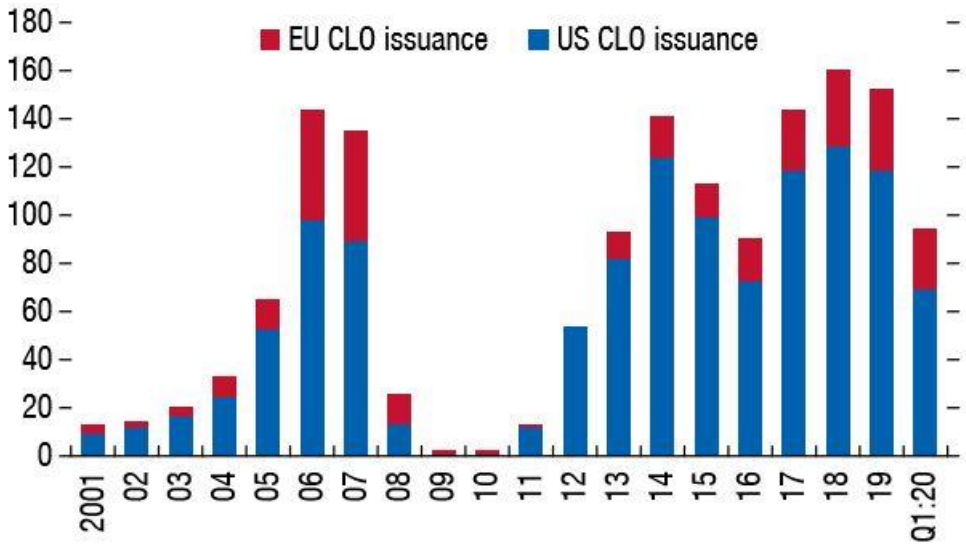
Market conditions within the risky credit markets have worsened harshly since the Covid-19 irruption. Risky corporate credit markets have quickly widened after the global financial crisis. Looking on the bright side, the usage of financial leverage by investors and direct exposures of banks, which were fundamental to amplify the global financial

crisis, have diminished. However, in the CLOs world, few things got worse including weaker credit quality of borrowers and looser underwriting standards.

At the end of March 2020, the situation in US and European markets for high-yield and leveraged loans had suffered major falls of almost two-thirds of the declines observed over the global financial crisis of 2008, since investors heightened interests on the decline of the economic outlook. Being the corporates financial situations worsened, rating agencies had delivered their forecasts and signalled doubts bringing speculative-grade defaults to recessionary levels. Another factor that fuelled the doubts was the companies earning negative forecasts for the next future due to countries lockdown. Downgrades on credit rating have gathered pace in risky credit markets. Such markets fastly gained momentum over the 10 years also due to the investors' support towards significant yields and advantageous funding conditions for businesses. In addition, the fast growth of risky credit markets raised regulators and market insiders' interests. The role of non-bank financial institutions grew consistently, becoming influent players over the credit cycle play.

Globally, leveraged loans outstanding reached $5 trillion at the end of 2019. CLO market grew robustly until Covid-19 eruption. As shown in the chart below, the number of CLO issued after the financial crisis heavily dropped right after. The number of CLO issued kept constant until the first quarter of 2020.

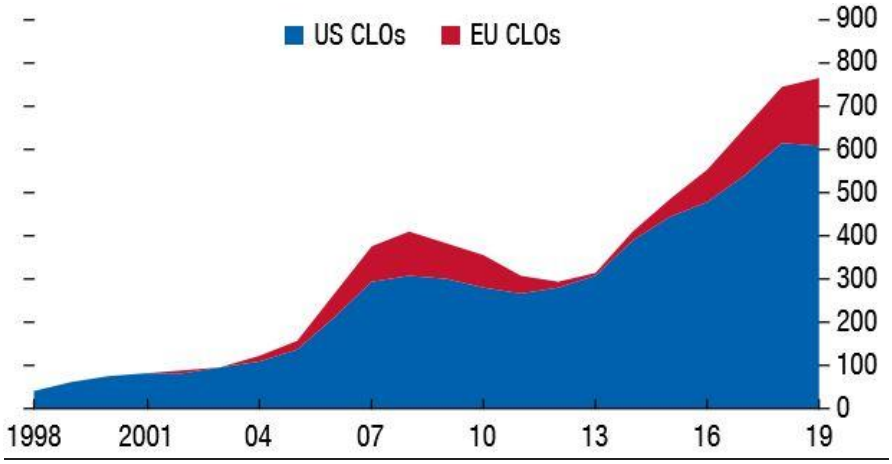
Graph 3.4 (7): EU and US new issuance CLO volume (Billions of US dollars)



However, the amount of CLOs outstanding doubled from the global financial crisis. Such trend has been pushed by investors who were captivated by the strong advantage of

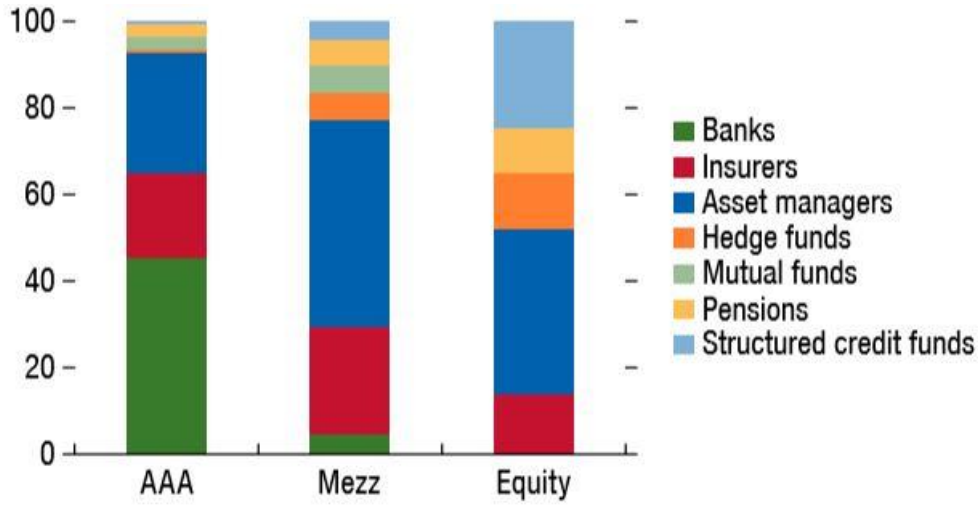
diversification, more flexibles structures compared to 2008 CDOs and their transparency. Another reason to reinforce the tendency has been the pursuit for consistent yield in a low-interest-rate context by investors that have long investment horizon as pension funds.

Graph 3.4 (8): EU and US CLO outstanding (Billions of US dollars)



In the US market, banks are vulnerable to CLOs mainly via AAA tranches. On the other hand, investors in the CLO equity and mezzanine debt tranches belong to a more assorted group, composed among others by hedge funds and other structured credit funds. Asset managers and hedge funds are the most exposed to riskier tranches of CLOs.

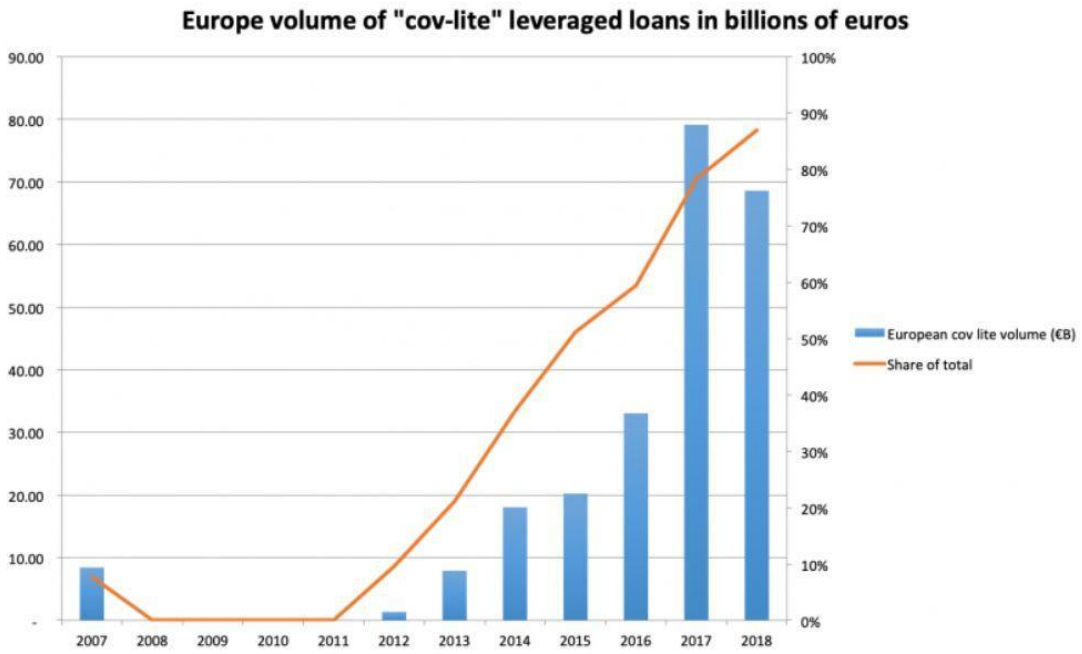
Graph 3.4 (9): US CLO investor base (Percent, as of 2019)



As we mentioned before, vulnerabilities in risky credit markets have increased. The union of an increasing borrower leverage and weaker earnings has exposed univocally risky credit markets to the Covid-19 shock. In addition, underwriting standards and investor protections have worsened in the last years in both the high-yield and leveraged loan

market, as outlined by weaker covenants and thinner loss-absorbing buffers of loans. Moreover, in case of economic breakdown, recovery rates for leveraged loans tend to be lower than usual. However, lately, due to the coronavirus situation, some actions have been taken in the primary market of risky credit where the market turn more disciplined, using more protections and lowering the leverage being the lenders prone to apply more prudent underwriting standards. The rating downgrades have been deteriorating since 2012 considering most of these CLOs are covenant-lite loans (85%). This implies that such loans have poor underwriting standards and will have lesser credit protections than what they ought to bear losses. The big banks are highly exposed on these CLOs.

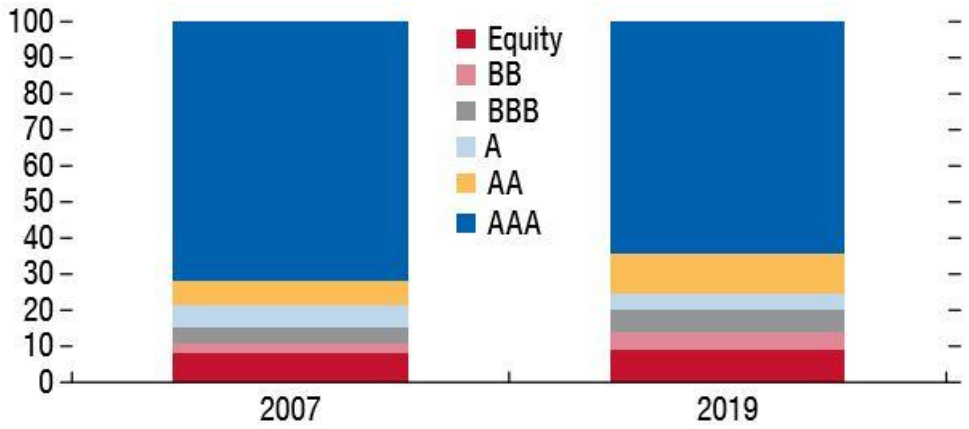
Graph 3.4 (10): EU volume of covenant-lite loans (2007-2018)



In the aftermath of the global financial crisis, the worsening in ratings quality in risky credit markets, in particular as regards the growth of B-rated credit, has been more prominent. Consequently, ratings for CLOs declined as well. The influence and the volume established by non-bank financial institutions led to an increase in leverage in the loan market. Nevertheless, the CLOs nowadays have less deep-rooted leverage against the CLO structures present during the 2008 financial crisis. Now the CLOs possess a larger portion of equity and mezzanine debt (rated A and below) in order to shield the most senior tranches. It follows that AAA tranche holders might not bear credit losses even in the worst case of market breakdown, as might happen in case of another global

recession. On the other hand, equity and mezzanine tranche holders are more likely to suffer losses in case of acute market downturn.

Graph 3.4 (11): Average US CLO liabilities by type and credit rating 2007 vs 2019



At the same time, one of the key factors that worsened the global financial crisis was financial leverage[16]. However, in the past few years, financial leverage declined substantially and it is currently under control. Bank seems to have adopted a more prudent approach when it turns out to give out underwritten risk in new loans they will retain, this process is called pipeline risk. CLO warehouse lines[17], presently, deliver first-loss risks to third parties such as portfolio managers in order to exclude banks from such risks.

Graph 3.4 (12): Estimated lines of credit and derivatives in US leveraged loan markets

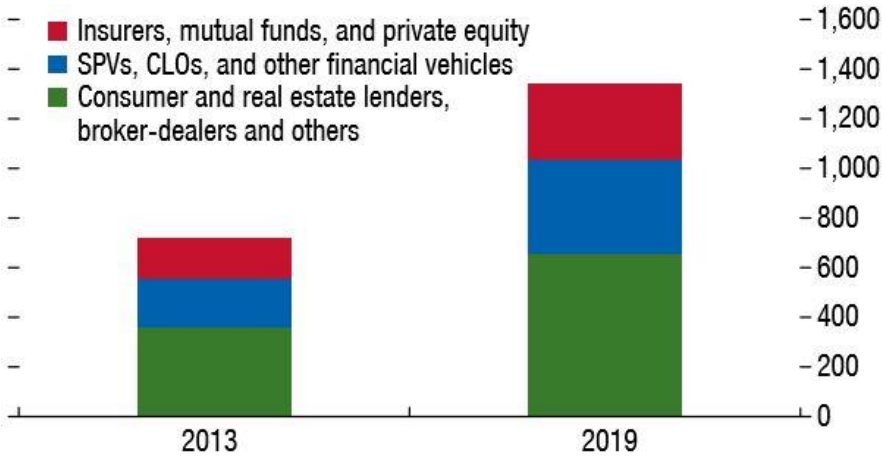
Loan Pipeline or Bridge Risk Is Lower		Risk Management Has Improved for CLO Warehouses	
Total Loans and Bonds		**CLO Warehouses**	
2007	$330 billion	2007	$40–50 billion
Today	~$50 billion	Today	$15 billion
Less Investor Leverage in the Loan Market			
Total Return Swap Lines	**Total**	**Leverage**	
2007	$250 billion	8–10×	
Today	~<$75 billion	~3–4×	

In general, it appears that banks have reduced their indirect exposure via financial leverage. Though, the relationship amid banks and other financial institutions have been increasing given that bank lending towards non-bank financial institutions almost

[16] It means the leveraging of risk positions via the use of derivatives, repurchase agreements, and bank lines of credit.
[17] Lines of credit to fund CLO creation.

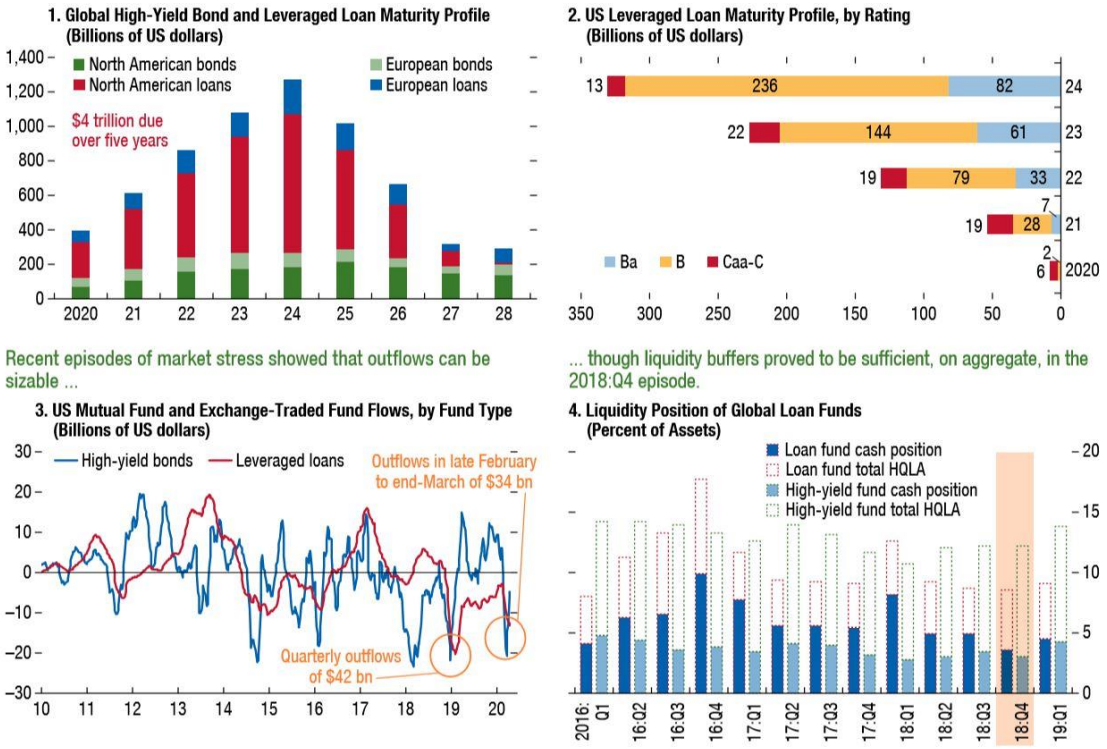
duplicated from 2013 hitting $1.3 billion in US. To summarize, even if financial leverage diminished considerably after the 2008 financial crisis, banks increased their exposure to non-bank lenders.

Graph 3.4 (13): US large banks lending to non-bank financial institutions (Billions of US dollars)



However, there is another challenge ahead for high-yield bonds and leveraged loans. In the short-term, their refinancing difficulties are at low level but as regards for medium-tem refinancing, the amount of loans maturing is going to reach his record in 2024. Besides, what raise concern is that the maturing debt is condensed in lower-rated loans. This means that in cause of potential financial crisis, numerous downgrades and defaults would probably taking place. At the end of 2018, in the US market, high-yield bond and leveraged loan funds faced $42 billion in outflows when the financial situation became tense. Looking at the recent situation, between February and March 2020, the same US high-yield bond and leveraged loan funds have suffered $34 billion in outflows. If the economic pressure would get more severe, perhaps following an economic downturn, there will be a serious liquidity issue in the short-term. The maturity issue and the outflows are displayed in the figure below.

Figure 3.4 (14): Maturity issued outflow in high-yield bonds and leveraged loans



3.4.1. Policymakers response

In order to confine the effect of Covid-19 outbreak on the economy, policymakers have taken different measures to sustain the economy. In particular, they focused their attention over the economic assistance to the corporate sector. They concentrate their measures to push the flow of credit to firms by providing a shield to the impact of the virus over the corporate sector.

The role of central banks has been and will be vital for the success of the intervention. In fact, major advanced economy central banks have started, or increased, to buy investment-grade corporate debt. Besides, at the beginning of April 2020, the US Federal Reserve widened its help to several investment-grade bonds downgrade to speculative grade after March 22nd and few others products such as ETFs invested in high-yield bonds, newly issued CLO tranches and some SMEs. On the other shore of the Atlantic Ocean, at the end of April 2020, the ECB extended its support for loans to banks to include investment-grade bonds downgraded to speculative grade after the 7th of April. The measures taken seems to have improved market functioning and relieved some stress in short-terms in the markets. If Covid-19 keeps spreading, deteriorating financial conditions further and leading downgrade and defaults to continue steadily, major central

economic authorities may need to endure the expansion of the support in risky credit markets. The efforts taken to sustain the flow of credit in such markets might support the prevention of possible disorders, which may cause issues to firms and thus problems to real economy. Crisis management tools are the first priority. Since during crisis firms counted on banks as important source of liquidity such as credit lines, overseers have to keep a close eye on the banking system to make sure they keep supporting speculative-grade firms in the leveraged loans context. One of the factors makes the practitioners compare the CLO situation today and CDO's market crush back then, it is market prices collapse in the high-yield bond and leveraged loan markets, which hit two thirds of the drop during the global financial crisis of the late 2000s. In March 2020, the pace at which the markets we just mentioned deteriorated has been exceptional. The forecasts of rating downgrade and defaults have been pushed by the already-existing alarms about many features we have already spoken about such as borrower leverage and reduced investor protections due to weak covenants.

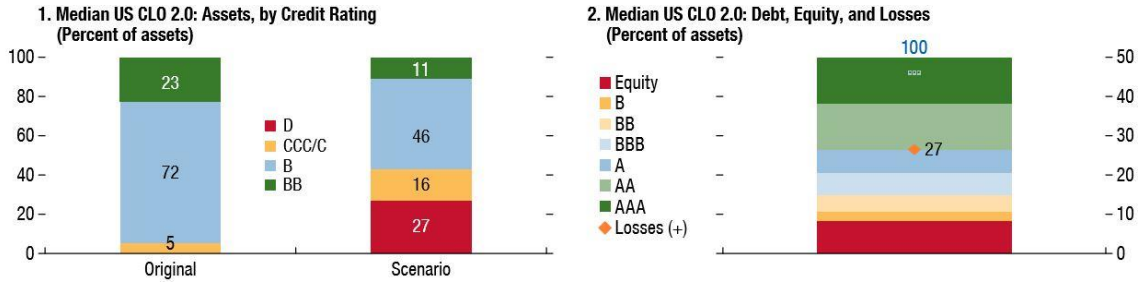
3.5. Possible losses in worst case scenario

In order to provide an idea of what could be the losses in case of economic downturn triggered in the aftermath of the Covid-19 outbreak, we present the austere scenario that International Monetary Fund produced in his Financial Stability Report in April 2020.

One of the assumption used is the application of the credit rating transition matrix estimated for speculative-grade credit after the 2008 financial crisis to the current credit rating compositions of high-yield bond and leveraged loan markets in order to obtain downgrades and defaults in such markets. The very same recovery rate on high-yield bond and leveraged loan markets undergone throughout the financial crisis is applied. Another assumption take into account that the recovery rate on leveraged loans is 20% lower than during the 2008 crisis in order to consider the decrease in credit protections namely covenant-lite actions. Market prices are considered to face the same drop during the financial crisis. Nonetheless, banks now are more solid and do not abuse of financial leverage as they used to in the global financial crisis. However, this model examined only the losses coming from the direct exposures of banks and other financial institutions and CLOs to risky credit markets. This implies that the losses could be much larger if we take into account as the impact on banks from their lending to non-bank lenders that would have bear losses in risky credit markets.

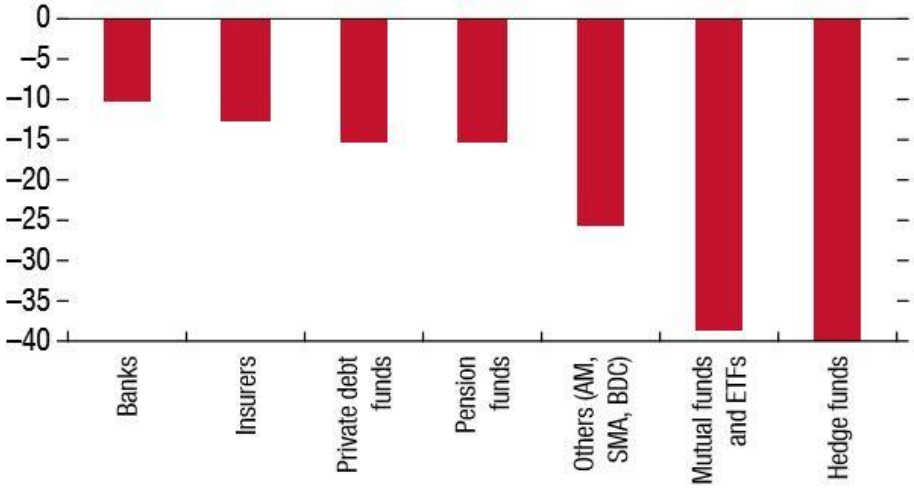
Since the proportion of B credit is larger than in the past, a median CLO's credit quality worsens faster, considering the assumptions. CLOs have a high share of lower-rated credits, which deteriorate quickly in severe adverse scenario, this leads to substantial mark-to-model losses on the equity and mezzanine debt tranches. In case of economic downturn, in the scenario mark-to-model losses impacts 27% of the capital stack, achieving mezzanine debt (A and below) and thus wiping out the value of both mezzanine and equity notes. Just consider that recently, resulting from the Covid-19 outbreak, weaker CLOs, composed by a large portion of CCC credits, have already suffered losses due to the increase in the number of downgrades.

Graph 3.5 (1): Median SU CLO 2.0 1) assets by credit rating 2) debt, equity and losses



The scenario considered totals losses of 1.25 trillion, roughly 20% of total exposures. Within type of institution, the ones suffering the most losses are CLO equity and mezzanine note holders and those with mark-to-market positions, namely mutual funds and ETFs. Fortunately, bank's exposure seems to be limited. In fact, banks would bear fewer losses having the lowest loss rates among the other institutions by share of exposures since they retain mostly senior loans with the largest recovery rates and highest-rated CLO debt. On the other hand, hedge funds, mutual funds and ETFs (with CLO equity tranche holdings) would experience the highest loss rates.

Graph 3.5 (2): Scenario loss rates by investor type (percent of own exposure)



3.6. CDOs in 2008 vs CLOs in 2020

An analysis of the main differences between CDOs during the GFC in 2008 and the CLO nowadays is now presented. We have already explained what these products are and how they work. The issue of subprime CDOs almost ended after 2008 leaving room to the growth of other form of securitisation as CLOs products. From June 2019, more than 50% of the total outstanding leveraged loans in US dollars and around 60% of those in euros have been securitised via CLOs.

3.6.1. The markets involved

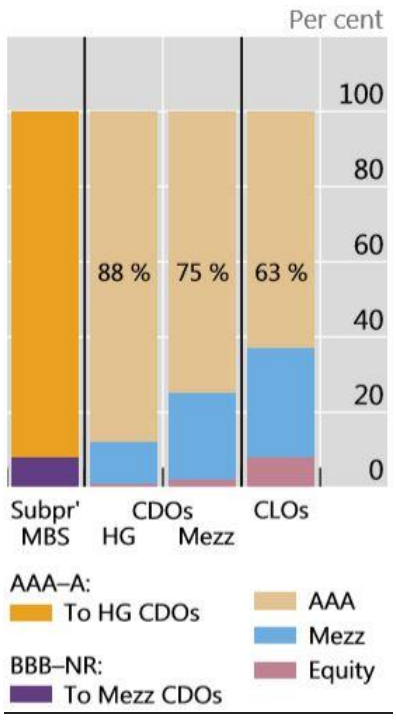
Many market practitioners have pointed out how similar is the fast growth of leveraged finance and CLOs to the evolution during the global financial crisis of the US mortgage market and CDOs. However, there are considerable dissimilarities between the CDO market in 2008 crisis and the CLO market today. CLOs do not make use of credit default swaps (CDS) and resecuritisation and thus, they are less complex products. Moreover, they are not heavily exploited in repo transactions and they are less funded by short-term borrowing than was the CDOs circumstance. Besides, there is better information over the exposures of banks.

Even so, there exist also likenesses between CLO market today and the CDO market then, especially with regard of what may cause financial distress. These involve the deteriorating quality of CLO's underlying assets, the cloudiness over the indirect exposures, the high concentration of banks direct holdings and the dubious elasticity of senior tranches upon the dependence on the correlation of losses within underlying loans.

CLOs are backed by a more simplified and diversified pools of collateral compared to CDOs. At the time, CDOs were constituted mostly by subprime MBS, and CDO squared were numerous. In 2006, the percentage of subprime MBS in the newly issued CDOs was about 70 percent. An additional 15 percent was backed by other CDOs. Furthermore, more than 40 percent of the collateral collected by the CDOs issued in 2006 was not cash MBS, but CDS written on such securities. Yet, once the housing market collapsed, the complexity and the cloudiness fuelled the economic crisis. Conversely, CLOs are simpler since their collateral is well diversified across firms and sectors. The amount of synthetic collateral or resecuritisation is almost negligible.

We now focus on default risk and loss correlation risk. If we look at the current most senior CLO tranches, they seems to have better use of a larger buffer which bear losses in a better way than CDOs did back during the financial crisis. In fact, as shown in the graph below, mezzanine and equity tranches are part of a larger portion of the capital structure of CLOs than the CDOs back then.

Graph 3.6.1 (1): Capital structure of CLOs and CDOs (percentages indicate the fraction of the CLO capital structure with the indicated seniority)



Still, the true protection on senior tranches relies on their sensitivity to default risk and loss correlation risk. In fact, default risk and loss-given-default rely on the quality of the underlying assets. The growth in investor demand drove to a decline in the underwriting

standards for both CLOs and CDOs. To bring more evidence, consider that US subprime mortgages lacking of full documentation of borrowers' income rose, during the five years between 2001 and 2006, from 28 percent to more than 50 percent. Similarly, as we already said, the number of leveraged loans without proper maintenance covenants grew considerably from the beginning of 2010s. Furthermore, in the past years, the share of low-rated leveraged loans in CLOs almost doubled and the debt-to-earnings ratio of leveraged borrowers increased dramatically. The loosening in underwriting standards may cause a rise in potential credit losses when a default ultimately takes place.

The CDOs, in the global financial crisis, were exposed to possible losses since there was a high sensitivity of the structures to correlation risk. A number of other factors stimulated the dangerousness. The main problems were: the lack of diversification in the underlying collateral composed mainly by low-rated tranches of subprime MBS, the high synthetic exposure (CDS) and the frequent use of resecuritisation (CDO squared). Therefore, being the CDO payoff mostly driven by low-quality securities, when the housing prices drop, the amount of defaults on subprime mortgages went up. Returns on CDO mezzanine and senior tranches demonstrated to be deeply correlated with the losses on equity tranches much more than many investors had expected. In contrast, CLOs uncertainty over loss correlation is mild whilst remaining the danger. Although CLOs show to be more historically reliable in terms of number of defaults, and the loss correlations for leveraged loans more easily measured, the exceptional high portion of deals with poor investor protection might influence heavily the timing and clustering of defaults, leading the estimations not to be fully reliable.

Banks vulnerability is quite different between the CDO market in 2008 and CLOs nowadays. Banks back then were much more exposed compared to the exposure they have over CLOs. Now the system seems to be clearer. At the time, the total exposure of financial institution was difficult to measure due to the opaqueness of the whole banking system. Banks were holding senior tranches but also junior or even equity tranches depending on the investors' demands since banks warehoused securities of low-rating grade before selling them off. The total exposure to such products was unsure. Now banks retain senior tranches and the system appear more transparent. However, currently banks may suffer losses from indirect exposures; in any case, the density of CLO holding among banks is large.

Graph 3.6.1 (2): Main characteristics of CDOs in the past and CLOs now

	CDOs in 2007	CLOs in 2018
Type of underlying asset	MBS, other CDOs and ABS (eg credit cards), CDS	Leveraged loans
Size of underlying market	USD 1.2–2.4 trillion (subprime MBS)	USD 1.4–2.0 trillion
CDOs/CLOs outstanding	USD 640 billion	USD 750 billion
Non-price terms (underwriting standards)	50% without full documentation	80% covenant lite
Complexity		
Resecuritisation[1]	14% of outstanding	Minimal
Synthetic securitisation[2]	40–50% of issuance	Minimal
Maturity transformation	Common as repo collateral; SIVs funded with asset-backed commercial paper	Minimal
Banks' exposures		
Direct	Unclear at the time	At least $250 billion
Indirect	Multifaceted (SIVs, prime brokerage)	Prime brokerage
Concentration	Unclear at the time	High in some jurisdictions
Type of tranche held	Mostly senior, some lower-rated	Mostly senior
Non-banks' exposure	Unclear at the time	About 20% of holders unknown

[1] Share of securitisation market represented by CDOs (CLOs) that invested in other CDOs (CLOs). [2] Through CDS or other derivatives.

3.7. The indicators

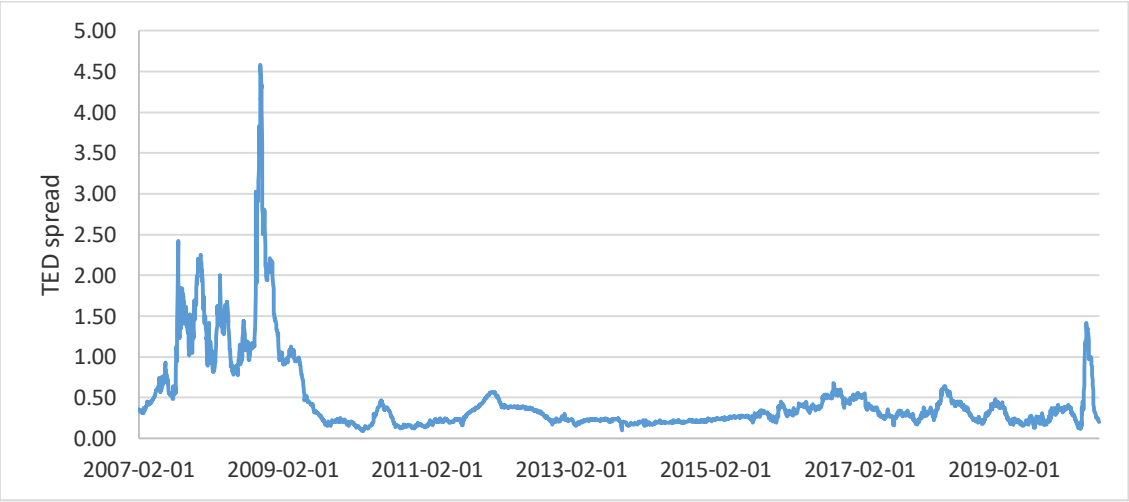
In this section, I analyse the indicators that are suggesting a similarity between what happened in 2008 in the CDO market and what is happening today in the CLO market. These indicators are market indices that help to explain where the market as a whole is heading. We will see only few of the many indices available, those that have shown the most striking similarities with the ones that caused the Great Financial Crisis. Depending on the indices, we may try to differentiate between the European and American markets, distinguishing the data to explain better the possible different dynamics between the two markets.

TED spread

The first index we are going to see is the TED spread. The indicator is solely considering the US market but since it is the largest in terms of leveraged loans and CLOs, it will allow to better understand some syllogisms with the 2008 financial crisis. Investopedia describes TED spread as the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars. To put it another way, TED spread is the difference between the interest rate on short-term US government debt and the interest rate on interbank loans. The TED spread is used as an indicator of credit risk. This is because U.S. T-bills are considered risk free and measure an ultra-safe bet, the U.S. government's creditworthiness. Moreover, the LIBOR is a dollar-denominated gauge used to reflect the credit ratings of corporate borrowers or the credit risk that large international banks assume when they lend money to each other. T-bills are considered

risk-free while LIBOR reflects the credit risk of lending to commercial banks. An increase in TED spread is a sign that lenders believe the risk of default on interbank loans is increasing. Thus, interbank lenders request a higher rate of interest, or accept lower returns on safe investments such as T-bills. When the risk of bank defaults is perceived to be decreasing, the TED spread decreases. TED has been rising considerably from the beginning of 2007 reaching his historical peak in October 2008 at 458 basis points. At the end of February 2020, TED spread was at one at his lowest points since the global financial crisis. However, starting from that moment, following the coronavirus outbreak spread, it started to increase steadily hitting his maximum of 135 basis points in almost one month (the 1st of April) since 2008. Nonetheless, the spread, since then, plummeted reaching the same level at the end of May.

Graph 3.7 (1): TED spread across time

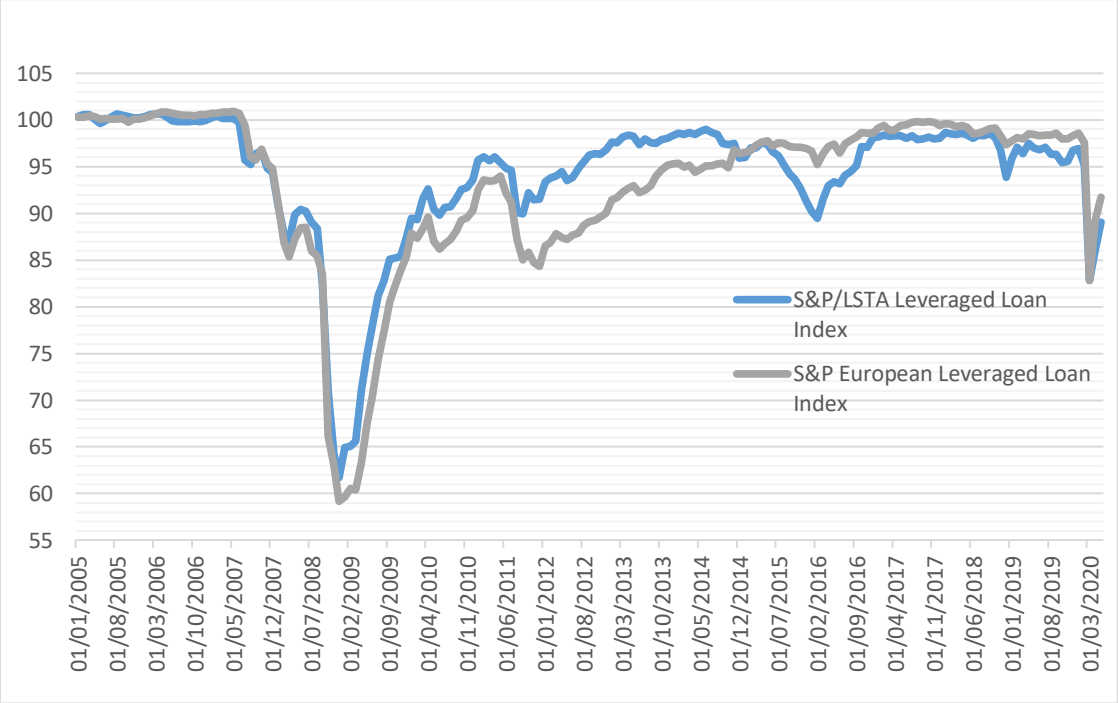


S&P LLI (Leveraged Loan Indexes)

S&P Leveraged Loan Indexes (S&P LL indexes) are capitalization-weighted syndicated loan indexes based upon market weightings, spreads and interest payments. A leveraged loan index (LLI) monitors the performance of institutional leveraged loans. Various indexes exist and differ on market criteria. A LLI serves as a benchmark for performance measurement of fund managers dedicated to leveraged loan investment strategies and as a basis for passive investment vehicles such as exchange-traded funds (ETF). The S&P/LSTA Leveraged Loan Index (LLI) covers the U.S. market back to 1997 and is calculated on day-to-day basis. The S&P European Leveraged Loan Index (ELLI) covers the European market back to 2003 and currently calculates on a weekly basis. In the fourth quarter of 2008, both indexes, LSTA LLI and ELLI, rapidly dropped due to the economic

crash. In 2007 summer, they both started to shrink, falling down 40 points in one and half year. For just the second time in its history, the S&P/LSTA Leveraged Loan Index (LLI) reported a double-digit loss in March 2020 as other risk assets, including equities and high yield bonds, experienced their own historic losses. At -12.37%, March's loan return trailed only the 13.2% loss it reported during the height of the financial crisis in October 2008. In comparison, the only two other instances where the LLI incurred a monthly loss of worse than 5% were comprised around October 2008 at 8.5% and 6.1% respectively. The Covid-19 induced March selloff, which included an estimated $14 billion of mutual fund outflows.

Graph 3.7 (2): S&P/LSTA Leveraged Loan Index and S&P European Leveraged Loan Index (calculated as average bid price)

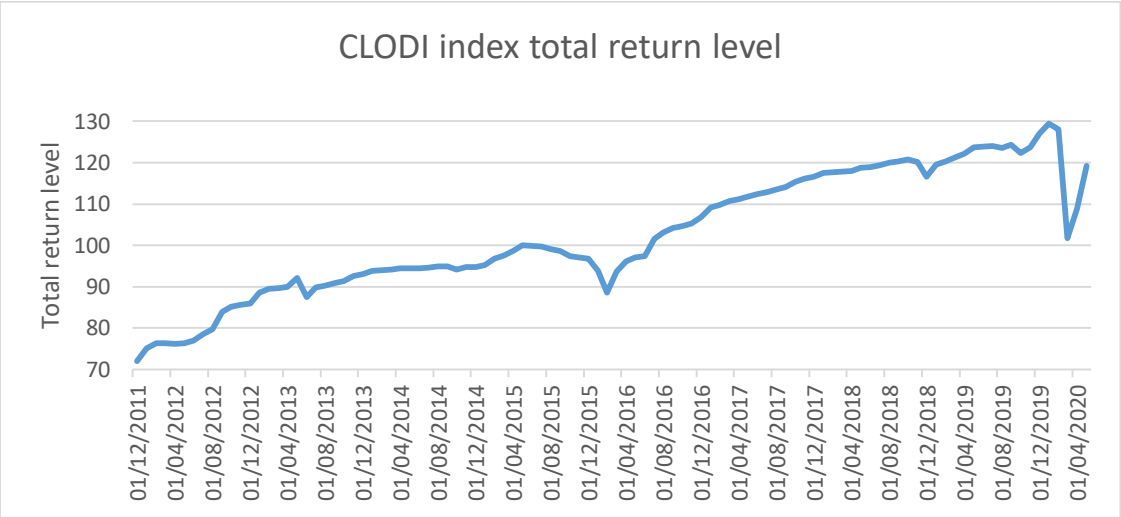


CLODI index

Also known as Palmer Square CLO Debt Index, the CLODI index is defined as a rules-based observable pricing and total return index for collateralized loan obligation debt for sale in the US, original rated A, BBB, or BB or equivalent. Not all the types of CLOs are eligible for inclusion in the index. The index is comprised uniquely of cash and arbitrage CLOs backed by broadly syndicated leveraged loans. The index aims to study the sphere of CLOs denominated in US dollars. Its total return plummeted in the second half of March 2020, as many other indicator in risky credit markets did. Since 2012, its

performance has always been largely positive. However, on 29th May 2020 it recorded YTM equals to -6.16%, as a demonstration that the US CLO market has been hit heavily by coronavirus outbreak and the stress over CLOs is increasing.

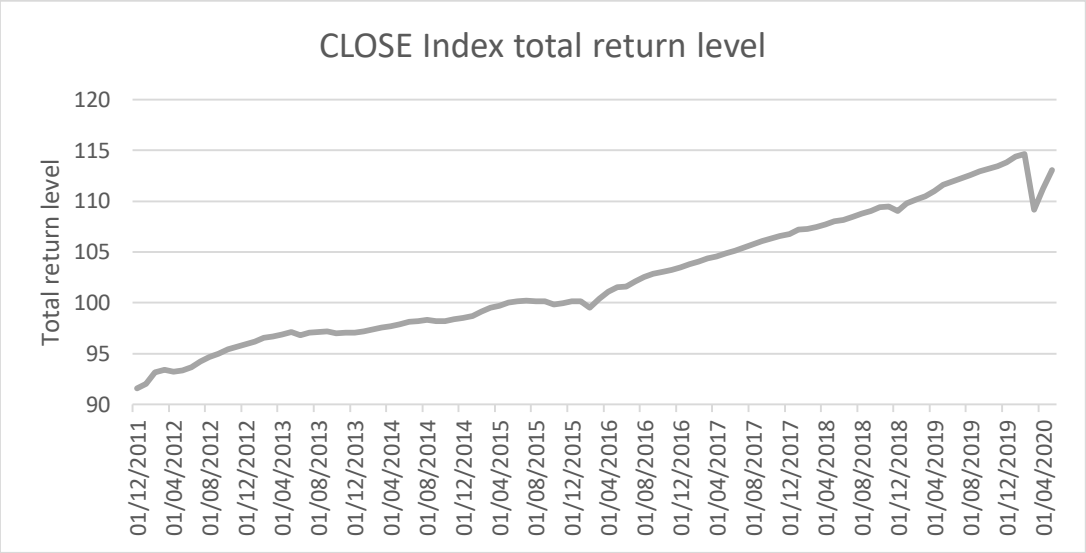
Graph 3.7 (3): Total return level of CLODI index



CLOSE index

The CLOSE index is very much similar to the CLODI index and belongs to Palmer Square as well. It is not as volatile as the CLODI index considering it is the total return index for collateralized loan obligation debt for sale in the US, original rated AAA and AA, meaning the senior debt underlying CLO US-based. It has suffered no significant fluctuations in the last ten years, but a slow steady growth until the end of March 2020 when the index dropped 5 points. Since CLO is solid, CLOSE index is important to monitor how the most secured tranches are affected and how reliable they are across time being historical very consistent.

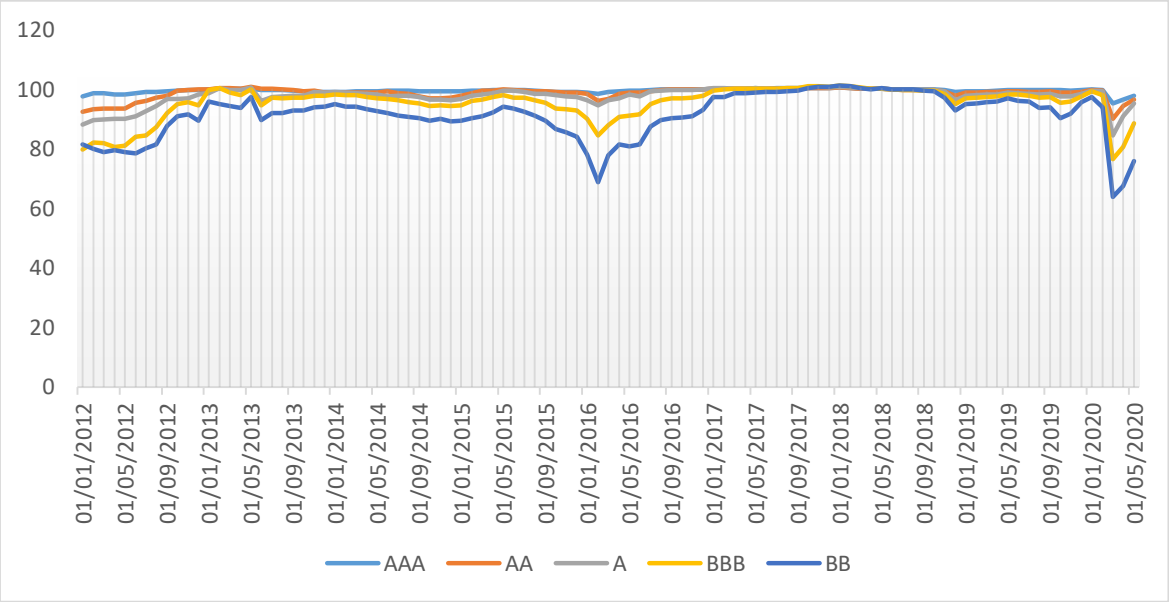
Graph 3.7 (4): Total return level of CLOSE index



CLO US data analysis

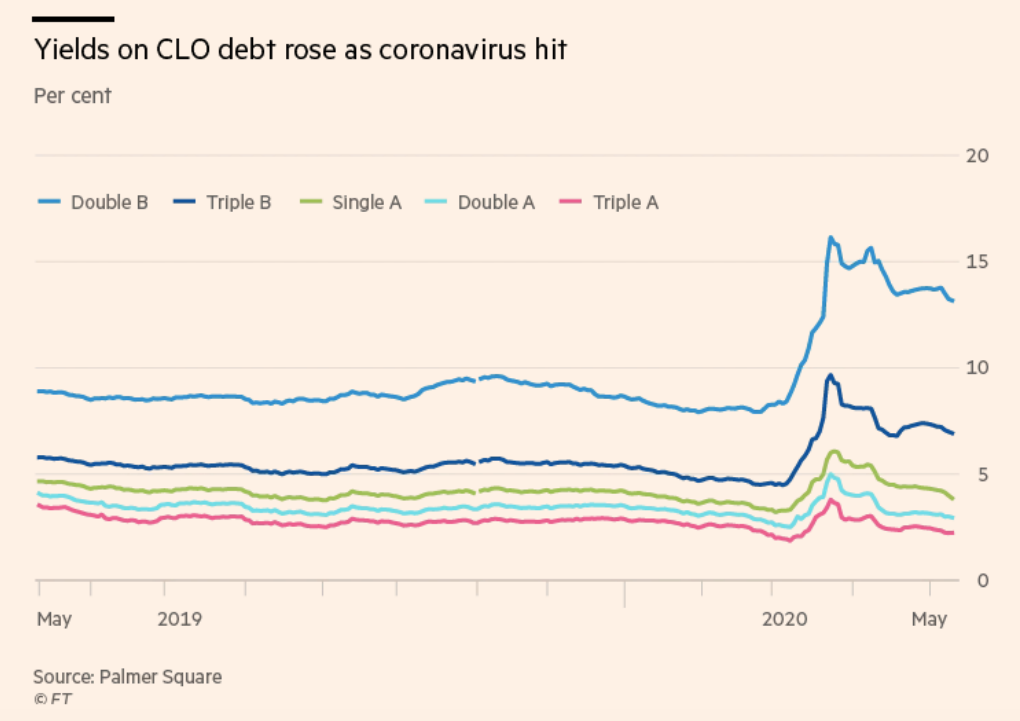
We continue our study by going through the analysis of the CLO US market examining its price variation by rating and the yield of its underlying debt. To proceed with our study, we rely on data from Palmer Square Capital Management, which also includes CLODI index we have just seen. We take into consideration the indexes and data from Palmer Square. Firstly, we look at the price changes over time of CLOs depending on their rating. At our disposal CLOs, from the most senior (AAA) to the most junior (BB), were taken into account. As you can see from the chart below, prices are quite stable over the last eight years (apart from a short fall at the beginning of 2016). Nevertheless, with the arrival of more pressing news about the virus and threats of a long lockdown, prices have plummeted unexpectedly. However, as was already the case in 2016, prices for junior CLOs, i.e. the most risky ones, have fallen much steeper than for the senior ones, which have remained almost unchanged.

Graph 3.7 (5): CLO US prices variation by rating



Secondly, as the prices dropped, the yields, taking into account their rating, has skyrocketed once the Covid-19 outbreak approached. As happen for CLOs prices, this time, depending on their seniority, the yield on BB debt rose rapidly at much higher degree than its more senior ones.

Graph 3.7 (6): CLO US yield by rating



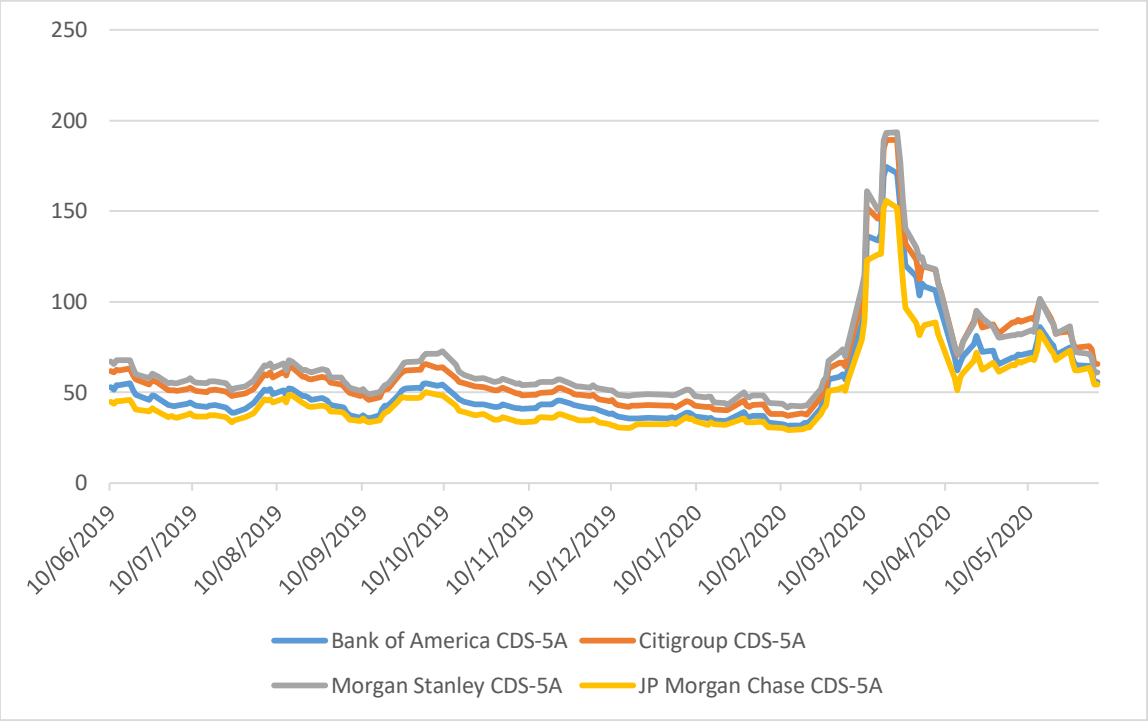
Banks' CDS

The last indicator we consider are banks' Credit Default Swaps[18] (CDS). CDS are derivative instruments that enable market participants to transfer or redistribute credit risk. Since early 2008, regulators, market participants and academic debated over the role of CDS in the global financial crisis. A credit default swap is, in effect, insurance against non-payment. Through a CDS, the buyer may avoid the consequences of a borrower's default by shifting some or all that risk onto an insurance company or other CDS seller in exchange for a premium. Thus, the buyer of a credit default swap receives credit protection, while the seller of the swap guarantees the creditworthiness of the debt security. It is important to remember that credit risk is not erased; it has just been moved to another player, the CDS seller. There still exists the risk that the CDS seller defaults together with the borrower. In fact, this is what happen in 2008 financial crisis. CDS sellers as Lehman Brothers and AIG, defaulted on their CDS obligations.

Therefore, if we look at banks' CDS, we may understand the trust the market has on them. In our study, looking at CDS of financial institutions may let to understand how troubled they are especially considering the situation in the risky credit markets. They are highly exposed to possible downturn in the CLO market where they play a big role. A sample of the most important banks in US market is taken. These banks are massively involved in the "making" and the selling of CLOs. They show an extremely high correlation in their CDS values. As for other indicators, due to Covid-19 worrying news, in March 2020 their CDS-5-years value increased enormously. This remarks how the market lost creditworthiness in institutions such as investment banks.

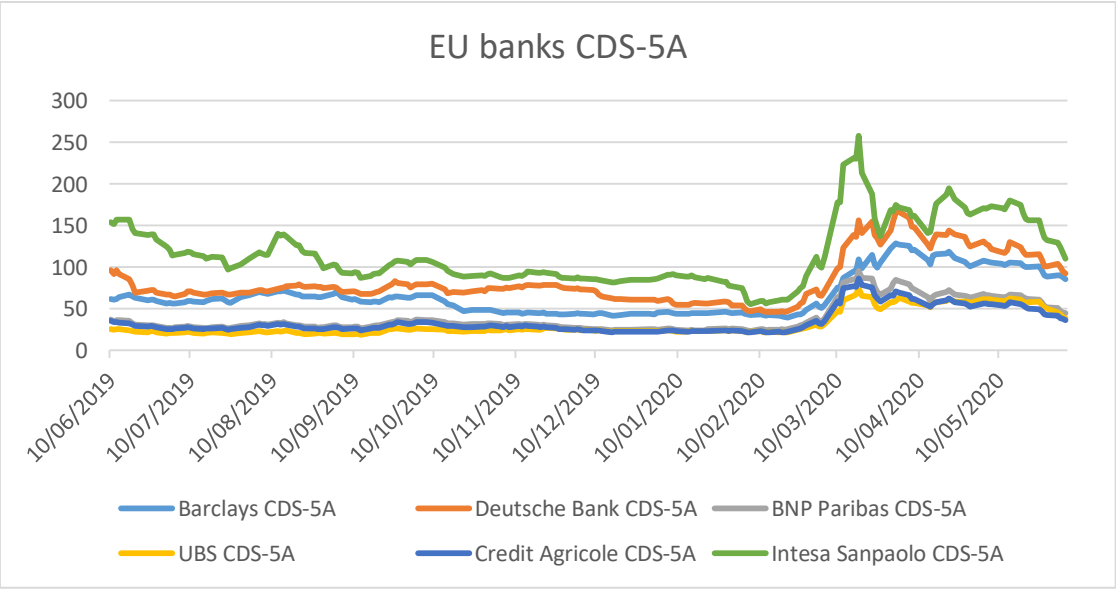
[18] Credit default swaps are the most common type of OTC credit derivatives and are customized between the two counterparties.

Graph 3.7 (7): US banks CDS-5A



The same rise happened in Europe were the most influent banks' CDS prices grew considerably. However, being the EU banks not as correlated as the US ones, the values of their CDS do not rise in the same proportion. Deutsche Bank and BNP Paribas are the most exposed in the EU framework having largely invested in securitisation and being major leaders in CLO production. As happened with US banks, EU banks lost reliability being under the same fire of coronavirus threat.

Graph 3.7 (8): EU banks CDS-5A



3.8. A regression-based empirical analysis

In this section, we use some of the indicators that we have considered above to run an empirical study on the relation between CDS spreads and CLO indices.

The indicators show that, although the market in general had a positive ascendancy, i.e. continued to grow over the past few years, it came to a sharp halt with the Covid-19's arrival. We explained how banks, those that produce and hold large amounts of CLOs, are greatly exposed to the risk that this market, as was the case with subprime CDOs in 2008, might plummet. However, we want to analyse how significant is the correlation between the various indices and the CDS spread. Thus, we will monitor not only the market of CLOs (CLODI/CLOSE indexes) but also that of leveraged loans (the main underlying of CLOs) using LLI indexes. If we set our study in the GFC, the CDOs would be the equivalent of CLOs, and subprime mortgages would be the equivalent of Leveraged loans.

As far as the regression study is concerned, we will take Bank of America (BofA) as a reference point since the indices taken into account are part of the US market. We will only study the case of BofA since the CDS spread correlations of these banks with each other is very high.

We consider monthly observations between the end of 2011 (30/12/2011) and the end of May 2020 (29/05/2020).

We run the regressions to understand how the performance of the various indices, the most relevant, have influenced the price of BofA's CDS.

We begin the analysis with the regression between BofA CDS and CLODI index. The two series show a high inverse correlation (R-squared $=$ 0.6). We find that the regression has very low p-value and therefore high significance values. The results are shown below. We have run a simple linear regression to predict BofA CDS spread based on CLODI index total return level. Bofa CDS is measure in basis points. A significant regression equation was found $F(1, 100) = 147.636, p < 0.000)$, with $R^2 = 0.6$. BofA CDS spread is predicted to be equal to $445.015 - 3.444$(CLODI index) basis points.

Table 3.8 (1): Regression output to explain BofA CDS spread movement from CLODI index fluctuations

Regression statistics	
Multiple R	0.772127
R Square	0.596181
Adjusted R Square	0.592143
Standard Error	42.04492
Observations	102

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	260986.5	260986.5	147.6356	2.09E-21
Residual	100	176777.5	1767.775		
Total	101	437764			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	445.0153	29.36197	15.15618	1.18E-27	386.762	503.2686
CLODI Index	-3.44422	0.283462	-12.1505	2.09E-21	-4.0066	-2.88184

We run another regression dividing our sample of monthly observations of BofA CDS and CLODI index into two parts. Considering our sample of 100 monthly observations, we run in the first regression the first fifty observations (30/12/2011-29/02/2016) and the second regression the last fifty observations (31/03/2016-29/05/2020). In the regression we considered the monthly differences of the two series. The sample that includes Covid-19 shock indicates greater significance of CDS variations to CLODI variations. The results are reported in the tables below, 3.8 (2) and 3.8 (3). R-squared and and the SS analysis show that the results in the second regression are more significant than the results in the first regression. It evidences how, supported by the Covid-19 outbreak observations, the variations in CLODI index have been affecting BofA CDS spread more in the latter half of 2010s than at the beginning of the decade. It means that the influence of CLO market movements on the soundness of banks has increased lately leading to a sort of “change in regime”.

Table 3.8 (2): Regression output to explain BofA CDS spread movement from CLODI index fluctuations considering monthly observations (30/12/2011-29/02/2016)

Regression statistics	
Multiple R	0.580875
R Square	0.337416
Adjusted R Square	0.323612
Standard Error	20.38243
Observations	50

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	10154.95	10154.95	24.44362	9.75E-06
Residual	48	19941.29	415.4436		
Total	49	30096.24			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-2.88782	2.950106	-0.97889	0.332545	-8.8194	3.04377
diff CLODI	-9.30698	1.882462	-4.94405	9.75E-06	-13.0919	-5.52204

Table 3.8 (3): Regression output to explain BofA CDS spread movement from CLODI index fluctuations considering monthly observations (31/03/2016-29/05/2020)

Regression statistics	
Multiple R	0.662782
R Square	0.439279
Adjusted R Square	0.427598
Standard Error	8.780553
Osservazioni	50

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2899.208	2899.208	37.60414	1.57E-07
Residual	48	3700.709	77.09811		
Total	49	6599.918			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.179379	1.25036	0.143462	0.886526	-2.33464	2.693395
diff CLODI	-1.75917	0.286873	-6.13222	1.57E-07	-2.33597	-1.18237

We have just seen how the CLODI index return affects the BofA's CDS spread. The results just seen have highlighted the inverse relationship between CLO index development and the CDS spread course. Obviously, the better the CLO index performs, the safer banks are and lower their CDSs should be. However, we want to look even more closely at the relationship between the underlying of a CLO, i.e. Leveraged loans, and the CDS spread. We are interested in whether the underlying of CLOs has as much influence (as it should be, given that the value of CLOs is closely related to Leveraged loans as they drive CLO performance) on CDSs spread.

Thus, we performed the regression to capture how the variability in CDS spread is explained by the variability in S&P/LSTA Leveraged Loan Index (LSTA US). In this case we have taken the delta of BofA CDS spread and the log difference of LSTA US average bid price. The results are quite significant but not as consistent as they were compared to the previous regression. Almost half of the variation in delta BofA CDS spread may be inversely explained by the regression, being $R^2 = 0.432$. This means that the better the US Leveraged loans index perform, the lower BofA CDS spread is. There are good significant values $F(1, 99) = 76.965, (\, p < 0.000)$, but the SS residuals (1.57) are quite high compared to SS regression (1.22) meaning that much of the variability in Y is explained by the residual more than the variability in X.

Table 3.8 (4): Regression output to explain delta BofA CDS spread movement from log difference of LSTA US average bid price

Regression statistics	
Multiple R	0.661353
R Square	0.437387
Adjusted R Square	0.431704
Standard Error	0.125914
Observations	101

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.220227	1.220227	76.9647	5.16E-14
Residual	99	1.569583	0.015854		
Total	100	2.78981			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.993256	0.01253	79.272	2.19E-91	0.968394	1.018117
log LSTA US	-6.45061	0.735284	-8.77295	5.16E-14	-7.90958	-4.99165

In order to offer a wider analysis, considering the European context, we tried to regress in the same way S&P/LSTA European Leveraged Loan Index (LSTA EU) and the CDS of a referenced European bank, which in our case was Barclays. We run the regression taking into account again the delta of Barclays CDS spread and the log difference of S&P/LSTA European Leveraged Loan Index. However, the results show that, differently from the US case, CDS spread of Barclays is almost not affected by movements in LSTA EU ($R^2 = 0.025$). Essentially, there is no significance in the regression since the SS of residual is very high and P-value of the regressor is very high as well.

Table 3.8 (5): Regression output to explain delta Barclays CDS spread movement from log difference of LSTA EU average bid price

Regression statistics	
Multiple R	0.157118
R Square	0.024686
Adjusted R Square	0.014734
Standard Error	0.206429
Observations	100

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.105701	0.105701	2.48047	0.118491
Residual	98	4.176084	0.042613		
Total	99	4.281785			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*

Intercept	1.014807	0.020757	48.89014	1.22E-70	0.973616	1.055999
log LSTA EU	143.3165	90.99743	1.574951	0.118491	-37.265	323.8979

To complete our review, the BofA CDS spread has been studied in relation to other Palmer Square indexes such as CLODI index we have seen before. We have run different regression in order to understand if bank CDS spread is related to specific type of CLO indices classified by tranche ratings. Interesting results showed up. Palmer Square CLO A Price index (PCLOAPX) and Palmer Square CLO BBB Price index (PCLOBBBPX) are both indices which replicate the performances of CLOs depending on tranche ratings. We dwell deeper in these two indices (rather than the whole spectre of the other indices, which are categorized from the AAA-most-senior debt tranche to B-rated tranche) since they show the most significant outcomes.

The results show that Palmer Square CLO A Price index (PCLOAPX) and Palmer Square CLO BBB Price index (PCLOBBBPX) both inversely influence BofA CDS trend. We also run the regressions using changes in the BofA CDS and the log difference of the indices. The correlation of the first index with bank's CDS displays R-squared is equal to 0.4, meaning a good inverse correlation. The analysis of the p-values shows significant values pointing to a consistent regression.

Table 3.8 (6): Regression output to explain delta Bank of America CDS spread movement from log difference of Palmer Square CLO A Price index

Regression statistics	
Multiple R	0.631434
R Square	0.398708
Adjusted R Square	0.392573
Standard Error	0.12852
Observations	100

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.073339	1.07333	64.98248	1.88E-12
Residual	98	1.618701	0.01651		

Total	99	2.69204

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1.001579	0.012861	77.8743	6.04E-90	0.976055	1.027102
log PCLOAPX	-5.06998	0.628938	-8.06117	1.88E-12	-6.31809	-3.82187

Almost the same output follows studying the relation between BofA CDS and Palmer Square CLO BBB Price index. R-squared is similar to the previous one and the level of significance of the regression keeps its consistency. Nonetheless, in both output regression we may see a high SS residual value compared to the SS regression value showing that the regression should be improved to better explain the variability of BofA CDS.

Table 3.8 (7): Regression output to explain delta Bank of America CDS spread movement from log difference of Palmer Square CLO BBB Price index

Regression statistics	
Multiple R	-0.617164
R Square	-0.380892
Adjusted R Square	-0.374574
Standard Error	0.13041
Observations	100

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.025376	1.025376	60.29222867	8.03E-12
Residual	98	1.666663	0.017007		
Total	99	2.69204			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1.000957	0.013048	76.71246	2.57328E-89	0.975063	1.026851
log PCLOBBBPX	-3.18242	0.409852	-7.76481	8.02745E-12	-3.99576	-2.36908

Actually, also the other indices related to other tranche ratings show almost the same inverse correlation as Palmer Square CLO A Price index (PCLOAPX) and Palmer Square

CLO BBB Price index (PCLOBBBPX) do. However, bank CDS spreads are much more sensitive to CLO indices related to mezzanine-rated tranches.

If conversely, we consider the Palmer Square indexes that replicate the trend of CLOs divided by tranche but no longer consider the price but the yield, we see that the results are even more different. Since yield and price behave in the opposite way, we may think that as the CDS spread decreases as the index value increases, it increases as the yield increases. However, the correlation between the Palmer Square CLO AAA Yield index and the BofA CDS spread is almost zero. While if we consider the correlation between the Palmer Square CLO BB Yield index and the BofA CDS spread, R-squared is 0.316. Therefore, this shows that the CDS trend is more affected by the yield movements of junior tranches than senior tranches.

Table 3.8 (8): Regression outputs to explain delta Bank of America CDS spread movement from log difference of Palmer Square CLO AAA Yield index (on the left) and Palmer Square CLO BB Yield index (on the right)

Regression statistics	
Multiple R	0.221261
R Square	0.048956
Adjusted R Square	0.039252
Standard Error	0.161632
Observations	100

Regression statistics	
Multiple R	0.562334
R Square	0.31622
Adjusted R Square	0.309243
Standard Error	0.137052
Observations	100

Conclusion

Is the situation in the financial world today different from that preceding the GFC? Have banks, financial institutions and policymakers taken different measures and behaved more carefully this time than they did in the last financial crisis?

In the first chapter of the thesis, we have introduced credit risk and the securitisation mechanism. In this context, we explained the role of banks, their exposure to certain products and how they have to comply with regulations imposed by central supervisors.

In the second chapter, in order to understand more closely the riskiness of structured products, their main players were analysed in detail. Their characteristics, their behaviour and above all how their risk have been carefully described. Relative models have been taken into account to assess the exposure they may induce and have been analysed to understand what their limits are and to what extent they can be reliable.

In the third chapter, with reference to current events following the outbreak of the coronavirus, we have analysed the CLO market in comparison with the CDOs during the 2008 financial crisis. We saw the impact of Covid-19 on the respective derivatives markets and the risk that the virus has brought to the leveraged loans market directly linked to the CLO market. We run several regressions to capture the influence of CLOs over banks CDSs.

However, the questions we asked ourselves still stand. Although the CDO sub-prime market, the core element that crashed the economy not too long ago, no longer exists, it has been replaced by CLOs that are essentially corporate sub-prime. Identifying the risks and default correlation of CDOs hides many pitfalls and is by no means straightforward. The markets have moved from subprime mortgages to leveraged loans. Rather than securitizing mortgages to low-rated individuals, we observe the securitization of loans of companies that are already heavily leveraged and economically stressed.

In the same way, many companies have binged on mortgages in the 2000s, which fuelled the economy upswing back in the days, they have done so in the past decade with leveraged corporate debt. Although banks limit their CLO investments largely in the most-senior tranches (AAA tranches), what they actually own is exposure to billions of dollars on high-risk debt. However, they do not even consider it as a gamble since historically AAA-layers of CLOs have never defaulted. Does it sound familiar? “Have

never defaulted"? Yet, AAA rating is deceptive. Alchemy is the name of the game and credit-rating agencies have known that game for too long and far too well. They grade CLOs and their underlying debt separately. If CLO is rated triple-A, it does not mean that its underlying debt is rated AAA. Far from it. Quick remainder: CLOs are composed of loans to businesses that are already at risk.

How is possible that credit rating agencies, the referees of this game, are able to do that? The answer is what we have been trying to explain throughout the second chapter; it is called "default correlation". It is the likelihood on which loans are defaulting simultaneously. The main reason CLOs have been so safe is the same reason CDOs appeared safe before 2008. Back at that time, the underlying loans, subprime loans, were risky too. Everyone knew that eventually some of them would default. However, nobody deemed that many of them would default all together simultaneously. Diversification is the factor that made think this could not happen since loans were spread across a whole country and among many lenders. Then housing prices dropped 30% and defaults soared. Well ahead Covid-19 got the news; credit-rating agencies were underestimating the correlation across unrelated industries that could affect loans to businesses. In a 2017 article by John Griffin, of the University of Texas, and Jordan Nickerson, of Boston College, they have shown that the assumptions related to default-correlation to rate a group of 136 CLOs were actually inaccurate. The default correlation assumptions should have been three or four times higher than they were and so the mistake led to much higher than what should be appropriate. The financial system appears robust for the time being. Banks can still run their business, complying regulatory capital tests and pay off their debts. However, call back that the last financial crash took more than a full year to stretch out. Currently, it seems not to be in autumn 2008, but most likely in summer 2007, when some securities were sinking but the outcome was still unknown.

In conclusion, the sad story could repeat itself. Banks appear to have falling back right in the misconduct they had in the last financial crash: taking too many risks, masking debt in complicated vehicles and overall taking advantage of loopholes designed to restrain their greed. In my view, the authorities should prevent the infamous statement "too big to fail", applying rigorous reforms to demolish the system as we know it. Banks should play a much simpler role in the economy, deciding for themselves in lending decision rather than faming it out to credit-rating agencies. What to do with CDOs and CLOs? They are products intended to help and to facilitate banks' job. However, they just let

everyone worry. Perhaps banks should move far from such products for their and our own safety. “Transparency” should be the word of the new economy. Shall a bank allowed to keep $1 trillion worth off assets its books? Maybe. However, again they seem to have taken a bet they cannot afford to lose. Insiders and authorities are worried and as we tried to show so far, they are right to be. The next step shall be to keep track on how the CLO market will evolve and have a close eye on what will happen in the near future hoping that Covid-19 will not strike again, for our own health and for the economy itself.

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