REVISITING THE PRICING OF SYSTEMATIC RISK PREMIA FOR COLLATERALIZED LOAN OBLIGATIONS IN PRACTICE

- AN EMPIRICAL STUDY OF WESTERN EUROPEAN COLLATERALIZED LOAN OBLIGATIONS

PETER HOLM YDE

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ADVISOR: DAVID LANDO

Abstract

This thesis explores whether investors require a risk premia for systematic risk when pricing Western European collateralized loan obligations (CLOs) from 2017 to 2020. I derive a set of special purpose vehicle (SPV) characteristics which are suggested to drive the systematic risk of issued tranches. If investors require risk premia according to the systematic risk of the tranche, the systematic risk drivers derived are hypothesized to have a significant impact on required launch spreads. None of the systematic risk drivers are found to have a robust significant impact on launch spreads for CLOs in this thesis. The implication of the results is that investors do not require a risk premia for the systematic risk in CLOs which implies CLO tranches to be overpriced. The complexity of structured debt is suggested to be the reason as it leaves investors barred from properly understanding the risk profile of the tranches. Instead, the risk assessment is suspected to be delegated to rating agencies which do not consider systematic risk in their rating methodologies. Further research is suggested to provide insight into what causes the lack of systematic risk premia and the methodologies used by investors for systematic risk assessment in practice.

Keywords: CLO, Collateralized loan obligation, CDO, collateralized debt obligation, structured debt, systematic risk, risk premia.

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1 Introduction

> *"Since the onset of the credit crisis, in mid-2007, analysts, politicians and researchers grapple to understand why such a disaster was possible... There were also a larger number of sophisticated investment bankers, fund managers and central bankers than ever before who were equally caught by surprise. Due to the high level of complexity that characterizes structured finance instruments, investors are effectively barred from carrying out any serious due diligence exercise directly. Thus, delegated monitoring is a sine qua non in structured finance markets, and the major line of delegation in ABS markets relies on rating agencies."*
>
> - Brennan, Hein, and Poon (2009)

The quote from Brennan, Hein, and Poon (2009) describes investors which delegated risk assessment to rating agencies as they were unable to map the risk characteristics of complex structured debt themselves. As a result of the lack of proper risk assessment, they were found to be caught by surprise by the instruments' sensitivity towards deterioration of the economic states.

The reliance on rating agencies to assess risk for structured debt seems puzzling. The models used by rating agencies are solely based on real-world default probabilities and fails to account for systematic risk[2]. As a result, the market consensus of relying on rating agencies do not capture systematic risk and in particular has been criticized in previous literature[3].

Some indications exist that market participants have changed their flawed practices of risk assessment after the Great Financial Crisis (GFC). The Financial Times stated in December 2007 that "some funds have rued their heavy dependence on ratings" and the SEC has suggested developing a differentiated rating methodology for structured debt which in particular accounts for systematic risk (Brennan, Hein, and Poon, 2009). In sum, market participants seem aware of the necessity to arrive at their own opinion of systematic risk in the wake of the repercussions from the GFC.

After the GFC, the market for structured debt has changed. In particular, the issuance of Collateralized Debt Obligations (CDOs) has ceased and has been replaced by Collateralized Loan Obligations (CLOs) (Aramonte and Avalos, 2019). CLOs are perceived as less complex compared to CDOs and less used for questionable practices, such as resecuritations of structured debt tranches. However, the low resilience of issued tranches against deterioration of the economic state is a shared characteristic between CDOs and CLOs (Aramonte and Avalos, 2019). Understanding systematic risk is thus still important in the structured debt market post-GFC. With an offset in the quote by Brennan, Hein, and Poon (2009) it therefore seems appealing to ask the question: "Have investors adjusted their risk assessment practices and are now capable of understanding systematic risk for structured debt in the aftermath of the Great Financial Crisis (GFC)?".

[2]See section 2.2
[3]See section 3

A natural starting point for answering this question is assessing the findings and research methods applied in previous studies of the subject. However, previous empirical studies focusing on systematic risk in structured debt are scant. Pinto, Marques, and Megginson (2020) found a difference in spreads between structured debt and corporate bonds and inferred that the difference is caused by systematic risk. However, I argue that the methodology applied by Pinto, Marques, and Megginson (2020) cannot isolate the effect from systematic risk and is vulnerable to other spread determinants systematically influencing the conclusions[4].

New discoveries regarding systematic risk in structured debt have emerged post-GFC. In particular, previous literature has identified a set of characteristics for the Special Purpose Vehicle (SPV) which drives the magnitude of systematic risk in their issued tranches. For example, the systematic risk of the loans in the collateral portfolio is found to influence the systematic risk of the issued tranches. In section 4.2, I extend the findings of the literature by using an intuitive model which connects selected SPV characteristics with the systematic risk of issued tranches. I suggest that systematic risk drivers so far not applied in empirical studies can provide further insights into systematic risk assessment for structured debt. The research method for this thesis is based on the intuition that if investors recognize systematic risk, these systematic risk drivers should have a positive impact on the required spread at issue.

1.1 Research question and contribution to the literature

Previous literature on structured debt has mainly focused on identifying spread determinants and only a few studies have conducted empirical studies of the effect of systematic risk on required spreads for structured debt. No studies (to the author's knowledge) have investigated the impact of SPV characteristics which drives systematic risk on spreads to assess whether systematic risk is considered by investors. Hence, this thesis aims to provide additional insight into the question of whether investors price systematic risk into required spreads for structured debt in practice. Other studies empirically investigating the pricing of systematic risk investigates the differences in spreads between structured and unstructured debt (Pinto, Marques, and Megginson, 2020). However, I argue that the methodology applied in this thesis is less prone to be influenced by other, well established factors which also drives spread differences between structured and unstructured debt.

No previous research has investigated the link between SPV characteristics driving systematic risk and required spreads for structured debt. In this thesis, I combine a derivation of systematic risk drivers using a theoretical framework with an empirical study of spread determinants. The main contribution of this thesis is to provide new insights into the question of whether investors identify systematic risk and prices structured debt accordingly post the GFC.

The main research question of this thesis is defined below:

[4]See section 4.

"Is systematic risk priced into spreads at launch for Western European CLO tranches with floating coupons issued post GFC?"

To answer this question, four sub research questions (SRQs) are defined. These are formulated to guide the focus of the studies undertaken and align them with the overall research objective. For each SRQ, the specifics of financial instruments, time period, and global region are as stated in the main research question.

SQR1: "Is there a significant difference in required launch spreads between CLOs and unstructured corporate bonds?"

SQR2: "Can the difference in required launch spreads between CLOs and unstructured corporate bonds partly be explained by perceived differences in systematic risk by investors?"

SQR3: "What is the sign and significance of the impact from each SPV characteristic found to drive systematic risk on the CLOs' launch spreads?"

SQR4: "Does systematic risk have an impact on required spreads for CLO tranches?"

1.2 Delimitation of scope

The number of topics covered within existing literature concerning structured debt is vast and a delimitation of scope for this thesis is necessary.

First, I provide a delimitation of the type of debt considered in my analyses. The studies undertaken for this thesis are solely conducted on debt issued in Western Europe[5] with a time period of issue limited to between January 2017 and April 2020. Additional restrictions have also been imposed on the type of debt included in the analyses. Only unstructured and structured instruments with floating coupons priced at par is included. Furthermore, only CLOs[6] are considered for structured debt while only corporate bonds are considered for unstructured debt.

Secondly, a delimitation of the analyses conducted is provided. For this thesis, my sole endeavour is to examine whether systematic risk is considered by investors in practice when pricing tranches of CLOs. Many other important topics within structured debt exist but will not be considered in this thesis.

Finally, my approach for assessing whether systematic risk is considered is by testing the impact of systematic risk drivers on spreads at launch for CLOs. Alternative methodologies not used in

[5] Andorra, Austria, Belgium, Channel Islands, Denmark, Faeroe Islands, Finland, France, Germany, Gibraltar, Greece, Greenland, Guernsey, Holy See, Iceland, Ireland, Isle of Man, Italy, Jersey, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Seborga, Spain, Sweden, Switzerland and the United Kingdom.

[6] See section 2.1.

this thesis could be applied for testing whether systematic risk is considered by investors, including interviews and other qualitative studies.

1.3 Structure

Section 2 introduces structured debt and CLOs in particular and describes the rating methodology applied by one of the market leading rating agencies, Standard & Poors (S&P). Section 3 provides a literature review concerning spread determinants for structured debt. In section 4 I formulate a set of hypotheses based on central contributions from previous literature and derivations of relations between SPV characteristics and systematic risk. The methodology applied to test these hypotheses in this thesis is elaborated in Section 5, while section 6 provides an insight into data sources and the data creation process. In section 7 the findings are presented along with sensitivity analyses and an assessment of the robustness of the findings. Finally, the implications of my findings and suggested next steps in future studies are discussed in section 8 before I provide a conclusion of the thesis in section 9.

2 Theoretical background

This section presents the theoretical background of the undertaken study in this thesis. Section 2.1 introduces various terminology applied in this thesis and the anatomy of structured debt. Section 2.2 elaborates on the rating methodology of S&P for structured debt and emphasis is put on whether systematic risk is captured by their applied methodology.

2.1 Introduction to CLOs

This section provides an in depth description of the process of securitization and collateralized loan obligations (CLOs) in particular. It also aims to align the terminology for the rest of the thesis and set the scene for a description of S&P's rating methodology.

When structuring debt, a special purpose vehicle (SPV) is established to pool debt products into a portfolio. Most leveraged loans used in CLOs are originated by banks, with a smaller role for non-bank financial institutions (NFBIs) (FSB, 2019). The acquisitions of the debt products are funded by issuing collateralized debt obligations (CDOs) from the SPV. The interest and principals earned from the underlying pool of collateral are then used to pay interests to the holders of the CDO issues. The CDOs are designed to have different seniorities. For example, the typical SPV structure has senior, mezzanine and junior CDO tranches. Finally, they also contain a "first-loss" vehicle, or the equity tranche. Losses in the SPV's portfolio are then absorbed according to the seniority of the CDO tranches. The first-loss vehicle takes the first loss and each issue is protected by all subordinate tranches to that issue (FSB, 2019). Usual investors in the tranches issued by the SPV are banks, investments funds, insurance companies, pension funds and other non-banks institutional investors (FSB, 2019).

There are different types of CDOs, defined according to the type of pooled debt collateral. Collateralized loan obligations (CLOs) are a type of CDO which are backed primarily by a portfolio of loans. Specifically, Bloomberg defines a CLO as debt issues from an SPV which are backed by primarily by corporate loans.

This thesis is delimited to collateralized loan obligations as defined above. The paper does not cover "synthetic CLOs" either, which are issued from SPVs backed by credit default swaps.

A SPV is a complex entity with many topics possible to be addressed. For example, an SPV is defined according to the type of underlying loans, the priority ranking of the issued tranches, the legal restraints of the portfolio manager and whether it has an active or passive portfolio management among others. Many of these topics are extensive and are not relevant for this thesis. Hence, a delimitation of what characteristics of the SPV I describe in this thesis is required. I focus on the parts of the SPV which are assessed to be important inputs in the rating methodology for S&P. S&P uses the underlying asset types and the capital structure of the issued CLO tranches as main inputs in their credit rating methodology. These themes are elaborated below.

2.1.1 Capital structure

The flow of payments from the collateral portfolio of loans to issued CLO tranches follows a set of clearly defined rules in order to protect the investors according to the tranches' seniority.

The distribution of payments to CLO issues follows two sets of mechanisms. The first mechanism is called a "waterfall" - the payments are distributed according to a "waterfall" where payments to the CLO issues are prioritized according to their seniority. For example, the most senior CLO tranche receives payments first. Only when the senior tranche is paid will the payments flow down the waterfall to the next tranche. If payments from the loan portfolio turn out to be insufficient to pay all tranches, the most senior tranches are then prioritized (FSB, 2019).

The second mechanism which governs the payments to CLO issues are compliance tests. Compliance tests are conducted periodically and can be divided into two groups - the first group includes eligibility tests and concentration limits which governs the assets acquired to the collateral portfolio. For example, eligibility criteria can have a minimum requirement of credit ratings for the loans before they are allowed to be added to the portfolio. The second group governs how the payments from the loan portfolio are allocated and usually comprises overcollateralization (O/C) and interest coverage (I/C) tests. For the discussion of capital structure, I focus on the second group.

The capital structure has to pass the O/C and I/C tests at each tranche layer at every payment period, before payments can be allocated to more junior tranches. The O/C test imposes a minimum ratio between the principal of the loan portfolio and the principal of outstanding tranches. The I/C test imposes a minimum ratio between total interest income from the loan portfolio and total interest due to CLO issues outstanding. If the ratios are above the minimum requirements, the payments can flow to the next tranche. If not, the payments are redirected to pay principal on the tranche in question, until the minimum levels are met. Finally, if any funds remain after the waterfall is completed, including the O/C and I/C tests, the remaining payments are allocated to the equity tranche.

O/C and I/C tests and the waterfall of payments in sum governs the flow of payments to the CLO issues according to their seniority. The payments to the portfolio manager are usually placed on the top of the waterfall.

The number of CLO issues and size of each tranche are at the portfolio managers discretion and need to be adjusted according to the risk appetite of investors. Each tranche can be designed to cater to the demands of the investors according to their seniority and size (Reuters, 2020).

2.1.2 Asset types

CLOs are structured debt backed primarily by a portfolio of loans. The underlying portfolio usually consists primarily of below investment grade, broadly syndicated leveraged bank loans (BSLs), of which the SPV takes part in the syndicate. Below investment grade is defined as loans with a credit rating below BBB. The average rating of collateral for CLOs has been found in previous literature to be slightly above B (Benmelech and Dlugosz, 2009). The SPV may also invest in unsecured debt and middle market loans (Johnson, 2018).

The loans used in CLOs are mainly used for financial engineering by the obligor. For example, common uses for loans used in CLOs are leveraged buy-outs (LBOs), mergers and acquisitions (M&As), and recapitalization or refinancing of existing debt. When comparing with corporate bonds, the loans usually have a first lien against the obligor's assets and are usually senior to corporate bonds in the obligor's capital structure. The loans are usually characterized by high indebtedness of the obligor and high spreads at issue (FSB, 2019).

The collateral can either be static or managed through the life of the vehicle. For a static deal, the underlying collateral is fixed throughout the life of the deal and investors have full knowledge of what the collateral will be. For managed deals, the collateral is subject to changes in a predefined reinvestment period, where the portfolio manager reinvests cash flows and trade loans according to certain criteria. An amortization period then follows the reinvestment period, where trading is more restricted and focus is on repaying the CLO issues (Morningstar, 2017).

Eligibility criteria and concentration limits are typical restrictions applied to the loans in the collateral portfolio. The eligibility criteria set requirements on the credit quality of the loans in the loan portfolio. For example, the criteria can require a minimum rating on each loan or requirements for the weighted average rating factor (WARF) for the pool. Concentration limits pose restrictions to issuer and industry concentrations in order to ensure that the portfolio is sufficiently diversified.

2.2 Credit rating methodology for structured debt

The rating methodologies used by major rating agencies play a central role in the derivation of hypotheses in this thesis as most literature used for my hypotheses derivation assumes investors to solely price tranches based on its assigned rating. This section provides a description of the rating methodologies necessary to understand the literature review conducted in section 3.

A detailed description of the rating methodology of S&P is included in this thesis to infer whether or not systematic risk is considered to some extent in the methodology. Whether or not the rating methodology considers systematic risk has important implications on the proper methodology to test whether systematic risk has an impact on spreads using regression analyses. For example, If the rating methodology considers systematic risk I can't infer that systematic risk is not considered solely from the impact of my systematic risk drivers. Systematic risk could have an impact on spreads through the credit rating even if my systematic drivers' impact turns out to be insignificant.

S&P, Moodys and Fitch are referred to as "The Big Three" rating agencies. In this section I focus on the rating methodology applied from S&P. S&P is chosen as its rating has been shown to carry the most explanatory value of the three agencies (Cuchra, 2004). Fitch and S&P's rating methodology are both based on the physical probability of default, while Moodys are based on expected default losses (Brennan, Hein, and Poon, 2009).

This section is structured as follows. First, S&P's rating methodology is briefly introduced followed by a description of each element comprising the rating methodology.

2.2.1 An introduction to Standard & Poors' rating methodology

S&P offer credit ratings to a large number of financial products, often with different rating methodologies. The focus of this section is the rating methodology for what S&P calls "Corporate CDOs". Corporate CDOs are defined as SPVs backed by diversified pools of corporate debt (loans and bonds). It also covers SPVs with credit default swaps or sovereign securities as underlying collateral.

The cornerstone of the rating methodology is a stochastic modeling of default rates used to assess each tranche's risk of default. The modeling takes into account the risk characteristics in the loan portfolio as well as tranche specific characteristics including the waterfall and seniority of the tranche as described in section 2.1.

Additional qualitative and quantitative tests are also made as supplemental tests to the stochastic modeling. These supplemental tests are made to address event and model risks not captured by the stochastic modeling. They are used as additional constraints of the rating level for a given tranche. Finally, S&P may assess additional qualitative factors on a case-by-case basis (Standard and Poors, 2019a).

The rating methodology from S&P is described in detail in a number of easily available articles. They even provides software which can be used to mimic the stochastic modeling conducted. I have used the articles available as well as an ongoing dialogue with S&P representatives to understand the rating process.

2.2.2 Stochastic modeling

Stochastic modeling is used as the primary analysis in S&P's rating methodology. The analysis calculates two key metrics, Scenario Default Rate (SDR) and Break-even Default Rate (BDR).

For each rating, an SDR is calculated. The SDR is the default rate of the collateral portfolio that a tranche should be able to withstand while still repaying note holders in full and on time. The required SDR increases with the credit rating. For example, a AAA rating requires a larger SDR than a BBB rating.

The SDR for a given credit rating depends on the risk characteristics of the loan portfolio. S&P runs a Monte Carlo simulation of the default rate distribution of the collateral portfolio for a given time horizon. Each credit rating is assigned quantiles of this distribution for each tenor. The quantile decreases as the credit rating increases. For example, the quantile for a AAA rating with a 5-year tenor is 0.051%, while it is 5.418% for a BBB rating [7].

[7] See Appendix D in Standard and Poors (2019a).

The rating quantiles are then used to derive the SDR from the simulated distribution of default rates of the collateral portfolio. The SDR is the default rate of the collateral portfolio at the given quantile in the distribution.

The relation between the SDR and the rating quantile can be written as below. Let X be the default rate of the loan portfolio, let $\%_{AAA}$ be the rating quantile for a AAA rating and let SDR_{AAA} be the SDR for the AAA rating.

$$P(X > SDR_{AAA}) = \%_{AAA} \tag{1}$$

As the loan portfolio becomes more diversified, the distribution becomes lighter tailed. As a result, the SDR for a given rating decreases as the diversification increases and vice versa.

In order to run a Monte Carlo simulation of the default rate distribution, one needs to make assumptions of how the loan defaults are related. S&P use a one-factor Gaussian Copula function to model the correlations between asset loans (Standard and Poors, 2019a).

The one-factor Gaussian Copula model is an algorithm used to simulate values of normally distributed variables with a given correlation. The model is used by S&P to simulate defaults of loans in a collateral portfolio and to capture the assumed correlations between the defaults. The model can be summarized as below.

Let $Z_1, Z_2, ..., Z_N$ be N independent identically distributed random variables with distribution $\sim N(0,1)$. N denotes the number of loans in the portfolio. Hence, there exists a Z denominated iid. variable for each loan. The Z denominated variables represent the idiosyncratic risk of each loan defaulting and the variables are thus made independent of each other.

Let $M \sim N(0,1)$ be a single random variable independent of all Z denominated variables. The M variable represents the common factor across each loan which affects all loans in the portfolio and thus makes defaults correlated. The single common factor is what gives the name of the one-factor model.

Let $Y_1, Y_2, ..., Y_N$ be random variables defined as

$$Y_i = M\sqrt{\rho} + Z_i\sqrt{1-\rho} \tag{2}$$

Where ρ is the correlation parameter which can take any value between 0 and 1 $\rho \in (0,1)$.

In order to derive a simulation of number of defaulted loans in the portfolio, an indicator function is created. The indicator function takes the value 1 if the loan defaults and the value 0 if it doesn't. It can be written as

$$I_i \begin{cases} 1 & if\ \Phi(Y_i) < p \\ 0 & otherwise \end{cases} \tag{3}$$

Each loan in the loan portfolio has an indicator function. the default of the loan is defined as not being able to repay note holders in full and on time in accordance with S&P's definition.

Φ denotes the cumulative distribution function for a standard normally distributed variable, while p denotes the probability of default for the loan.

By simulating a vector of values for the Z denominated variables as well as the common factor M, a vector of simulated values for the Y variables can be created. Finally, values for the indicator functions can be derived. The output represents a single observation of the default rate for the loan portfolio. By repeating, the distribution of default rates can then be simulated.

For a given number of loans, the method based on the one-factor Gaussian Copula model only requires three inputs to determine the SDR - the probability of default, the correlation parameter and the rating quantiles. S&P calibrate their parameter values based on historical default rates and economic stress levels from their S&P Global Rating's CreditPro (1981-present) database (Standard and Poors, 2019a). Based on the definition that AAA rated tranches should be able to withstand extreme historical economic stresses they derive a table of targeted default rates for AAA rated tranches. The targeted default rates are then used to calibrate the parameter values for probability of default, the correlation parameter and the rating quantiles for each rating.

For the correlation values ρ, S&P make some simple assumptions. The values are assumed to be constant over time and across industries. The correlation values are assumed to be 0.2 for two firms in the same industry and 0.075 for two firms in different industries. Finally, it is 0.05 for two firms in different industries and geographic areas (Standard and Poors, 2019a).

S&P then derive a table of default rates and rating quantiles across credit ratings which can be used to derive SDR's for a loan portfolio, using the one-factor Gaussian Copula model.

All else equal, the SDR decreases as the loan portfolio becomes more diversified as increasing diversification will result in slimmer tails in the simulated default rate distribution, as described above. Under S&P's assumptions this would be the case if the loans in the portfolio are chosen to be from different industries and geographies as opposed to same industry and geography. Furthermore, the portfolio diversification also increases as the number of loans in the portfolio increases.

As mentioned, the calculation of rating SDRs for a given loan portfolio is only the first of two steps conducted, before the proper rating for a tranche can be determined. The second step in the methodology is calculating the tranche's Break-even Default Rate (BDR).

For each tranche, a BDR is calculated. The BDR is the maximum percentage of defaults in the collateral portfolio that the tranche in question can withstand, while still paying its note holders in full and on time.

The BDR is used in conjunction with the SDR to determine an appropriate rating for a given tranche. Specifically, in order to assign a given rating to the tranche, the tranche's BDR is expected to be equal to or higher than the rating's derived SDR. If the BDR is lower than the rating's SDR, the tranche does not qualify for the rating. I can write the condition as below.

$$BDR \geq SDR \tag{4}$$

The calculation of BDR is based on a cash flow analysis of the inflows and outflows of the SPV. The aim of the cash flow analysis is to take the deal components into consideration which influences the ability to pay the note holder in a timely manner. For example, this includes the risk and payment characteristics of the collateral portfolio, the tranche's covenants and protective mechanisms as well as the SPV's waterfall and coverage tests as described in section 2.1.1.

The collateral portfolio provides the inflow of funds to the SPV which is subject to both the payment profiles of the loans as well as their credit risks. Amortization profiles, maturity and frequency of payments of the portfolio loans comprises the payment profile. The frequency of payments poses a potential issue as it can cause payment timing mismatches if it differs from the tranches' payment frequencies. If tranche payments are more frequent than the portfolio loan payments, it can cause a potential liquidity issue.

Another important consideration is the collateral portfolio's credit risk. For example, if the defaults of loans cluster in periods, are the SPV still able to pay the tranche in full and on time in that period? And what size of the default rates can be assumed? These types of considerations are captured in S&P's cash flow modeling (Standard and Poors, 2019a).

The waterfall of funds is described in section 2.1.1 and governs the flow of funds from the SPV to its issued tranches and equity position. The transaction documents provide clear definitions of how interest and principal payments from the portfolio are to be distributed and can differ widely from deal to deal. For example, the waterfall defines the size of subordinated issues to the tranche, which I/C and O/C requirements are made and how principal payments from the portfolio are used. If principal payments are distributed down the waterfall instead of being reinvested in the portfolio, it can provide equity investors with an immediate return while reducing the credit support available to offset future defaults. High I/C and O/C requirements for issues more senior to the tranche in question can result in proceeds being used to pay down the senior issues more quickly, at the expense of the credit support to the more junior tranches.

These characteristics of the waterfall structure is modeled into the cash flow analysis, when calculating BDR of the tranche (Standard and Poors, 2019b).

The cash flow modeling described above provides a platform to test if the SPV is able to pay its tranches in full and on time in various simulated stress scenarios. Stress tests are conducted to test the sensitivity of tranche payments to loss timing and to identify vulnerabilities to various assumptions.

The assumptions used and scenarios conducted when calculating BDR are easily available and described in great detail in their publicly available articles. They even provide a Cash Flow Evaluator software, which can be used to imitate their cash flow analysis (Standard and Poors, 2019b).

The BDR in conjunction with the SDR comprises the stochastic analysis conducted by S&P. The analysis is then followed by a set of supplemental tests as elaborated below.

2.2.3 Supplemental tests

Supplemental tests are always run in conjunction with the stochastic modeling when assessing the appropriate tranche rating. The supplemental tests are intended to address event and model risk for the SPV's ability to pay in full and on time. Either test may act as a limiting factor for the appropriate rating for the tranche.

The two tests conducted are the largest obligor default test and the largest industry default test. The largest obligor default test assesses whether the tranche can withstand specified combinations of defaults, based on the underlying obligors. The loans in the collateral portfolio are sorted based on the obligor's credit ratings. For each group of obligors, the tranche should then be able to withstand a number of defaults from the largest obligors in that group (Standard and Poors, 2019b).

The largest industry default test is only relevant for rating AAA and all refinements[8] of AA. The test comprises a primary and an alternative test. If the tranche ends up failing the primary test, it can still achieve the desired rating if it passes the alternative test.

The primary test tests whether the tranche is able to withstand defaults of all obligors in the largest single industry in the portfolio, with an assumed flat recovery rate. If the tranche fails the primary test, it can still be assigned the desired rating if it passes the alternative test. The alternative test sorts the loans according to the obligors' industries and then effectively makes a largest obligor default test within each industry.

Finally, S&P leaves room for possible case-by-case qualitative considerations. For example, they can adjust the assumed values in the calculation of the SDR and BDR, if deemed appropriate for that specific SPV.

In sum, the stochastic modeling is used as the cornerstone of the rating assessment, while supplemental tests are used to assess potential event risks not accounted for in the model. The supplemental tests are used as limiting factors for the desired rating for the tranche. That is to say, it can not improve the rating, but only potentially limit it.

An observation can be made that no tests in the rating methodology by S&P described above captures systematic risk of the tranches. On the contrary, the methodology aims to capture the real-world probability of default of the tranche and assign a rating based on this probability of default. No distinction is made of how the probability of default changes as the economic states

[8]Refinements are defined for this thesis as all credit ratings within the given alphabetical order. For example, AA+ and AA- are two different refinements of the AA rated tranches.

deteriorates. A similar point can be made for the rating methodologies for Moody's and Fitch[9]. This has important implications of the appropriateness of using ratings to assess tranche risk. If investors solely rely on ratings to assess risk as suggested by Brennan, Hein, and Poon (2009)[10] they will not be able to assess the systematic risk of the tranche. It also has implications for the appropriate methodology to infer on systematic risk premia using regression analyses. As credit ratings do not carry any explanatory power wrt. systematic risk, I can infer on whether systematic risk is priced into spreads using the systematic risk drivers derived in section 4.

A literature review is provided in the next section which is used as the base for the hypotheses derivation in this thesis.

[9]Fitch also uses a real-world probability of default while Moodys uses real-world expected losses.
[10]See section 1 for a discussion.

3 Literature review

This section presents the literature review of this thesis. The literature review is divided into two groups of literature. Section 3.1 examines the first group of literature which conducts empirical tests of spread determinants for structured and unstructured debt. Section 3.2 then provides an overview of theoretical evidence of mispricing caused by systematic risk, assuming investors rely on ratings to price structured debt tranches.

3.1 Empirical evidence of spread determinants

3.1.1 Differences between unstructured and structured debt

Numerous articles have investigated spread size and proposed a series of spread determinants for corporate debt. For example, idiosyncratic risk from the issuer, maturity, and issue size are all found to influence spreads for corporate debt (Y. and Taksler, 2003; Elton et al., 2001; Chen, Lesmond, and Wei, 2007; Gabbi and Sironi, 2005).

While the pricing of corporate debt is not within the scope of this thesis, the differences in pricing between structured and unstructured debt might reveal some interesting insights. A branch of literature has focused on whether spread determinants differ between unstructured and structured debt and which factors could cause such a difference. Below, I will describe such factors found by previous literature. In this thesis, these factors causing spread differences between structured and unstructured debt are referred to as "deviation drivers".

Oldfield (2000), Jobst (2007), Fender and Mitchell (2005), Pinto, Marques, and Megginson (2020), and Pena-Cerezo, Rodriguez-Castellanos, and Ibanez-Hernandez (2019) argue that the originator of the SPV is able to design the tranches to cater to the risk and return preferences of different investors. For example, investors with limited information are suggested to prefer tranches with low risk, while investors better able to map the risk profile prefers junior tranches with larger risk and spreads (Boot, WA, and Thakor, 1993; Cumming et al., 2020). The segmentation of investors is also suggested to be a result of investment mandates or regulation (Pinto, Marques, and Megginson, 2020; Cumming et al., 2020; DeMarzo and Duffie, 1999; DeMarzo, 2005).

The ability of structured debt to cater to the different preferences of investors is suggested by Pena-Cerezo, Rodriguez-Castellanos, and Ibanez-Hernandez (2019) among others to result in lower spreads for structured debt compared to unstructured corporate debt. This is the first deviation driver suggested by previous literature.

Ashcraft and Schuermann (2008) identified a number of market frictions resulting from the process of securitization in the wake of the GFC. They identified an adverse selection problem caused by the asymmetric information of the collateral portfolio between the originator of the SPV and the investors. They argue that the originator has an incentive to security bad loans (the lemons) of her portfolio while keeping the good ones. The investors as well as the credit agencies are not able to obtain the same information as the originator and the investor should thus impose a haircut on the tranche price due to adverse selection. In particular, DeMarzo (2005) and Riddiough (1997) found securitization to mitigate the lemons pricing problem the originator might face, if she sold the loans unpooled. Originators thus have an incentive to use securitization for the lemons in their portfolio. The adverse selection should then be taken into account by investors and increase spreads for structured debt compared to unstructured debt. Adverse selection is the second suggested deviation driver from previous literature.

The grouping of assets also makes it more difficult to assess the risk characteristics of the tranche, compared to unstructured debt (Pena-Cerezo, Rodriguez-Castellanos, and Ibanez-Hernandez, 2019; DeMarzo, 2005). Pooling thus has an information destruction effect for investors, which could also increase required spreads for structured debt. Information destruction is the third deviation driver of this thesis.

Biased rating agencies is another issue for structured debt in particular. Cornaggia, Cornaggia, and Hund (2017) tested whether credit ratings where comparable across asset classes, specifically between corporate bonds and structured debt. They found that issuers who are least lucrative to the rating agencies, such as single issuers with relatively small issue sizes, face the harshest requirements before their issue can be assigned a desired rating. Meanwhile, issuers with larger issue sizes, such as structured deals, are more lucrative to the rating agencies and faces less strict requirements as a result. The ratings are thus suggested to "follow the money". As the issue of multiple tranches backed by a large loan portfolio have more and larger issue sizes than single corporate issues, the finding suggests that structured debt have a lower credit quality than unstructured debt for a given rating. The findings are also supported by Ashcraft and Schuermann (2008) which mentions the conflict of interest between rating agencies and investors as a market friction for structured debt. Informed investors might then expect structured debt to have poorer credit quality than unstructured debt for a given rating and require a higher spread for structured debt compared to unstructured debt as a result. This is the fourth identified deviation driver in this thesis.

Finally, a series of papers have examined the role of systematic risk for structured debt. Cornaggia, Cornaggia, and Hund (2017) suggests a fundamental difference in the risk profile between structured and unstructured debt. Structured debt is suggested to carry more systematic risk while unstructured debt carry more idiosyncratic, diversifiable risk. Wojtowicz (2014) arrived at a similar conclusion. He found fair spreads to be higher for structured than unstructured debt. He also suggested that the systematic risk component in structured debt is not appropriately taken into account by the methodologies of rating agencies. One strand of literature has investigated the impact on systematic risk on structured debt and is elaborated further in section 3.2. The higher systematic risk associated with structured debt might also result in a higher spread requirement for structured debt compared to unstructured debt, if investors are able to take it into account. This is the fifth deviation driver of this thesis.

In sum, numerous factors are suggested by previous literature to account for any spread difference between structured and unstructured debt. Few papers have however conducted empirical tests of the factors' effect in practice. Cornaggia, Cornaggia, and Hund (2017) examined whether credit ratings are comparable across asset classes. They found default rates to be much larger for structured debt than for corporate debt for a given rating. They also found that credit ratings given at issue were inflated for structured debt compared to unstructured debt. Cornaggia, Cornaggia, and Hund (2017) explains the differences by differing risk profiles caused by higher systematic risk in structured debt. They also suggest rating agencies applies more strict requirements to unstructured debt, compared to structured debt.

Pinto, Marques, and Megginson (2020) analyzed differences in spreads between unstructured, corporate bonds and structured debt using regression analyses. In their paper, the hypothesis that investors do take systematic risk into account is tested by comparing the spreads of unstructured and structured debt. If structured debt has significantly higher spreads than unstructured corporate bonds when controlling for a number of factors, the hypothesis is accepted. The idea is that the difference in spreads are caused by the higher systematic risk in structured debt than in unstructured debt, which is appropriately priced by investors.

They also test the hypothesis that the capability of structured debt to cater to the risk and return preferences of investors results in lower required spreads for structured debt compared to unstructured, corporate bonds. If structured debt has significantly lower spreads than unstructured corporate bonds when controlling for a number of factors, the hypothesis is accepted. For CDOs, spreads are found to be larger than for corporate bonds and they infer that systematic risk is taken into account when pricing CDOs. Meanwhile, they reject the hypothesis that the capability of the tranche design to cater to investors' risk and return preferences for structured debt results in lower spreads for structured debt compared to unstructured debt.

It is worth noting that Pinto, Marques, and Megginson (2020) do not distinguish between the deviation drivers that are described above when inferring on spread differences. For example, the identified higher spreads for structured debt is used to infer that systematic risk is accounted for. However, the literature suggests that the higher spreads found could equally be caused by adverse selection or information destruction.

3.1.2 Spread determinants for structured debt

As elaborated in section 3.1.1, significant attention has been given by both academics and practitioners to the analysis of spreads for corporate bonds and unstructured debt in general. However, the amount of literature focusing on spread determinants for structured debt has been relatively scarce (Pinto, Marques, and Megginson, 2020). Only a handful of articles which focus on price determinants of structured debt before the GFC have been found and only a single paper which tests price determinants after the GFC. Empirical analyses of price determinants for structured debt with data set from before the GFC have been conducted by Cuchra (2004), Vink and Thibeault (2008), Fabozzi and Vink (2012) and Buscaino et al. (2012).

Cuchra (2004) was the first to analyze price determinants for structured debt and focused in particular on the importance of credit ratings for launch spreads. Cuchra found that credit ratings seemed to carry more explanatory power for structured debt than for corporate bonds. He also found characteristics of the market placement like market liquidity had a statistically significant impact on launch spreads.

Vink and Thibeault (2008) followed the same methodology and used a regression model with similar price determinants as Cuchra (2004) to test how price determinants' impacts differ between Asset-Backed Securities (ABS), Mortgage-Backed Securities (MBS) and Collateralized Debt Obligations (CDO). In accordance with the findings of Cuchra (2004), they found credit ratings to carry the largest explanatory power for launch spreads and its impact to differ between ABS, MBS and CDOs.

The article of Fabozzi and Vink (2012) was motivated by the attack on investor's reliance on credit ratings post-GFC and they aimed to test whether investors addressed price determinants on their own. They used a data set of ABSs issued from 1999 to 2006 and also used a regression model with highly comparable control variables to the ones used in the work of Cuchra (2004) and Vink and Thibeault (2008). They also found credit ratings to be the main determinant of launch spreads of structured debt. However, other credit factors which were taken into account by credit agencies were also found to be significant. They concluded that, although credit ratings indeed were the main determinant of launch spreads, investors seemed to be able to derive their own view of the credit risk of structured debt tranches.

The analysis conducted by Buscaino et al. (2012) deviated from the aforementioned articles by focusing on CDOs backed solely by project finance loans. Project finance loans were defined as debt created for single-purpose and capital-intensive projects. They use a proprietary data set of only 43 tranches of project finance CDOs issued in Europe between 1998 and 2007. They based their methodology on the one used by Cuchra (2004) and Vink and Thibeault (2008) and used a regression model with similar controlling variables. They also found credit ratings to be the primary explanatory factor for spreads in project finance CDOs.

After the GFC, only one paper has been found to focus on spread determinants for structured debt. Pinto, Marques, and Megginson (2020) derived a set of hypotheses on the pricing of structured debt and tested them by comparing the pricing of structured debt to unstructured debt. Their main findings were that while credit ratings remain the primary price determinant contractual terms for the tranche and macroeconomic factors also carries explanatory power, even when credit ratings are accounted for.

Within the scarce number of papers testing spread determinants for structured debt, the number of papers focusing on systematic risk is even more restricted. No paper with data from before GFC tests hypotheses based on systematic risk. The only paper found which conducts an empirical test on systematic risk for structured debt are Pinto, Marques, and Megginson (2020) as described in section 3.1.1.

3.2 Theoretical evidence of systematic risk in structured debt

A strand of literature focusing on a theoretical derivation of systematic risk in structured debt has appeared in the wake of the GFC. Academics started deriving the nature of systematic risk in structured debt and how this risk should be reflected in required spreads.

To provide the reader with an overview, previous findings and methodologies applied within this strand of literature is briefly elaborated below. The models used to simulate the fair spreads in these articles have been kept relatively simple, with Merton's model of debt from 1974 playing a central role[11]. Many authors strive to keep the framework simple to maintain intuition. The aim of this section is to illustrate the highly consistent view in the literature that systematic risk is an important aspect of structured debt and is not appropriately accounted for by investors as a result of rating dependency. The view seems consistent across papers and the methodologies applied.

Coval, Jurek, and Stafford (2009a) was one of the first authors to investigate the risk and pricing of structured debt in the wake of GFC. In order to do so, they assumed a CAPM styled asset return of the obligors' company values and applied Merton's model from 1974. They reached the conclusion that senior tranches from structured debt replicate the payments from "economic catastrophe bonds", which only defaults under severe economic conditions.

Following Coval, Jurek, and Stafford (2009a), a number of articles emerged working from the assumption that spreads were entirely priced using credit ratings. The work of Brennan, Hein, and Poon (2009) were motivated by a proposal from the SEC to use rating modifiers for structured debt to account for the different nature of its risk. They tested the mispricing based on the assumption that investors are not able to assess the true value themselves, but must rely on the rating agencies' assessment. Similar to Coval, Jurek, and Stafford (2009a) they also assumed the obligor's company value followed CAPM and used the Merton model to simulate defaults. They estimated the size of the pricing errors from ratings based on expected default losses (Moodys) and default probabilities (S&P) respectively. They found that investors overprice the tranches with a larger pricing error when pricing is based on default probabilities from S&P instead of expected default losses from Moodys.

Hamerle, Liebig, and Schropp (2009) uses the same model based on Merton's simulated defaults and asset values following CAPM. They aimed to identify sources of arbitrage for the SPV originator due to systematic risk mispricing. In accordance with Coval, Jurek, and Stafford (2009a) they found

[11] In the Merton model, a firm defaults if its terminal value of its assets falls below the face value of the debt (Merton, 1974).

the risk profiles between unstructured and structured debt to be different with systematic risk to play a central role of the credit risk in structured debt. Idiosyncratic risk were found to be replaced by systematic risk in the securitisation process. They then concluded that spreads for structured debt tranches are far too low to compensate for its high systematic risk, assuming investors price entirely on credit ratings.

The works of Wojtowicz (2014) and Krahnen and Wilde (2009) are based on a different modeling of the loan distribution to Coval, Jurek, and Stafford (2009a), Brennan, Hein, and Poon (2009) and Hamerle, Liebig, and Schropp (2009), but arrive at the same conclusion. They use what Wojtowicz (2014) and Hull (2015) call the 'market standard' model. The market standard model simulates the correlation and defaults in the underlying loans using a one-factor Gaussian copula model and Monte-Carlo simulation. See section 2.2 for a description of the one-factor Gaussian copula model. They both found credit ratings to be insufficient to price structured debt tranches due to systematic risk and the tranches to be overpriced.

The findings and intuition from the literature mentioned in this section are used to derive the hypotheses of this thesis in the section below.

4 Hypotheses derivation

All papers included in the literature review in section 3.2 reached the same conclusion; systematic risk is an important aspect of tranches' credit risk and rating reliance will result in mispricing. However, recent empirical evidence showed that this might not be an issue in practice. As described in section 3.1, Pinto, Marques, and Megginson (2020) concluded that investors did not solely rely on credit ratings when pricing, but were able to price systematic risk into tranches of structured debt. The hypothesis that systematic risk was taken into account when pricing CDOs were tested by comparing spreads between structured and unstructured debt while controlling for a series of variables. The hypothesis that systematic risk were taken into account were accepted If CDOs were found to have higher spreads than corporate bonds.

In their analysis, CDO spreads were found to be larger and the hypothesis that systematic risk is priced into spreads were accepted. However, one might ask if the difference in spreads can be caused by other factors than systematic risk. As described in section 3.1, the literature has proposed a series of deviation drivers which equally could explain the higher spreads in structured debt found by Pinto, Marques, and Megginson (2020). Adverse selection has been suggested to be an issue for structured debt in particular as originators might pool all its "lemons" in the SPV at the expense of investors. Rating agencies have been found to be less strict when assigning ratings to structured debt, resulting in structured debt having higher probability of default compared to unstructured debt with the same rating. Finally, the process of pooling loans is found to create knowledge destruction, making it hard for investors to understand the risk profile of the tranche. These factors could equally explain the spread differences found by Pinto, Marques, and Megginson (2020).

Even though the spread difference observed might be a result of other factors, the findings of Pinto, Marques, and Megginson (2020) certainly raises the question whether the spread difference is actually caused by systematic risk as the authors argues. This thesis aims to test whether this is the case.

A thorough mapping of the causes of the difference in spreads between structured and unstructured debt is beyond the scope of this thesis. Instead, my more modest endeavour is to test whether systematic risk has an impact on the spread difference and spreads for structured debt in particular.

To ease the hypotheses derivation, I introduce some terminology. As mentioned, all factors which are suggested by previous literature to create spread differences between structured and unstructured debt are called "deviation drivers".

In the papers described in section 3.2, the authors identified a number of SPV characteristics which drives the systematic risk in the issued tranches. For example, the number of loans in the loan portfolio is found to be positively related to the size of systematic risk. The SPV characteristics found to drive systematic risk will be referred to as "systematic risk drivers" in the remainder of this thesis.

In the following sections, the hypothesis derivations are divided into two sets according to the nature of the hypotheses. The first hypothesis concerns the deviation drivers and how spreads deviate between structured and unstructured debt. The second set of hypotheses concerns whether systematic risk is priced into the spreads of structured debt.

4.1 Spread differences between structured and unstructured debt

In this section, I derive a hypothesis regarding deviation drivers and how they are priced by investors in practice. As described in section 3.1.1, previous literature has defined a set of deviation drivers which should result in unstructured and structured debt being priced differently. My hypothesis in this section is derived to test whether this is the case.

When deriving my hypothesis, emphasis is put on the effect of the deviation drivers as a group. The hypothesis derived in this section are formulated against a null hypothesis as stated below.

> $H0_a$*: Investors do not consider deviation drivers when pricing debt*

As argued in section 4, it is difficult assigning an observed difference in spreads between structured and unstructured debt to a particular deviation driver. Hence, I do not make any distinction between the impacts of deviation drivers for the first hypothesis of this thesis. Instead, I am examining their impact as a group, consistent with the methodology of Pinto, Marques, and Megginson (2020).

In the hypothesis, I do not attempt to argue which derivation drivers has the highest impact, and thus which sign the joint effects of the group has. Instead, I merely make the hypothesis that the group has a significant impact on spread differences as a whole. The hypothesis is formulated as below.

> *H1: Structured debt has significantly different required spreads than unstructured debt*

In section 4.2, I derive a set of hypotheses used to examine whether investors price systematic risk in structured debt. I work from the intuition that if investors are not capable of pricing systematic risk in structured debt, systematic risk has no explanatory power in the impact from the deviation driver group found when testing H1.

4.2 Systematic risk pricing in structured debt

In this section, I work from the intuition that if systematic risk is accounted for as Pinto, Marques, and Megginson (2020) argues, the systematic risk drivers later derived should have a statistically significant impact on spreads for structured debt. If they have, the hypothesis that systematic risk is accounted for to some extent in structured debt is accepted.

I should be careful interpreting on the output of the regression analysis; even if systematic risk drivers turn out to have a significant impact on spreads, I can only infer that investors are able to identify the presence of systematic risk and to some extent adjust their demanded spread as a result. However, I can't infer that they are able to adjust the spread so mispricing is effectively mitigated. To remove mispricing, investors need to understand each systematic risk driver and its exact impact on tranche risk. This entails not only significant impacts from the systematic risk drivers, but also calculating the correct coefficient and whether the relation is linear or non-linear. The hypothesis that mispricing is mitigated is thus stronger than the hypotheses tested in this thesis.

In the following, a set of systematic risk drivers suggested by previous literature is described. To develop an intuition of how the systematic risk driver affects systematic risk, I also derive the relation between systematic risk and the systematic risk driver using a predefined model. [12] For each systematic risk driver, hypotheses are then formulated based on the theoretical findings from the literature and the derivation made in this thesis from the model in section 4.2.1.

All hypotheses in this section are formulated against the overall null hypothesis below.

> $H0_b$*: Investors are not able to identify and price systematic risk into spreads for structured debt*

4.2.1 Model applied for hypotheses derivation

In his analysis of systematic risk for structured debt, Wojtowicz (2014) found that systematic risk was dependent on certain SPV characteristics. For example, he argued that the systematic risk for a tranche increased as the diversification of the collateral portfolio increased. Other authors made similar observations. Coval, Jurek, and Stafford (2009a) and Brennan, Hein, and Poon (2009) both found that systematic risk were dependent on tranche seniority, while Hamerle, Liebig, and Schropp (2009) suggested it was dependent on the number of loans in the loan portfolio.

While previous literature certainly provides a number of suggestions for systematic risk drivers, they do not seem to offer much intuition as to why these variables should drive systematic risk. For example, it does not seem straightforward why increasing the number of loans in the portfolio increases the systematic risk in the tranches.

To develop intuition, I introduce a model from which I can deduce the relation between the drivers suggested by previous literature and systematic risk carried by tranches. The deduction is carried out for each systematic risk driver and emphasis is placed on the intuition as to why the driver is related to systematic risk.

[12] See section 4.2.1.

Inspired by Coval, Jurek, and Stafford (2009a), I consider a tranche backed by a portfolio of N homogeneous and equally weighted risky loans. The tranche pays off 1 if the percentage loss of the collateral portfolio is below $1 - X$ and zero otherwise at maturity[13]. The value X is referred to in the literature as an attachment point and specifies the maximum default percentage of the collateral portfolio before the tranche is no longer able to pay in full and on time. It can be thought of as the tranche's credit enhancement. The payoff of the tranche can be written as

$$CF \begin{cases} 1 & if\, L < X \\ 0 & if\, L \geq X \end{cases} \tag{5}$$

Where L is the percentage loss of the collateral portfolio.

To model the correlation between loan defaults I assume that given a realization of the economic state s, loan defaults are independent. In a given economic state, each homogeneous loan in the portfolio has the same state dependent default probability $p_L(s)$. Assuming state contingent independence of loan defaults, the number of loans which defaults in a given economic state $\#_L(s)$ thus follows a binomial distribution with parameter $p_L(s)$ and N trials. The number of loans N can be large in practice. In this case, the number of defaults $\#_L(s)$ can be approximated by the normal distribution with mean $N * p_L(s)$ and variance $N * p_L(s) * (1 - p_L(s))$.

$$\#_L(s) \sim N\left(N * p_L(s), N * p_L(s) * (1 - p_L(s))\right) \tag{6}$$

The normal distribution approximation simplifies my derivations, while keeping the intuition[14]. Alternatively, I can also derive the percentage loss of the collateral portfolio in a given economic state $L(s)$ to be normally distributed with a mean of $p_L(s)$ and variance $\frac{p_L(s)*(1-p_L(s))}{N}$.

The state contingent probability that the percentage loss of the loan portfolio L exceeds the attachment point X can be written as below (Coval, Jurek, and Stafford, 2009a).

$$p^X(s) = P(L(s) \geq X) = 1 - \Phi\left(\sqrt{N}\frac{(X - p_L(s))}{\sqrt{p_L(s) * (1 - p_L(s))}}\right) \tag{7}$$

Where Φ is the cumulative distribution function (CDF) for the standard normal distribution.

Please note how the default probability for each loan, as well as for the tranche, is dependent on the economic state, s. For example, if the loan obligors' capability of making payments on time and in full are positively correlated with the market factor, $p_L(s)$ should increase as the economic state worsens.

For the application in this thesis, I extend the model to consider the relation between the probability of default for a given loan, $p_L(s)$ and the economic state, s. The economic state s is considered a

[13] Called a digital tranche by Coval, Jurek, and Stafford (2009a).

[14] The normal distribution do allow for a negative number of loan defaults, which of course is inappropriate. However, the probability mass for negative loans shrinks and is considered negligible as N increases.

discrete variable, as it allows for some intuitive interpretations. For low values of s, the economic state is poor and for high values of s, the economic state is good. In order to derive the relation between the probability of default for the tranche and the economic state I assume a simple, linear relation between $p_L(s)$ and s as below.

$$p_L(s) = a - \beta * s \tag{8}$$

Where a and β are parameters. The accuracy of the relation between $p_L(s)$ and s is not of interest for my application. Instead, I solely aim to model the intuitive relation that the probability of default decreases as the economic state improves and vice versa.

The value of a is not of interest for this application. However, the value of β is. If $\beta > 0$, the obligor's ability to make payments on time and in full are positively correlated with the market factor and vice versa. The interpretation of β is thus similar to the interpretation of beta in a CAPM setting.

Compared to the models used in previous literature this model allows to trace the portfolio characteristics to the risk characteristics of the tranche without using Monte Carlo simulation in a simple and intuitive setup.

When deriving hypotheses below, I aim to develop intuition based on how the state contingent probability of default for the tranche behaves across states of the economy. The hypotheses are derived in the sections below.

4.2.2 Number of loans in the portfolio

Coval, Jurek, and Stafford (2009a) developed a set of propositions for structured debt tranches and its fair prices using the model described in section 4.2.1. They used a normal distribution to describe the number of defaults in the underlying portfolio, conditional on a given state in the economy. From the assumed distribution, they derived the proposition that the fair value of a structured debt tranche declines as the number of loans in the loan portfolio increases. The decline in value is a consequence of the increase in systematic risk (Coval, Jurek, and Stafford, 2009a).

The proposition was later supported by Wojtowicz (2014) and Hamerle, Liebig, and Schropp (2009) and no inconsistencies in the literature have been found. Wojtowicz (2014) found fair spreads to depend on the diversification of the loan portfolio. The higher diversification, the larger systematic risk of the tranche and thus larger fair spreads.

While the literature agrees that the number of loans should have an impact on systematic risk, the intuition as to why does not seem straightforward. In order to assess the proposition from the literature and build an intuition, I derive the relation between number of loans and systematic risk using the model described in section 4.2.1.

I start by refreshing some assumptions and terminology applied in the model. A tranche defaults if the loan percentage loss L is larger than the tranche's attachment point X. The loan percentage loss is assumed normally distributed conditional on a given economic state. Conditional on an economic state s, the loan percentage loss L is normally distributed with mean and variance as shown below.

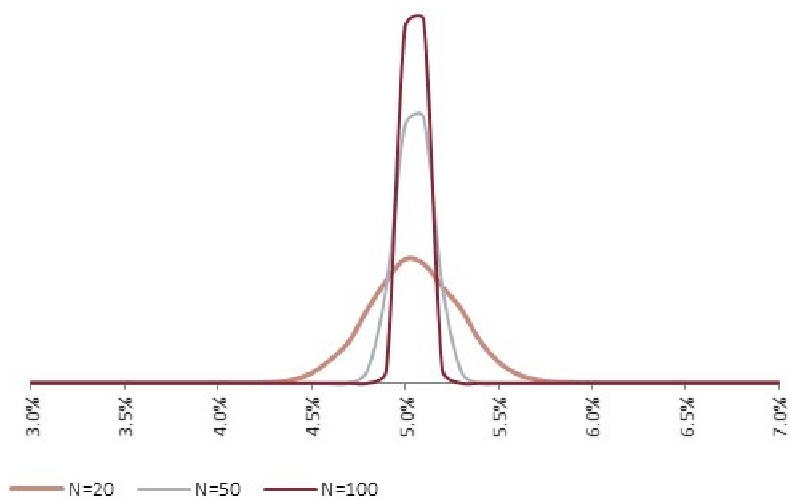
$$E\left(L(s)\right) = p_L(s) \tag{9}$$

$$Var\left(L(s)\right) = \frac{p_L(s) * (1 - p_L(s))}{N} \tag{10}$$

For this application, we are interested in how L's distribution changes as $N \to \infty$. It is immediately evident from equation (10) that as N increases, the tails for the loan percentage loss are getting slimmer. In particular, the loan percentage loss L of the collateral portfolio converges to $p_L(s)$ as $N \to \infty$.

With only a few loans in the portfolio, the loan percentage loss is highly sensitive to the idiosyncratic risk of few loans. Recall that when the economic state s is given, the loans are assumed to be independent of each other. However, as the number of loans increase, the impact from each loan is diversified away and the loan percentage loss converges to $p_L(s)$, dependent on an economic state s. This has an important implication on the probability of default for a tranche with attachment point X. Recall that a tranche is assumed to default if $L(s) > X$. If the attachment point X is chosen to be larger than the state dependent probability of default ($X > p_L(s)$), the loan percentage loss can still end up being larger than the attachment point. However, as $N \to \infty$ the loan percentage loss converges to $p_L(s)$ and the probability mass for the loan percentage loss being above the attachment point decreases as N increases. The effect on the distribution for the loan percentage loss for a given economic state is simulated below.

Figure 1: Loan percentage loss across N



Note: Simulated distributions with $p_L(s) = 5\%$ with 10000 simulations.

This observation can be applied to understand how the number of loans in the portfolio affects the systematic risk of the tranche. Recall from equation (8) that $p_L(s)$ is dependent on the economic state s. This intuitively makes sense; for a good state economy, $p_L(s)$ is low compared to its value in a poor state economy. I now make the thought experiment that only two states of the economy are possible; a good state where the probability of default for each loan is just below the attachment point $p_L(Good) < X$ and a poor state where it is just above the attachment point $p_L(Poor) > X$. For only a few loans in the portfolio, the tranche can easily default in both economic states. The distribution for the loan percentage loss has fat tails and large distribution mass above the tranche's attachment point for both economic states. However, the loan percentage loss converges to $p_L(s)$ in each economic state as $N \to \infty$. In the good state, this results in the probability of default for the tranche to decrease as N increases. In the poor state, it results in the probability of default for the tranche to increase as N increases.

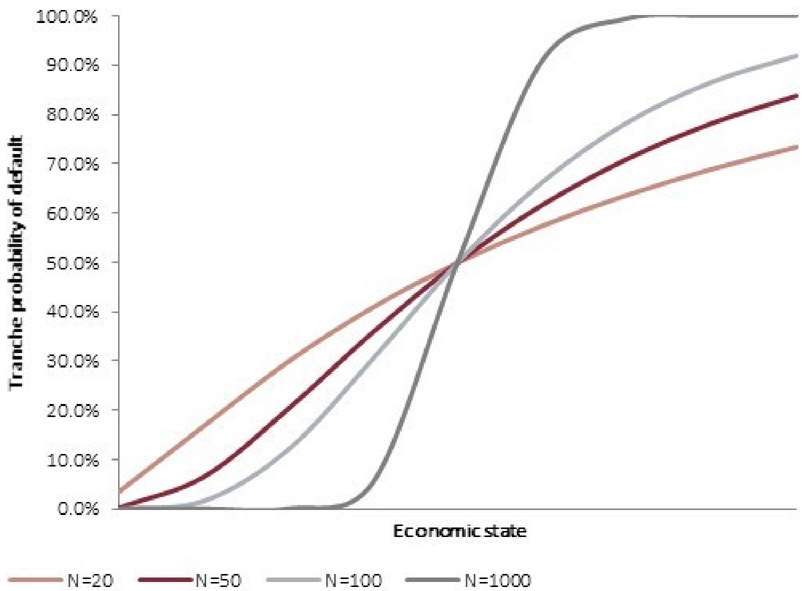
This behavior is exactly what to expect if the systematic risk increases with N. As N increases, the tranche would increasingly imitate an economic catastrophe bond and only default under poor economic conditions as suggested by Coval, Jurek, and Stafford (2009a).

The relation between N and systematic risk can also be observed from the probability of default, conditional on an economic state as given in equation (7). The partial derivative of the conditional probability of default wrt. N is given below.

$$\frac{\partial P(L(s) \geq X)}{\partial N} = -0.5 * \frac{(X - p_L(s))}{\sqrt{p_L(s) * (1 - p_L(s))}} * \Phi \left(\sqrt{N} \frac{(X - p_L(s))}{\sqrt{p_L(s) * (1 - p_L(s))}} \right) * \sqrt[-2]{N} \qquad (11)$$

For good economic states where $X > p_L(s)$, an increase in N results in lower probability of default for the tranche. For poor economic states where $X < p_L(s)$, an increase in N results in a higher probability of default for the tranche. This in accordance with the findings above[15]. The impact of increasing the number of loans on the tranche's probability of default across economic states is simulated below.

Figure 2: Tranche probability of default across N



Note: Probability as given in equation 7. Attachment point is given as 5% and the economic states are "worsening" from left to right.

It is immediately evident from figure 2 that the tranche's probability of default increasingly resembles the "economic catastrophe bonds" as defined by Coval, Jurek, and Stafford (2009a) as N increases.

In sum, I find that an increase in the number of loans makes a tranche's default in a poor economic state more certain, while also making the survival in a good state more certain. This is in accordance with what to expect if N drives systematic risk as suggested by previous literature.

[15] As a tranche is designed to be given a certain credit rating, it could be argued that the attachment level should not be held constant when investigating N's impact on the tranche's conditional probability of default. Instead, it could be adjusted so the tranche's unconditional probability of default is held constant. However, this author argue that such adjustment makes the point unnecessary complicated while not changing the intuition derived.

The rating methodology of the rating agencies do take the diversification effect into account when estimating real-world probability of default[16]. Thus, any effect from the number of loans on tranche spreads are interpreted as a result of the effect on systematic risk when controlling for credit ratings. Motivated by the findings above, I formulate the hypothesis below.

H2: Number of loans in the loan portfolio has a positive impact on spread for structured debt tranches

4.2.3 Systematic risk in collateral loans

Hamerle, Liebig, and Schropp (2009) found that systematic risk increases when loans with high systematic risks are included in the collateral pool. A similar point was made by FSB (2019) and Wojtowicz (2014) who argued that an originator has an incentive to acquire loans with relatively high spreads and systematic risk for its credit rating and this behavior will increase the tranches' credit risk. In fact, Hamerle, Liebig, and Schropp (2009) suggests a scaling effect where the systematic risk for the tranche increases dramatically as a function of the systematic risk in the underlying portfolio.

Why the systematic risk of the tranche should behave in this way is not clear. The findings in previous literature therefore raise the question of how systematic risk in the underlying loans impacts the tranches' risk and why.

Below, I investigate how the securitization process creates this relation between systematic risks using the model described in section 4.2.1. I derive two hypotheses. The first hypothesis concerns how the size and sign of the loans' systematic risk impacts the systematic risk of the tranche. The second hypothesis concerns what determines the scaling effect as suggested by previous literature.

I start by developing some intuition as to how systematic risk is represented in the model used in this thesis. Systematic risk is the difference in probability of defaults for the tranche across economic states. If a tranche has high systematic risk, its probability of default should differ greatly across economic states. Specifically, the probability of default should increase in a poor economic state and decrease in a good economic state. If the tranche does not have any systematic risk, its probability of default should not depend on the economic state.

In order to assess the impact from the underlying loans' systematic risk, I consider three different portfolios of 20 homogeneous loans. The first portfolio is comprised of loans which probability of default is not correlated with the economic state s. The second and third portfolio are comprised

[16] See section 2.2 for a description of the rating methodology of S&P.

of loans which are positively and negatively correlated with the economic state, respectively. Using (8), we can write these characteristics as $\beta = 0$, $\beta > 0$ and $\beta < 0$ respectively.

I also consider three different economic states; A good state, a neutral state and a poor state. In the neutral state, the probability of default $p_L(s)$ for all types of loans are assumed to be the same.

However, the three types of loans react differently when the economic state changes. For example, the loans which are positively correlated with the economic state has the lowest probability of default in a good economic state while the loans which are negatively correlated with the economic state has the largest probability of default and vice versa.

I consider an attachment point X equal to the probability of defaults for each loan in the neutral economic state. I can write

$$X = p_{\beta>0}(s) = p_{\beta=0}(s) = p_{\beta<0}(s) \; for \; s = Neutral \tag{12}$$

$$p_{\beta>0}(s) < X = p_{\beta=0}(s) < p_{\beta<0}(s) \; for \; s = Good \tag{13}$$

$$p_{\beta>0}(s) > X = p_{\beta=0}(s) > p_{\beta<0}(s) \; for \; s = Poor \tag{14}$$

The differences in how the probability of default changes according to the economic states have some important implications for the systematic risk of issued tranches as the expected loan percentage loss in the portfolio is $E\left(L(s)\right) = p_L(s)$. As a result, a tranche backed by positive beta loans has the lowest probability of default in the good state while the tranches backed by negative beta loans has the highest. The tranche backed by neutral loans is unaffected by changes in the economic state. I can thus write the relative probability of default for tranches backed by the different portfolios as below.

$$P(L_{\beta>0} > X) = P(L_{\beta=0} > X) = P(L_{\beta<0} > X) \; for \; s = Neutral \tag{15}$$

$$P(L_{\beta>0} > X) < P(L_{\beta=0} > X) < P(L_{\beta<0} > X) \; for \; s = Good \tag{16}$$

$$P(L_{\beta>0} > X) > P(L_{\beta=0} > X) > P(L_{\beta<0} > X) \; for \; s = Poor \tag{17}$$

The equations above allow for some easy interpretations of the loans' systematic risk effect on the tranches' systematic risk. Loans with a positive systematic risk results in tranches with a positive systematic risk. The risk of the tranche backed by positive beta loans behaves like it has systematic risk. In the good economic state it has a low probability of default, while it has a high probability of default in the poor economic state.

I can also show that the higher systematic risk in the underlying loans, the higher systematic risk in the tranche, all else equal. For example, if I include a portfolio of loans with an even higher systematic risk than the positive beta portfolio, the tranche's probability of default in the good and bad state would have more "extreme" values than the positive beta tranche currently assessed. Specifically, the probability of default would be even lower in the good state, and even higher in the bad state.

I can thus infer that the size of the systematic risk of the underlying loans are transferred to the systematic risk of the tranche. The higher systematic risk of the loans, the higher systematic risk of the tranche, all else equal.

Another observation can be made regarding the loans' sign of systematic risk, and how it influences the tranche. Loans which are uncorrelated with the economic state creates tranches which are also uncorrelated with the economic state. Loans which are negatively correlated with the economic state creates tranches which are negatively correlated with the economic state. The sign of the systematic risk from the loans is thus transferred to the tranche's systematic risk.

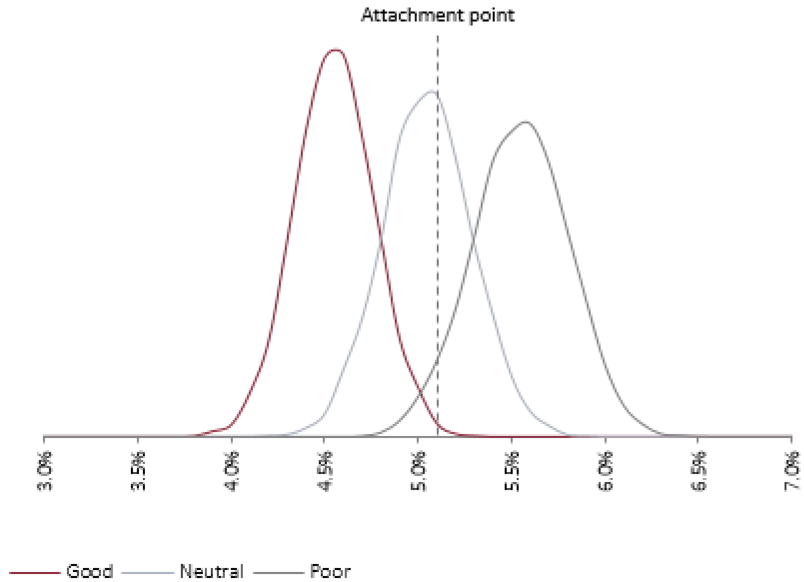
The observations made for the positive beta tranches above are consistent with the findings in previous literature. Furthermore, I have made the additional proposition that the sign of the systematic risk is transferred to the risk of the tranche. In sum, the first hypothesis regarding systematic risk of the loans is formulated below.

> *H3: The systematic risk of the loans in the portfolio has a positive coefficient to the required spreads for structured debt*

To derive the hypothesis regarding the scaling effect I once again use the model described in section 4.2.1 and aims to derive some intuition as to why the securitization process should cause such a scaling effect.

Once again, I take offset in equation (12), (13) and (14). For a portfolio size of 20 positive beta loans, the differences in L's distribution are simulated across economic states below, where the attachment point is placed just above 5%.

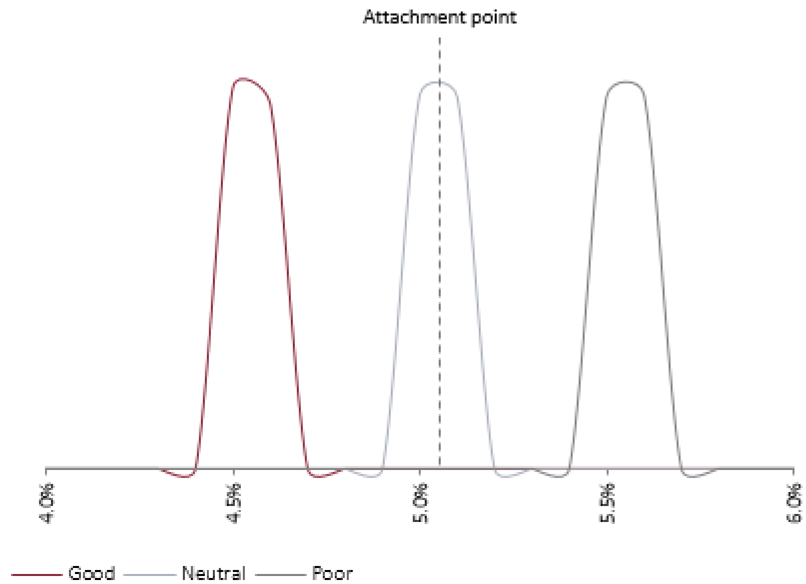
Figure 3: Loan percentage loss across economic states (N=20)



Note: Simulated distribution with $p_L(Good) = 4.5\%$, $p_L(Good) = 5.0\%$ and $p_L(Good) = 5.5\%$ with 10000 simulations.

A key observation is that the tranches still do not resemble "economic catastrophe bonds" as suggested by Coval, Jurek, and Stafford (2009a). For example, in the poor state, there still is substantial probability of the tranche surviving. Using this graphic, the effect of increasing the number of loans in the portfolio is easily observable. Recall from equation (10) that the variance of the loan percentage loss decreases as N increases. Hence, the tails of the loan percentage loss distribution L get slimmer as the number of loans increases. Using the intuition from figure 3 I can show how the behavior of the default of the tranche changes as the number of loans increases. The effect is shown below where the portfolio size are increased to 200 loans for illustration.

Figure 4: Loan percentage loss across economic states (N=200)



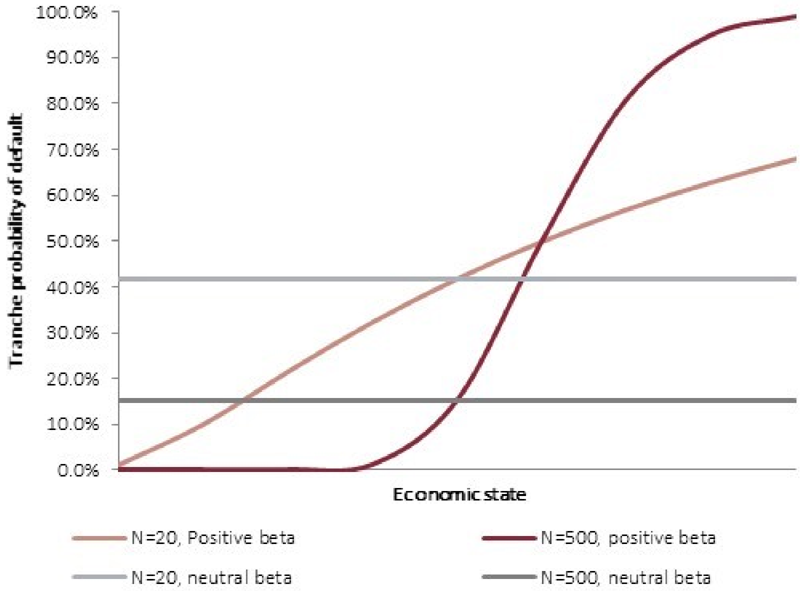
Note: Simulated distribution with $p_L(Good) = 4.5\%$, $p_L(Good) = 5.0\%$ and $p_L(Good) = 5.5\%$ with 10000 simulations.

For the positive beta portfolio, the systematic risk surges as the number of loans increases. This is exactly the scaling effect suggested by previous literature. As the number of loans increases, the default behavior of the tranche becomes increasingly binary; it defaults in a poor economic state and survives in a good economic state with a high certainty.

One interesting observation is that increasing N increases the absolute value of the correlation with the economic states. For example, the tranche's negative correlation with the economic state is more negative when increasing N. The sign of the correlation is thus maintained.

I illustrate the effect on increasing N for the tranche backed by positive beta loans versus the zero beta loans below. The Y axis is the probability of default for the tranche $P\left(L(s) > X\right)$. The X axis is the economic state.

Figure 5: Tranche probability of default across betas



Note: Probability as given in equation 7. Attachment point is given as 6% and the economic states are "worsening" from left to right. Positive beta is created by making $p_L(s)$ dependent on economic states, while the neutral betas have p_L independent of the economic states.

From here, it is easy to infer that the number of loans have a scaling effect on the beta coefficient from the underlying loans. For $\beta = 0$ loans, the systematic risk can't be scaled.

In summation, I find that N has a scaling effect on systematic risk. Specifically, it scales the absolute value of the correlation with the economic state.

This finding is consistent with previous literature which has suggested such a scaling effect. I derive the second hypothesis regarding the systematic risk below.

> *H4: The effect of systematic risk of the loans in the portfolio increases with the number of loans in the portfolio*

4.2.4 Tranche seniority

All papers included in the literature review in section 3.2 agrees that systematic risk is dependent on the seniority of the issued tranche. For example, a AAA rated tranche and a BBB rated tranche from the same SPV should have different systematic risks.

The literature does not, however, agree on whether senior or junior tranches carry the largest systematic risk. Coval, Jurek, and Stafford (2009a) was the first to document a difference in mispricing caused by systematic risk across seniority. They found senior tranches to carry the largest systematic risk and thus the largest mispricings. They even called senior tranches "economic catastrophe bonds" as they were found only to default under severe economic conditions. Senior tranches were also found to be the most mispriced by Krahnen and Wilde (2009).

Brennan, Hein, and Poon (2009) did however find that junior tranches in particular were most prone to mispricing caused by systematic risk. In short, the literature seems to agree that seniority of the tranches drives systematic risk, but some inconsistencies exist around whether junior or senior tranches carries the most systematic risk.

The inconsistencies in the literature motivates the derivation of my own opinion. Again, I aim to use the model described in section 4.2.1 to derive a set of intuitive propositions as to why the systematic risk differs across seniority.

Using a very simple setup from the model I make the proposition that senior tranches are most exposed to systematic risk.

Consider an issue of a very subordinated junior and a super senior tranche in a neutral state of the economy. Within each state of the economy, the very subordinated junior tranche is designed to have a considerable probability of default. Even for neutral and good economic states, the probability of default is designed to be substantial. Meanwhile, the super senior tranche is designed to be highly unlikely to default for most of the economic states of the economy.

The different designs of the tranches have some interesting implications to what type of risk they carry. The junior tranche is designed to be relatively exhausted solely due to idiosyncratic risk without any changes in the economic state. When the economy deteriorates, the junior tranche's ability to carry loss is limited as a result; the tranche has already lost a relatively large part of its value solely due to idiosyncratic risk and can only incur a limited change in its probability of default as a result.

The senior tranche, however, is left largely untouched given no major changes in the economic state. When the economic state deteriorates, the senior tranche is left unprotected as the junior tranches is already relatively exhausted within normal economic conditions. As a result, the senior tranches should experience a surge in its probability of default as a result of changes in the economic states. The junior tranches should of course also experience an increase in their probability of default as the economy deteriorates. However, the relative increase in probability of default is more limited as they already have a considerable probability of default mainly driven by idiosyncratic risk. The tail risk of changes in economic states are thus carried in a larger degree by senior tranches than junior tranches.

From the intuition derived above, I derive that the value of senior tranches are more exposed to systematic risk than the value of junior tranches.

Tranche seniority has an obvious impact on spreads besides carrying systematic risk. As described in section 2.2, flow of funds from the SPV are prioritized to the issued tranches according to their seniority. Hence, seniority also affects the real-world probability of default. A senior tranche has a lower probability of default than a junior tranche. However, this affect is accounted for by controlling for credit rating in the regression analyses. Any effect on spreads after credit ratings are controlled for is interpreted as a result of the changes in systematic risk due to seniority of the tranche.

Therefore, I formulate the hypothesis below.

> *H5: Seniority of the tranche has a positive impact on spreads for structured debt tranches when controlling for real-world probability of default*

4.3 Hypotheses overview

The hypotheses of this thesis are divided into two areas of interest. First, a hypothesis is formulated for examining the differences in spreads between structured and unstructured debt. The second set of hypotheses are derived to examine whether systematic risk is priced into structured debt. Table 1 below provides an overview.

Table 1: Overview of hypotheses

Effect tested	Hypothesis
Spread differences	*H1: Structured debt has significantly different required spreads than unstructured debt*
Systematic risk	*H2: Number of loans in the loan portfolio has a positive impact on spread for structured debt tranches*
	H3: The systematic risk of the loans in the portfolio has a positive coefficient to the required spreads for structured debt
	H4: The effect of systematic risk of the loans in the portfolio increases with the number of loans in the portfolio
	H5: Seniority of the tranche has a positive impact on spreads for structured debt tranches when controlling for real-world probability of default
Research question	*SQR1: Is there a significant difference in required launch spreads between CLOs and unstructured corporate bonds?*
	SQR2: Can the difference in required launch spreads between CLOs and unstructured corporate bonds partly be explained by perceived differences in systematic risk by investors?
	SQR3: "What is the sign and significance of the impact from each SPV characteristic found to drive systematic risk on the CLOs' launch spreads?"
	SQR4: "Does systematic risk have an impact on required spreads for CLO tranches?"

The next section presents the methodology applied in this thesis for testing the hypotheses above. It also provides a discussion of which challenges the methodology chosen imposes and which tools are used in an attempt to mitigate them.

5 Methodology

As discussed in the literature review in section 2, few papers have made an empirical analysis on spread differences between structured and unstructured debt. Within those papers, there seems to exist a consensus regarding the methodology applied for examining spread determinants. All articles included in the literature review use OLS regression analyses to test hypotheses, with spread as the endogenous variable and a common set of control factors. Only few authors have chosen different methodologies. For example, Ammer and Clinton (2004) used an event study to test the effect on credit ratings on spreads on structured debt while Pena-Cerezo, Rodriguez-Castellanos, and Ibanez-Hernandez (2019) used structural equation modeling (SEM) to test whether tranching offers higher yields in total than issuing unstructured debt.

To test the hypotheses derived in section 4 I follow the consensus methodology from previous literature and use OLS regression analyses. Section 5.1 describes the cross sectional regression analysis applied for all hypotheses. I describe the analysis approach for the spread difference hypothesis in section 5.3 and for the structured debt systematic risk hypotheses in section 5.3[17].

5.1 Cross-sectional regression analyses

The regression equation used in this thesis is defined as:

$$Y_i = b_h X_{i,h}^{'} + b_c X_{i,c}^{'} + \epsilon_i \, \forall \, i = 1, 2, ..., N \tag{18}$$

Y_i is a $(N \, x \, 1)$ vector of dependent variable observations. For this thesis, each element in the vector is thus an observation of the launch spread for an issued tranche. b_h $(H x 1)$ and b_c $(C x 1)$ are vectors where each element is an estimate from the regressors $X_{i,h}^{'}$ $(N \; x \; H)$ and $X_{i,c}^{'}(N \; x \; C)$ respectively.

N is the number of observations in the data set, H is the number of exogenous variables used to test the derived hypotheses and C is the number of control variables included in the analysis, inspired by previous literature within structured debt. The estimates are obtained using the OLS estimator below.

$$b = (X^{'}X)^{-1}X^{'}y \tag{19}$$

The OLS estimator can be shown to be the best linear unbiased estimator (BLUE) under the Gauss-Markov assumptions[18]. The estimates as written in equation 18 are unbiased and consistent

[17] See section 4.3 for an overview of the hypotheses.

[18] As defined in Woolridge (2012): Assumption 1: Linear in parameters. Assumption 2: Random sampling in the population model. Assumption 3: No perfect collinearity, meaning no exact linear relationships among the exogenous variables included in the model. Assumption 4: The error term has a zero conditional mean given any values of the independent variables. The assumption can be written as $E(u|x_1, x_2, ..., x_N) = 0$ where N is the number of exogenous variables. Assumption 5: Homoscedasticity. the error term u has the same variance across any values of the exogenous variables. The assumption can be written as $Var(u|x_1, x_2, ..., x_N) = Var(u)$.

if assumption 1 to 4 are satisfied (Woolridge, 2012).

The estimated variance of the parameters are unbiased and consistent if assumption 5 concerning homoscedasticity is satisfied. Finally, The assumption that the error terms are normally distributed is convenient to make in order to draw inference of the results. Specifically, when adding the normality assumption to assumption 4 and 5, I can write

$$u \sim N(0, \sigma^2) \tag{20}$$

Inference in OLS regression analyses are often conducted using the t-test for single coefficients and the F-test for a set of coefficients. Under assumption 1 to 6 described above, the t statistic follows a t distribution under H0 and the F ratio follows a F distribution[19]. Knowing the distribution of the estimators under H0 allows for inference of whether or not the chosen H0 can be rejected. However, all six mentioned assumptions need to hold in order to know the distribution.

One assumption often breached in empirical analyses is that the unobservable error term is normally distributed (Woolridge, 2012). In that case, the OLS estimators is not normally distributed and the test statistics' distributions are unknown. Fortunately, my inference can rely on the asymptotic properties of the t and F statistics. Specifically, the central limit theorem (CLT) can be used to conclude that the OLS estimators have asymptotic normality. Hence, the t statistic approximately follows a t distribution and the F statistic approximately follows a F distribution for large sample sizes.

Even for asymptotic inference, homoscedasticity is still required to make inference based on the t- and F statistics. The estimated variance of the OLS estimators will be biased and not valid for constructing t statistics and confidence intervals used for inference in the case of heteroscedasticity, .

Fortunately, the White heteroscedasticity consistent variance can be applied to estimate the variance, even when heteroscedasticity is present (White, 1980). The use of White's robust estimators is only valid in relatively large sample sizes. The estimate is given below.

$$Var(b_j) = \frac{\sum_{i=1}^{n} r_{ij}^2 * \hat{u}_i^2}{SSR_j^2} \tag{21}$$

Where r_{ij} is the i^{th} residual from regressing variable j against all other independent variables. Woolridge (2012) makes the case for always using the robust estimators when sample size is large. Thus, I use heteroscedasticity robust estimators for all inference in this thesis.

For my data set, the fact that a group of tranches come from the same deal almost certainly results in correlated error terms for observations within that deal, which results in an assumption breach.

[19]The t statistic follows a t distribution with N-k-1 degrees of freedom under H0, where k is the number of slope parameters $\frac{b-\beta}{se(b)} \sim t_{N-k-1}$. The F ratio, or F statistics follows a F distribution under H0 with a numerator degrees of freedom equal to the number of independent variables dropped in the restricted model denoted q and a denominator degrees of freedom equal to N-k-1 in the unrestricted model $\frac{(SSR_r - SSR_{ur})/q}{SSR_{ur}/(N-k-1)} \sim F_{q,N-k-1}$.

However, the issue can be solved by the use of robust variance estimators for specified clusters. I use a modification of the Huber-White robust estimators with specified clusters, which allows me to relax the independence of errors assumption while also allow for heteroskedasticity (Rogers, 1993; Williams, 2000). For each regression, I specify clusters according to the deal the tranche is in. The same approach were used by Cuchra (2004) and Buscaino et al. (2012) when dealing with structured debt tranches among others.

Carefully choosing the appropriate functional form of the included variables in equation (18) can be used to mitigate bias and enhance asymptotic normality for a given number of observations (Woolridge, 2012). In section 6.5 I discuss the functional form applied for the set of variables used in this thesis.

Finally, in order to reduce omitted variables bias I identify a set of independent variables suggested by previous literature and include it in my regressions. The variables are described in section 6.

5.2 Inference for spread differences between structured and unstructured debt

In this section, I elaborate on the methodology applied to test the first hypothesis concerning the spread differences between structured and unstructured debt[20]. Before diving into how the hypothesis is tested in this thesis, I examine some of the challenges that pooled cross section data presents in regression analyses.

The data set used for the first hypothesis can be divided into two groups; Structured debt and unstructured debt. When pooling the two groups of data into a single data set, differences in the intercept and slopes across independent variables needs to be taken into account and appropriately dealt with in the regression analyses. One way to address these differences is to allow the intercept and slope to deviate across groups. This is done by introducing a dummy variable which specifies which group the observation in question belongs to. The dummy variable can be written as below.

$$SD = \begin{cases} 1 & if\ structured \\ 0 & if\ unstructured \end{cases} \tag{22}$$

The dummy SD, which stands for structured debt, is equal to 1 if structured debt and 0 if unstructured. The dummy can be applied to allow for deviating intercepts and slopes between the two groups.

Pinto, Marques, and Megginson (2020) investigated a set of hypotheses quite similar to H1 of this thesis. They derived two hypotheses based on whether spreads deviated between structured and unstructured debt when controlling for a set of variables. In order to test these hypotheses, they

[20] See section 4.1.

created a dummy equal to 1 if the debt was structured and 0 if not. Based on the significance of the dummy's impact on spreads, they then made inferences regarding their hypotheses.

While the intuition is clear, one might be concerned that the difference in the pricing equation between structured and unstructured debt is not limited to the interaction term as implicitly assumed in Pinto, Marques, and Megginson (2020)'s analysis. It does not seem hard to imagine that some of the control variables have a different impact on spreads for structured debt compared to unstructured debt. The coefficient estimates in the model will likely be biased if interaction terms are excluded from the model when they shouldn't. As a result, I deviate from the model applied by Pinto, Marques, and Megginson (2020) and include interaction terms for a set of independent variables. The model used for testing H1 is defined below.

$$Spread_i = \alpha_0 + \beta_1 SD_i + \underbrace{\sum_{x=1}^{X} \beta_{x+1}\, SD_i\, RD_{x,i}}_{H1} + \sum_{y=1}^{Y} \beta_{X+y+1} RD_{y,i} + \sum_{z=1}^{Z} \beta_{1+X+Y+z}(C_{z,i} - \bar{C}_{z,i}) + \varepsilon_i \tag{23}$$

Where RD is rating dummies and C is control variables. Note that the control variables also include interaction terms with SD when deemed appropriate. As I am inferring on an intercept, I make all control variables equal to the deviation from its mean. The mean is denoted $\bar{C}$. Hence, when assessing differences in intercepts between structured and unstructured debt I assess it when the other control variables are set equal to their mean and not zero.

The set of coefficients in the third term on the right-hand side are called difference-in-difference estimators. Each coefficient measures the difference in average spreads between structured and unstructured debt between the rating in question and the benchmark rating. A difference-in-difference estimator can be written as

$$\delta = \left(\bar{Spread}_{AAA,S} - \bar{Spread}_{AAA,Un}\right) - \left(\bar{Spread}_{Benchmark,S} - \bar{Spread}_{Benchmark,Un}\right) \tag{24}$$

Where δ is the difference across ratings in the average difference in spreads between structured and unstructured debt and S and Un denotes structured and unstructured debt. In the example above, I have used AAA ratings against the benchmark rating.

H1 is tested based on the coefficient from the second and third terms on the right-hand side. If average spreads are identical for structured and unstructured debt with the same ratings all coefficients in the second and third terms on the right-hand side must not be significantly different from zero.

5.3 Inference for systematic risk in structured debt

As briefly touched upon in section 4.2 the systematic risk drivers derived in this thesis do not only drive systematic risk, but also real-world probability of default. Both effects have an intuitive implication on fair spreads. For testing the second set of hypotheses[21] the applied methodology needs to be capable of distinguishing between the two effects. Specifically, the hypotheses should only concern the effect of systematic risk.

In order to do so, I use cross-sectional regression analyses where I control for credit ratings when assessing the impact from the systematic risk drivers. While the methodologies of rating agencies as described in section 2.2 do not account for systematic risk, they have developed an arsenal of models and qualitative assessments to estimate the effects on the real-world probability of defaults. This includes the diversification effect from increasing the number of loans, as well as the different probability of defaults across obligor sectors. I argue that controlling for credit ratings is an adequate methodology for controlling for real-world probability of default. If the systematic risk drivers are shown to have a significant impact on spreads when real-world probability of default is accounted for, I infer the impact is caused by systematic risk.

In order to avoid omitted variable bias, I also include a set of control variables suggested by previous literature as described in section 6.

While the systematic risk drivers derived in section 4.2 are all expected to carry systematic risk, I do not consider them to be different proxies of the same effect on fair spreads. On the contrary, I argue that each systematic risk driver derived represents a distinct effect on systematic risk, which should all be taken into account by investors when pricing structured debt. The intuition derived from the applied model in section 4.2 has been a convenient tool to show why this is the case. For example, the derivations showed that the systematic risk of the loans in the portfolio has a distinct effect on systematic risk even when the number of loans are controlled for.

In sum, the equation used for testing the second set of hypotheses is defined as below.

$$Spread_i = \alpha_0 + \underbrace{\sum_{x=1}^{4} \beta_x SRD_{x,i}}_{H2,\, H3,\, H4,\, H5} + \sum_{y=1}^{Y} \beta_{4+y} RD_{y,i} + \sum_{z=1}^{Z} \beta_{4+Y+z} C_{z,i} + \varepsilon_i \tag{25}$$

Where SRD is systematic risk drivers, RD is rating dummies and C is other control variables. The second term on the right-hand side contains all independent variables and their coefficient estimates used to test hypothesis H2, H3, H4 and H5. The term is expanded below.

$$\sum_{x=1}^{4} SRD_{x,i} = \underset{H2}{\beta_1} N_i + \underset{H3}{\beta_2} L\beta_i + \underset{H4}{\beta_3} N_i\, L\beta_i + \underset{H5}{\beta_4} S_i \tag{26}$$

[21] See section 4.3.

Where N is the number of loans in the underlying portfolio and $L\beta$ is the estimated beta of the underlying portfolio. S is a variable measuring seniority. The exact definitions of the variables and how they are tested is elaborated in section 6 and section 7. The coefficients are related to the hypotheses by denoting the hypotheses below the coefficient in equation (26). The hypotheses H2, H3, H4 and H5 are tested using t tests on the coefficients in question across a set of regressions. Using terminology from the equations above, the hypotheses can be formulated as below.

$$H2 : \beta_1 > 0 \tag{27}$$

$$H3 : \beta_2 > 0 \tag{28}$$

$$H4 : \beta_3 > 0 \tag{29}$$

$$H5 : \beta_4 > 0 \tag{30}$$

In the next section, all variables applied in equation (23) and equation (25) in this thesis are described.

6 Data

This section provides an overview of the specific steps and choices taken from initial data screening to obtaining the final data set used in the empirical analyses. It also provides an overview of the variables used in my regression analyses and a short justification of why they are included.

6.1 Sample selection process

The primary data sets are constructed using Bloomberg, with supplementary data from Factset. In the following the data sources and selection process are elaborated.

6.1.1 Data sources

The most complete data set for structured debt tranches available to the author is provided by Bloomberg. The Bloomberg terminal allows for treating each tranche as an observation and provides a set of variables characterizing the tranche and its underlying collateral. Available variables include among others date of issue, principal size, spread at issue, amount of principal junior to the tranche (credit support), pricing and credit ratings across credit agencies. The initial data set from Bloomberg comprises 4,745 unique debt tranches across 589 deals issued in Western Europe from January 2010 to April 2020. The issue date variable is used to cross-match to time series for implied interest rate volatility, treasury yields and swap spreads.

Bloomberg is also used to obtain time series. Time series data from Bloomberg used in this thesis comprises daily observations for the implied volatility interest rate caps as well as interest rate swap spreads. The implied volatility is the only variable which has data limitations across time when considering the chosen time frame from January 2010 to April 2020. Specifically, the earliest obtainable observation for the time series is from October 2016. As a result, the cleaned data set only contains tranches issued from January 2017 to April 2020.

The data set for unstructured debt is also obtained through Bloomberg, where the chosen variables is a subset of the variables chosen for structured debt. Excluded variables in the unstructured data set are variables specific to structured debt. For example, the number of loans and geographic exposure in the collateral portfolio are intuitively not available for unstructured debt. The unstructured debt in this thesis are corporate bonds, also issued in Western Europe within the same time frame as for structured debt, i.e. January 2017 to April 2020.

I have used Factset solely to obtain time series data with daily observations for treasury yields. The data is also available through Bloomberg, but Factset are chosen due to Bloomberg's data limits. The date variable is used for cross-matching to the data sets from Bloomberg.

6.1.2 Sample selection steps

This subsection describes all steps taken in the selection process from search criteria in Bloomberg to cleaning of data in Stata. Each step is assigned a step number, making it easy to track each step and its implication on the number of observations in the data set in table 2. The process is stamped "1." for the steps taking for structured debt and "2." for unstructured debt, respectively.

The data set for structured debt is obtained by applying the following search criteria in Bloomberg's structured debt database: (1.1) The date of issue of the tranche has to be within the interval January 2010 – April 2020. (1.2) The data is limited to only include tranches which underlying collateral is comprised of corporate credit. Specifically, Bloomberg's CLO criteria is chosen which is defined as: "CLOs are backed by corporate credit in the form of leveraged loans. The leveraged loan market is regulated and loans cannot come to market with a leverage ratio of more than 6x... Additionally, each credit is analysed individually by hundreds of analysts at firms around the globe who seeks to hold the borrowing company to its covenants". (1.3) Finally, I only include deals where the originator is based in Western Europe[22].

For unstructured debt the sample selection is designed to create a data set aligned with the criteria for structured debt. Hence, the corporate bond has to be issued in Western Europe (2.1) between January 2017 and March 2020 (2.2). The bond is required to be denominated in EUR (2.3), has floating coupons (2.4) and priced at par (2.5). The composite rating variable as calculated by Bloomberg is also required to be available (2.6). A final requirement has been made in order to be able to retrieve the necessary data. The Bloomberg excel functions had difficulties extracting data for expired corporate bonds for some of the variables and Bloomberg representatives were not able to fix the error. As such, I have added the requirement that the corporate bonds had to be active at the day of data extraction (2.7)[23].

From Bloomberg, the data set for structured debt is narrowed down to 4,745 structured debt tranches. Further sample reduction is conducted in Stata. I list the sample steps conducted in Stata below: (1.4) I follow the example of Cuchra (2004) and Longstaff and Schwartz (1995) and only focus on floating rated issues. All observations with fixed rate coupons are removed. (1.5) I also remove all tranches of which the spread or pricing data is not available. (1.6) A number of critical variables in the pricing model depends on the denominated currency of the tranche payments. This include all variables for the yield curve factor, as well as implied volatility of the yield curve. 97.6% of the observations are denominated in EUR prior to this step. As a result, I limit the analyses to concern only EUR denominated currencies. (1.7) When assessing the development of ratings across years, it is noted that the data quality for credit ratings prior to 2017 is poor. Almost all tranches issued prior to 2017 are either not rated or have unavailable ratings. As credit rating is expected

[22] Andorra, Austria, Belgium, Channel Islands, Denmark, Faeroe Islands, Finland, France, Germany, Gibraltar, Greece, Greenland, Guernsey, Holy See, Iceland, Ireland, Isle of Man, Italy, Jersey, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Seborga, Spain, Sweden, Switzerland and the United Kingdom.

[23] 7th April 2020.

to carry high explanatory power in the analyses described in section 5, all tranches issued prior to 2017 are excluded from the data. (1.8) Finally, I remove observations which have non meaningful values in critical variables. The focus is on the credit support variable, which measures all principal junior to the tranche, as a percentage of the total principal of the deal. If the percentage is negative or above 100%, the observation is removed.

For the data set of unstructured debt, I imitate the same steps conducted for structured debt. All variables with unavailable spreads are excluded (2.8).

The steps above results in a data set where no tranche has currency risk. Currency risk is defined for this thesis as deviations between the denominated currency in the loans in the portfolio and the issued tranches in accordance with the definitions of Pinto, Marques, and Megginson (2020), Vink and Thibeault (2008) and Fabozzi and Vink (2012).

All steps described above and their implications on the number of observations in the data set are summarized in table 2 below.

Table 2: Overview of sample selection process

	Panel 1: Sample selection for structured debt	
1.1 - 1.3	CLOs issued 2010 - 2020 in Western Europe.	4,745
1.4	Only include floating rate issues.	3,622
1.5	Must be issued at par with available spreads.	1,601
1.6	Exclude tranches not denominated in EUR.	1,553
1.7	Exclude tranches issued prior to 2017.	1,017
1.8	Exclude not meaningful data.	1,013

	Panel 2: Sample selection for unstructured debt	
2.1	Exclude deals not in Western Europe.	1,097,472
2.2	Date of issue between January 2017 and March 2020.	245,305
2.3	Exclude bonds not denominated in EUR.	197,062
2.4	Only include floating rate issues.	5,026
2.5	Must be issued at par.	3,129
2.6	Exclude deals where the composite rating is not available.	3,129
2.7	Exclude non-active bonds.	2,824
2.8	Exclude bonds with unavailable spreads.	2,824
2.9	Available for extraction to*excel*[1].	311

Note: The Bloomberg terminal allows to track the selection steps of corporate bonds, but not for CLOs. Hence, the impacts from step 1.1 to 1.3 can't be assessed.

1: Some discrepancy exists between the size of the sample from the Bloomberg Terminal and the sample which is extracted to excel using BQL. The Bloomberg Help Desk could not solve the issue and concluded that some of the data simply were unavailable for BQL extraction, which is a function language undergoing development.

6.1.3 Descriptive statistics of samples

To provide the reader with an insight into the sample tranches a battery of descriptive statistics is provided in appendix 10.4. Some key observations are discussed in brief below. The reader is referred to the appendix for a more detailed overview.

It is noted that spreads seem to follow a highly right-skewed distribution across the years in the cleaned data set for both CLOs and corporate bonds. Average spreads and variances increase in 2019 and 2020 compared to 2017 and 2018 across asset types. Furthermore, CLOs seems to have more wide distributions with more "extreme" spread values than corporate bonds.

Another observation can be made regarding how the ratings are distributed across the two types of assets. For CLOs, a vast majority of the tranches are rated AAA which is not the case for corporate bonds. Meanwhile, a larger fraction is rated below investment grade[24] for corporate bonds than for CLO tranches.

Finally, it is noted that the data set of corporate bonds are represented across more countries than the data set for CLO tranches.

6.2 Launch spread

The dependent variable in the conducted regression analyses in this thesis is the launch spread. The launch spread is the basis points (bps) above a defined benchmark and acts as the price component from investors. The data set is limited to floating rate instruments with a spread above a defined benchmark, often including a floor. The chosen benchmark is often LIBOR or EURIBOR in EUR denominated issues. The data set does not contain information of the chosen benchmark. The launch spread has substantial variation in the cleaned data set for structured debt and ranges from 0 bps to 1,500 bps. For CLO tranches, the distribution is rightly skewed with a mean of 195 bps. The 95% fractile is 415 bps and issues above the 95% fractile are mainly non rated. For corporate bonds, the distribution is also right-skewed with a mean of 90 bps with a 95% fractile of 450 bps.

6.3 Systematic risk drivers

6.3.1 Number of loans in the collateral portfolio

I derive in section 4.2.2 that the number of loans in the portfolio drives the systematic risk of the issued CLO tranches. The number of loans at the day of issue is available from Bloomberg. The distribution is highly right-skewed with few extreme values and a mean of 604 loans. See appendix 10.4 for a more detailed overview.

6.3.2 Beta in the collateral portfolio

While the other systematic risk drivers used in this thesis are readily available from Bloomberg, the beta of the collateral portfolio is not available for structured debt. Instead, I have calculated the beta of the portfolios using the portfolios' relative industry weightings.

Specifically, I have used the portfolio's Moody's industry weightings. The intuition is that the industry of the loan obligor drives the loans' sensitivity towards changes in the economic state. For example, the utility sector is less exposed to changes in the economic state than luxury goods like automobiles. The industry weightings are thus deemed a relevant metric for the collateral portfolio's sensitivity towards changes in the economic state.

For a given CLO tranche, the industry weighting vector is multiplied to a vector of betas where each element represents a beta for a specific industry. The result is a beta estimate for the collateral

[24] Defined as below BBB.

portfolio, calculated as a weighted average of the industry betas. The calculation can be written as below.

$$L\beta_{i,t} = W_i \beta_t \tag{31}$$

Where W_i is a $(1\,x\,I)$ vector of industry weightings observed for tranche i and β_t is a $(I\,x\,1)$ vector of beta estimates for each industry. I is the number of industries considered. Please note how the vector of industry beta estimates β_t is made time dependent. Each industry dependent beta estimate is calculated as the slope of the linear regression line between the chosen industry index and the chosen market index. The regression is conducted based on two years of historical pricing data from the day of the CLO tranche's issue. Hence, the beta estimates in the beta vector are a function of the time of issue. The intuition for making the industry beta estimates time dependent is that the systematic risk perceived from the investors is assumed to depend on the industries' historical sensitivity to the market indices at the time of issue of the CLO tranche.

The chosen market indices is the S&P 350 Europe Index as this thesis analyses European CLO tranches which collateral portfolios are heavily weighted towards European countries. Likewise, the chosen industry indices are GICS indices based on the S&P 350 Europe Index[25].

The gathering of weighting data for each tranche has been very extensive work, as Bloomberg provides no tools for extracting the industry weightings into excel or similar[26]. Instead, the data is only available on the Bloomberg Terminal. The weightings used for this thesis are thus hard coded numbers I have manually gathered from the terminal. In the interest of time, I have limited my extraction of weightings to the 15 most heavily weighted industries for each tranche. Hence, the lowest weighted industries for a tranche are not extracted[27]. The terminal only provides industry weightings based on Moody's industry definitions[28]. Therefore, I have "translated" the industry definitions of Moody's to the industry definitions of GICS used for the indices to calculate beta estimates. Please refer to appendix 10.3 for an overview of the indices used and the applied relations between the industry definitions.

On average, Healthcare is the highest weighted industry with an average weighting of 15.4%. Other heavily represented industries on average are Professional Services and Capital Goods with average weightings of 10.8% and 8.9% respectively. Less heavily weighted industries are Energy, Utilities and Transportation with an average weighting of 0.1%, 0.2% and 0.7% respectively.

The beta variable for the CLO tranches has a mean of 0.99 and a standard deviation of 0.07. The

[25] The GICS classifications provide different level of granularity for the industry definition, which is divided in levels. For example, level 2 industries are subsets of level 1 industries and so on. For this thesis, only level 1 and level 2 industry indices are used.

[26] I have had discussions lasting weeks with Bloomberg representatives of how I could extract this data, before it was concluded that it was only available in the terminal.

[27] The industry weightings used are calculated as the principal for the industry as a percentage of the sum of principal from the 15 highest weighted industries for that CLO tranche.

[28] For a few CLOs, industry weightings based on S&P's industry definitions are also available. However, I have chosen to be consistent in my use of Moody's industry definitions as they provide most data.

distribution has few, large values around 1.3 while the rest of the distribution seems bell shaped around approximately 1.

6.3.3 Seniority

Previous literature has suggested that the carried systematic risk of the tranche is dependent on the tranche's seniority. I arrived at the same result in the discussion in section 4.2.4. In this thesis, seniority is given by Bloomberg's credit support variable. The credit support variable is the principal of all tranches junior to the tranche in question as a percentage of the principal of the total deal. The higher the credit support, the more protected is the tranche from defaults in the collateral portfolio. An overview of the variable's distribution across ratings is provided in appendix 10.4.

6.4 Control variables

All included control variables in my regression models are suggested in previous studies within structured and unstructured debt. Below, I briefly describe the included control variables and provide a short justification for their inclusion in my regression models.

4.2.3 Yield curve at issue

The yield curve is a common factor controlled for in the bond pricing literature (Cuchra, 2004). Litterman (1991) suggested that most of the return variation for fixed-income securities can be explained by the level, slope and curvature of the yield curve at the time of pricing. Specifically, the majority of the return variation is explained by level and slope alone according to Chen (1993) and Litterman (1991). I adopt the methodology of Cuchra (2004) and only include proxies for the level and slope of the yield curve at the time of pricing. Hence, a proxy for the curvature of the yield curve is not included.

Duffee (1998) measures the level of the yield curve using the 3-month Treasury bond yield while Cuchra (2004) used 10-year Treasury bond yields. Specifically, Cuchra (2004) used a synthetic Eurobond for EUR denominated securities. I follow the example of Cuchra (2004) and use 10-year government bond yields. In the Euro Area, public debt management is decentralized and the responsibility is assigned to each national agency. Hence, there is no single publicly traded government bond for the EUR yield curve. I use a synthetic EUR denominated government bond created by Factset. At each point in time, its 10-year yield is calculated as the minimum of the 10-year yield for the German and French government bonds.

The slope of the yield curve is proxied by the differences in yield between a 30-year and 3-month Treasury bond by Duffee (1998). Cuchra (2004) used the differences in swap yields between a 10-year and 2-year swap in the currency of issue to proxy the slope of the yield curve. I follow the methodology of Cuchra (2004) and use the difference between the swap yields for swaps with 2-years and 10-years tenor respectively. The swap market is considered to be more liquid across tenors and larger in size compared to the Treasury market (Brobst, 2018). The tenors are chosen based on the expected lifetime of the tranches. The maximum of the weighted average lifetime of the tranches in the cleaned data set is 9.5 years. As a result, I find a tenor of 10 years adequate. The swap yield is the rate in the fixed leg in the swap agreement. The swaps used have EUR denominated fixed and floating legs, where the floating leg follows a 6m EURIBOR. Daily observations are available from January 2000 to March 2020. The difference between swap yields has an intuitive interpretation. For example, for a yield curve with an upward slope the swap yield for the 10-year tenor is larger than the swap yield for the 2-year tenor. Hence, the variable is negative. The absolute value of the variable increases as the slope of the yield curve increases.

6.4.1 Value of embedded options

Option features and repayment options in particular are often included in structured debt (Cuchra, 2004). An embedded repayment option in the issue gives the option to accelerate repayments of the principal at the obligor's discretion. The value of the embedded option influences the spread and should thus be accounted for in the regression models. While all included CLOs in my data set has callable option features, the callability's perceived value from the investors can differ. I follow the methodology of Cuchra (2004) where the embedded option factor is proxied using implied interest rate volatility of a 5-year interest rate cap and the estimated weighted average life of the issue, respectively. Hayre and Thompson Jr (2001) finds early repayments of floating rate issues to be insensitive to interest rates. However, I do control for differences in option values due to the perceived interest rate volatility at the date of issue. The option value is expected to be positively related to the volatility of the interest rate as an increase in the volatility increases the callability's value for the obligor. I use the implied volatility from a 5-year EUR denominated interest rate cap at the date of issue. The data set contains daily observations for the implied volatility from October 2016 to March 2020.

The options' effects on the lifetime of the issue is expressed through the issue's weighted average life (WAL). The WAL is the expected lifetime of the tranche and is calculated by the arranger of the issue at launch. The calculation incorporates effects of embedded options in the estimate. The lower WAL, the higher probability of the embedded repayment options to become in the money and thus the higher option value. Furthermore, previous literature agrees that debt with longer expected maturities tend to be riskier than debt with lower expected maturities (Pinto, Marques, and Megginson, 2020).

Option value can also be partly explained by other variables used in the regression analysis. Previous literature suggests option value is correlated with macroeconomic conditions at the time of issue (Duffee, 1998). The yield curve at issue can act as a proxy for the economic condition and can thus be correlated with the option value. Finally, Hayre and Thompson Jr (2001) finds that repayment in

European structured debt is related to the country of origin of the collateral assets. The variable for the country of collateral thus might also partly explain the value of embedded options. Geographic dummies are also included in my regression models.

6.4.2 Cash-flow structuring

In this section, I briefly elaborate on included control variables which are a result of the cash flow structuring of the tranche.

Previous literature includes the principal of the tranche as a common control variable in debt pricing models (Pinto, Marques, and Megginson, 2020; Cuchra, 2004). The principal can serve as a proxy for the liquidity of the issue on the secondary market. Even if the security is not registered on an exchange, the tranche can be traded through a market maker. Large issues are more likely to be of interest for market makers and thus be more liquid in the secondary markets. As a result, the investor might require a haircut on small issues as the issue is unlikely to be sold in the secondary market (Cuchra, 2004). The principal is also suggested to be a proxy for the degree of diversification as larger issues are created by pooling a larger set of loans (Pena-Cerezo, Rodriguez-Castellanos, and Ibanez-Hernandez, 2019). In sum, I expect the principal to have a negative impact on spreads as found by Buscaino et al. (2012).

I also include the number of tranches issued for the deal in question as Weber and Franke (2009) found a negative relationship between the number of issued tranches and the yields of the tranches.

6.4.3 Credit ratings

In my data set, credit ratings are available for the three large rating agencies, S&P, Moody's and Fitch. Bloomberg also gives access to a composite rating.

The composite rating is calculated based on the ratings from Moody's, S&P, Fitch and DBRS. The composite rating is derived by taking the average of the ratings from the four mentioned rating agencies. Each rating agency is evenly weighted. If the average is between two ratings, it is rounded "down" to the lower rating. The composite rating variable follows the scaling rating terminology of S&P as described in section 2.2.

When using the composite rating in my regression analyses a linear relation between the composite rating and the spread of the tranche can't be reasonably assumed. I therefore create a dummy variable for each possible credit rating for the composite rating variable. All ratings below rating b are used as the benchmark.

Cuchra (2004) argue that the composite rating variable should carry additional information to single credit ratings, as it is a combination of multiple ratings. I suggest the composite rating calculation could result in information loss as it averages out deviations in credit ratings. For example, if a rating agency chooses to deviate from the market consensus for a given tranche I suggest the deviating rating is likely to be backed by proprietary or in depth information to justify such a deviation. The deviation from market consensus would, however, not be captured by the composite rating variable. Hence, the averaging out of rating can result in loss of information.

Cuchra (2004) finds that S&P's ratings have the largest explanatory power for structured debt spreads, followed by Moody's and then finally Fitch. The evenly weighted average calculation of the composite rating could thus be inferior to a prioritized weighting system, according to the explanatory power each rating agency has. I suggest an alternative credit rating variable called "adjusted rating". "Adjusted rating" is also calculated based on the ratings of S&P, Moody's and Fitch. However, in the calculation of "adjusted rating" I avoid any averages or rounding offs of credit ratings. Instead, the variable is equal to only one of the available credit ratings. The "adjusted rating" variable prioritizes the rating agencies according to their explanatory power found by Cuchra (2004) and is thus equal to the rating from S&P, if available. If not, it is equal to the rating of Moody's and finally the rating from Fitch, if the two others ratings are unavailable. The calculation of the variable allows for a prioritization of the ratings according to their explanatory power. It also avoids any averaging out of deviating credit ratings. It turns out that the adjusted rating variable has ratings available to more tranches than the composite rating in the cleaned data set.

Adjusted ratings are applied to assess the robustness of my findings of different calculations of the credit ratings. The adjusted ratings are only available for the CLOs and not for the corporate bonds. Hence, the adjusted rating variable is only used for the set of regressions based solely on the CLO data set.

6.4.4 Time control variables

For a final set of control variables, I include year and month dummy variables defined by the date of issue of the tranche. The time control factors are included to capture seasonal and year dependent market effects, which are not captured by the other time dependent variables.

6.5 Functional form specifications

Whether I assume a linear or non-linear relation between launch spreads and the independent variables has important implications for the possibility of inferring on the results from the regression analyses and create unbiased estimates. For example, if the relation is assumed linear in my analyses when the true relation is non-linear it will result in biased estimates.

Some non-linear relations between the spreads and the independent variables included in this thesis have in fact been suggested by previous literature. For example, Pinto, Marques, and Megginson (2020) and Sorge and Gadanecz (2008) found a non-linear relation between spreads and maturity.

In my regression analyses I include both a set of regressions which assumes a linear relationship and a set of regressions which assumes a non-linear relationship. For each of the two sets of regressions I then asses how well they capture the true relation between spreads and the independent variables using the RESET test as proposed by Ramsey (1969). This gives me a hint to what set of regressions are the most appropriate to infer from.

The non-linear relationship between spreads and the included independent variables are made by taking the natural logarithm of the launch spreads and using that as the dependent variable in my regression analyses.

Another possible advantage of using the natural logarithm of spreads as the dependent variable is that the distribution of the dependent variable then resembles the normal distribution to a higher degree. Unadjusted launch spreads have a highly right-skewed distribution with the majority of spreads having relatively low values while also having few observations with relatively large, extreme values. The distribution of the natural logarithm of spreads are on the contrary more bell shaped and resembles more the normal distribution. Recall from section 5.1 that one of the assumptions used in cross-sectional regression analyses is normally distributed residuals for any set of values for the independent variables. As the residuals are a linear function of the dependent variable for a given set of values for the independent variables, it follows the same distribution as the dependent variable. Making the distribution of the dependent variable closer to the normal distribution thus also makes the distribution of the conditional residuals closer to the normal distribution.

One might argue that whether or not the residuals are normally distributed is not problematic, as I can resolve to the asymptotic properties of the OLS estimators for inference if the residuals are not normally distributed. However, when holding the number of observations fixed at some value the asymptotic behavior of the OLS estimators are improved as the distribution of the residuals to a larger degree resembles the normal distribution (Woolridge, 2012). Using the natural logarithm of spreads as the dependent variable might then improve the appropriateness of inferring using t and F tests when the residuals are not normally distributed.

The next section presents the empirical findings of this thesis and an overview of rejected and accepted hypotheses.

7 Empirical findings

This section provides the empirical findings of the undertaken studies. First, the conducted regression analyses and their results are presented. I assess the assumptions applied in OLS regression analyses and the robustness of the findings. Second a summary of the findings is given. The analyses are conducted using Stata and the code from the applied DO files are attached in Appendix 10.7.

7.1 Regression analyses

Table 3, 4 and 5 presents the results of the undertaken regression analyses. The regression analyses are first divided into two groups, according to the study conducted. The first group of regressions are conducted for testing H1.

The regressions concerning H1 are divided into two groups, according to the dependent variable used. Specifically, I use two dependent variables in my analyses as discussed in section 6.5. The first being launch spreads as described in section 6.2 while the second being the natural logarithm of the launch spreads. The point of conducting regressions based on the two different dependent variables is to assess if the fit of the model can be improved by allowing non-linear relations between spreads and the independent variables using the natural logarithm of spreads.

The second group of regressions are used to test the remaining hypotheses for this thesis, which only concerns the spreads of CLOs. The regressions for these hypotheses are divided into four groups, again according to which dependent variable is used and which variable is used to derive rating dummies. Again, I use two types of dependent variables; Spreads at launch and the natural logarithm of spreads at launch. I also use two different sets of ratings. As described in section 6.4.3 the ratings are calculated using either Bloomberg's composite rating or the calculated adjusted ratings for this thesis. By sorting the regression analyses according to these methodologies, four groups of analyses are created as shown in table 4 and 5. For example, the first group of regressions use launch spreads as the dependent variable and composite ratings to account for credit ratings. The second group also uses composite credit ratings but the natural logarithm of spreads as the dependent variable and so on.

Each set of regressions used to test H1 comprise five regression analyses. In regression one and two variables are gradually added in the model. The variables in regression one is thus a subset of the variables in regression two. Regression three excludes geographic dummies due to multicollinearity issues with the variables of interest and includes instead interaction terms between the structured dummy[29] and rating dummies. Finally, regression four and five adds additional interaction terms to the model between the structured dummy and other independent variables. The details can be seen in table 3.

[29] See section 5.2.

For each set of regressions used to test the hypotheses which only concerns structured debt, six regression analyses are conducted. Regression one through three are gradually controlling for more factors. For example, regression number two has all independent variables used in regression one, plus geography dummies for the country of the SPV as well as the geography of the collateral portfolio's loan obligors. Regression four excludes the interaction term between number of loans in the collateral portfolio and beta in order to reduce severe multicollinearity issues found for the interaction term and the variable for number of loans. Finally, regression five and six includes interaction terms between beta and rating dummies and sector weightings in the collateral portfolio, respectively. All regressions are conducted to analyse the effects of systematic risk drivers as derived in section 4.2 on launch spreads for European CLOs.

The assumptions applied in each regression have been investigated and the results are presented in appendix 10.6. All analyses suffer, as expected, from heteroscedasticity as shown by using the Breusch-Pagan test (Breusch and Pagan, 1979). The robust standard errors proposed by White (1980) are applied to mitigate the issue. The RESET test, proposed by Ramsey (1969), is applied to test for any non-linear combinations of covariates, not accounted for by my models. Potential misspecifications in my model are furthermore assessed by plotting the predicted values against the residuals for each regression as presented in appendix 10.5. Problems with multicollinearity are assessed by calculating the variance inflation factor (VIF) and the normality of the residuals is evaluated using the normality test proposed by Royston (1992) and Royston (1983). For all applied regressions, the set of tests described above suggest severe problems with the OLS assumptions. In particular, issues with multicollinearity, misspecifications and heteroscedasticity are found for most of the analyses conducted. For a set of regressions, normality in the residuals is also rejected.

Some assumption breaches can be partly mitigated. For example, I can rely on the asymptotic properties of the distribution of the estimated coefficients when the residuals are not normally distributed. I can also apply robust standard error estimates for the coefficients when I face heteroscedasticity. However, a set of assumption breaches are not so easily mitigated. For a set of regression analyses conducted in this thesis misspecification of the model is identified by the RESET test, implying biased estimates for all coefficients in the models. I try to reduce the functional form misspecification and test the robustness of my results by applying a set of different models and variables in my analyses.

Multicollinearity issues are identified for most of the regressions. While multicollinearity is not a violation of the OLS assumptions, it heavily reduces the power of the regression models. In particular, VIF is very large for the regressions for solely CLOs when the interaction term between the number of loans in the collateral portfolio and beta is included. In the regressions below, I try to improve the statistical power of the model by excluding the interaction term in some of the regression analyses.

The large set of regression analyses is conducted to test the robustness of my findings. It is also conducted in an attempt to improve the statistical power of my analyses by inferring on the regressions which performs best in the set of assumption tests conducted. For example, normality of residuals, the degree of functional form misspecifications and VIFs are found to vary greatly across the set of regressions. See Appendix 10.6 for an overview of the regressions' performance in the different tests conducted.

The breaches of assumptions and issues with multicollinearity are taken into account in my final assessment of the robustness of my findings where I also discuss potential issues with endogeneity.

The results from the regression analyses conducted are presented in the tables below.

Table 3: Estimation results - Spread difference between CLOs and corp. bonds

	Launch spreads					Natural logarithm of launch spreads				
	1.1.1	1.1.2	1.1.3	1.1.4	1.1.5	1.2.1	1.2.2	1.2.3	1.2.4	1.2.5
SD	143.3**	-22.1	-462.4**	-460.5**	-456.7**	0.9**	0.1	-2.2**	-2.2**	-2.2**
	(9.9)	(33.0)	(40.5)	(42.5)	(48.5)	(0.1)	(0.2)	(0.2)	(0.3)	(0.3)
SD_AAA			511.9**	548.9**	552.6**			3.3**	3.4**	3.4**
			(42.0)	(45.1)	(50.8)			(0.5)	(0.5)	(0.5)
SD_AA			588.7**	576.7**	578.7**			3.5**	3.4**	3.5**
			(40.5)	(42.0)	(47.7)			(0.3)	(0.3)	(0.3)
SD_A			612.8**	598.0**	592.9**			3.2**	3.1**	3.1**
			(40.7)	(42.5)	(48.5)			(0.2)	(0.3)	(0.3)
SD_BBB			688.0**	665.3**	657.6**			3.3**	3.2**	3.2**
			(41.2)	(43.0)	(49.0)			(0.2)	(0.3)	(0.3)
SD_BB			776.6**	789.9**	784.3**			2.8**	2.8**	2.9**
			(75.2)	(76.5)	(80.4)			(0.4)	(0.4)	(0.5)
SD_B			660.1**	640.9**	630.6**			2.2**	2.1**	2.1**
			(126.9)	(124.7)	(123.7)			(0.4)	(0.4)	(0.4)
Control-*Dummies*[1]	T+Y+ W+P+R	T+ G+ Y+W+ P+R	T+Y+ W+P+R	T+Y+ W+P+R	T+Y+ W+P+R	T+Y+ W+P+R	T + G+ Y+W+ P+R	T+Y+ W+P+R	T+Y+ W+P+R	T+Y+ W+P+R
Control-SD-*Dummies*[1]				W+P	W+P+Y				W+P	W+P+Y
No. Obs	590	590	590	590	590	479	479	479	479	479
R^2	0.775	0.853	0.868	0.882	0.888	0.718	0.805	0.798	0.809	0.814
Adj. R^2	0.765	0.842	0.860	0.874	0.880	0.702	0.786	0.784	0.794	0.799

Note: *Significant at 5%, **at 1%. Robust White std. errors are reported in brackets.

1: T: Time dummies, G: Geography dummies, R: Rating dummies, P: Principal, W: Weighted Average Lifetime Y: Yield proxies

Table 4: Estimation results - Systematic risk, composite ratings

	Launch spreads						Natural logarithm of launch spreads					
	2.1.1	2.1.2	2.1.3	2.1.4	2.1.5	2.1.6	2.2.1	2.2.2	2.2.3	2.2.4	2.2.5	2.2.6
N	-0.7	-0.9	0.6	-0.0	-0.0	-0.1	-0.0	-0.0	-0.0	0.0	0.0	0.0
	(0.8)	(0.7)	(1.0)	(0.1)	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
β	-125.3	-168.8	194.0	59.0	263**	44.7	-0.6	-0.8	0.3	0.3	0.5*	0.8
	(170.7)	(177.6)	(241.6)	(48.9)	(61.5)	(163.8)	(0.9)	(1.0)	(1.6)	(0.3)	(0.3)	(1.0)
$N\beta$	0.7	0.9	-0.6				0.0	0.0	0.0			
	(0.8)	(0.8)	(1.1)				(0.0)	(0.0)	(0.0)			
CS	5.1*	4.9*	4.4*	4.1*	4.7*	3.6	0.0	0.0	0.0	0.0	0.0	-0.0
	(2.4)	(2.4)	(2.2)	(2.2)	(2.2)	(2.5)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
β_AAA					-350**						-0.4*	
					(61.0)						(0.2)	
β_AA					-282**						-0.3	
					(55.8)						(0.2)	
β_A					-156**						0.1	
					(43.0)						(0.2)	
Control-*Dummies*[1]	R+N+W+Y	G+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+S+R+N+W+Y	R+N+W+Y	G+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+S+R+N+W+Y
No. Obs	206	206	206	206	206	206	206	206	206	206	206	206
R^2	0.955	0.955	0.967	0.967	0.972	0.969	0.949	0.950	0.963	0.963	0.964	0.969
Adj. R^2	0.951	0.951	0.961	0.961	0.967	0.962	0.945	0.945	0.956	0.956	0.956	0.962

Note: *Significant at 5%, **at 1% (Systematic risk are one-sided tests. Else, two sided). Robust White std. errors are reported in brackets.

1: T: Time dummies, G: Geography dummies, S: Sector dummies, R: Rating dummies, P: Principal, W: WAL, Y: Yield proxies, N: # bonds

Table 5: Estimation results - Systematic risk, adjusted ratings

	Launch spreads						Natural logarithm of launch spreads					
	2.3.1	2.3.2	2.3.3	2.3.4	2.3.5	2.3.6	2.4.1	2.4.2	2.4.3	2.4.4	2.4.5	2.4.6
N	-1.1	-1.2	0.7	-0.0	-0.0	-0.3	-0.0	-0.0	0.0	0.0	0.0	-0.0
	(0.9)	(0.8)	(1.0)	(0.1)	(0.1)	(0.1)	(0.0)	(.0)	(0.0)	(0.0)	(0.0)	(0.0)
β	-215.5	-226.2	211.4	53.5	262**	-217.3	-1.2	-1.1	0.4	0.3	0.5	-1.0
	(196.4)	(191.0)	(246.8)	(53.1)	(62.4)	(119.5)	(1.1)	(1.1)	(1.6)	(0.3)	(0.3)	(0.7)
$N\beta$	1.2	1.2	-0.7				0.0	0.0	-0.0			
	(0.9)	(0.8)	(1.1)				(0.0)	(0.0)	(0.0)			
CS	3.9	3.8	4.3*	4.2*	4.8*	4.6*	0.0	0.0	0.0	0.0	0.0	0.0
	(2.7)	(2.7)	(2.2)	(2.2)	(2.2)	(2.4)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
β_AAA					-361**						-0.5*	
					(60.0)						(0.2)	
β_AA					-284**						-0.3	
					(55.3)						(0.2)	
β_A					-159**						0.1	
					(43.4)						(0.2)	
Control-*Dummies*[1]	R+N+W+Y	G+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+S+R+N+W+Y	R+N+W+Y	G+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+R+N+W+Y	G+T+S+R+N+W+Y
No. Obs	209	209	209	209	209	209	209	209	209	209	209	209
R^2	0.952	0.952	0.963	0.963	0.968	0.967	0.944	0.944	0.956	0.956	0.956	0.965
Adj. R^2	0.948	0.947	0.956	0.956	0.962	0.959	0.939	0.939	0.948	0.948	0.948	0.956

Note: *Significant at 5%, **at 1% (Systematic risk are one-sided tests. Else, two sided). Robust White std. errors are reported in brackets.

1: T: Time dummies, G: Geography dummies, S: Sector dummies, R: Rating dummies, P: Principal, W: WAL, Y: Yield proxies, N: # bonds

7.1.1 Differences between structured and unstructured debt

The first hypothesis tested in this thesis concerns whether the required launch spreads differ between structured and unstructured debt. Specifically, I test the differences in launch spreads between CLOs and corporate bonds when controlling for a set of common control variables.

For each regression, I test the hypothesis that the required launch spread differ between structured and unstructured debt. The spreads between the two types of assets are found to be significantly different across 8 of the 10 regression analyses conducted for any reasonable chosen significance level. When including interaction terms between the structured dummy and the rating dummies, differences in spread differences between ratings are also found to be significant across all included interaction terms.

Deviations exist across the conducted analyses regarding the relative sizes of spread differences across ratings. Specifically, for the analyses using the natural logarithm of spreads as the dependent variable, junior debt has the lowest increase in required spreads from unstructured to structured debt while senior debt has the largest. The opposite seems true when using spreads as the dependent variable.

Across all conducted regressions, severe issues with normality and heteroscedasticity are found. These are argued to be mitigated by using White's robust estimators of standard errors as well as the asymptotic properties of the OLS estimators' distribution as argued in section 5.

When examining the graphed residuals in appendix 10.5 there seems to be a non-linear relationship between spreads and the included independent variables not captured by the analyses using spreads as the dependent variable. This is also evident from the conducted RESET tests, where functional form misspecifications are found for all regressions using spreads as the dependent variable.

This is however not the case for the regressions using the natural logarithm as the dependent variable. When examining the graphed residuals, severe issues do not seem to be the case. The observation is confirmed when assessing the RESET tests, where functional form misspecifications are less significant for all regressions and insignificant for two of the regressions[30]. When inferring on the impact from ratings, I thus use the analyses with the natural logarithm of launch spreads as the dependent variable.

In sum, I find evidence to accept the hypothesis that required spreads differ between CLOs and corporate bonds (H1). For rating BB to AAA, required spreads are higher for CLOs than for corporate bonds. Only for B rated debt and below, the required spreads are found to be larger for corporate bonds than for CLOs.

My results are similar to the findings of Pinto, Marques, and Megginson (2020) across most of the ratings. Specifically, they found required spreads to be higher for CDOs than for corporate bonds. Their finding resembles my results for debt with ratings in the interval AAA to BB. Pinto,

[30] Using a significance level of 1%.

Marques, and Megginson (2020) explained the higher required spreads for structured debt with investors taking the larger sensitivity towards systematic risk in structured debt into account. In order to test whether this is the case, I analyze the systematic risk's impact on required spreads for structured debt in the following sections. I work from the intuition that if the differences in spreads identified in this section is caused by systematic risk, systematic risk should have a significant effect on spreads required for CLO tranches.

7.1.2 Number of loans in the collateral portfolio

The first systematic driver derived in this thesis is the number of loans in the collateral portfolio[31]. For each regression, I test the hypothesis that the number of loans should have a positive impact on the launch spreads. Across all 24 conducted regression analyses in this thesis, the hypothesis that the loan number has a positive impact is nowhere near accepted. As evident in table 4 and 5, many of the estimates are also negative. No evidence is thus found that investors price the impact on systematic risk from the number of loans into the launch spreads. The conclusion is the same across all conducted regressions and does not change when I exclude the interaction term between the beta and number of loans in order to reduce the issue of multicollinearity. I thus do not accept hypothesis H2 that loan numbers have a positive impact on spreads caused by the systematic risk it carries.

7.1.3 Beta in the collateral portfolio

To the best of my knowledge, this thesis is the first to analyze the impact on CLO spreads from beta from the collateral portfolio. As described in section 6.3.2, the beta of the collateral portfolio is calculated based on the industry weights of the portfolio at issue. In section 4.2.3, I derived that beta is expected to have a positive impact on the required spreads at issue which was formulated in hypothesis H3. The hypothesis is tested across 24 regressions.

The beta is not found to have a statistically significant positive impact on spreads in any regressions, when difference in beta's impact across credit ratings is not accounted for. For the regression analyses with relatively few control variables, the estimated impact is even negative.

For each group of analyses, I provide a regression which includes a set of interaction terms between beta and credit ratings. An interesting observation is that for all regressions which include interaction terms the impact from beta is increasingly positive for more junior tranches. For the regressions using spreads as the dependent variable, betas impact is even found to be negative for CLOs rated AAA or AA. No evidence is found that beta has a significant positive impact on spreads for senior tranches (AAA or AA) using a significance level of 1%. Beta is only found in one regression to have a significant positive impact on AAA rated tranches if a 5% significance level F-test is used.

[31] See section 4.2.2.

I conclude that beta is not found to have a robust significant positive impact on spreads and does not accept hypothesis H3. The conclusion is consistent across credit ratings.

I also test H4[32] by examining the impact on spreads from the interaction term between beta and the number of loans. The impact is estimated across 12 regressions and not found to be significantly positive for any reasonable significance levels across all regressions. I thus do not find evidence to accept H4 either.

7.1.4 Seniority

In section 4.2.4 I derived that seniority carries systematic risk as the most senior tranche carries most of the tail risk when the economy deteriorates.

As described in section 2.2 rating agencies only account for real-world probability of default and do not take systematic risk into account. This distinction has important implications for how I can test for the systematic risk carried by seniority. When estimating the impact on seniority as a systematic risk driver, it is necessary to control for the real-world probability of default which are also defined by the tranche's seniority. I use credit ratings to control for the real-world probability of default and infer that any impact from seniority when credit ratings are controlled for is due to systematic risk. The credit support variable as described in section 6.3.3 is used as a proxy for seniority.

I find that the estimated coefficients are positive for almost all regressions. The statistical significance is found, though, to depend on which group of analyses the regression belongs to. For the group of analyses which uses the natural logarithm of launch spreads as the dependent variable, the impact is not significant for any regressions. However, for the group of analyses which uses launch spreads as the dependent variable, the impact is found to be significantly positive for a series of the regressions if a significance level of 5% or 2.5% is used. However, if a significance level of 1% is applied, the impact is not found to be statistically significant for any regression.

The choice of whether to accept H5 or not depends on the choice of which of the different regressions are used for inference. When making this choice, I rely on the tests applied to investigate the statistical power of the regressions and to what extent assumptions are breached[33]. It turns out that the choice of dependent variable has an impact on the normality of residuals and whether the RESET test finds evidence for functional form misspecificactions. Specifically, the regressions using launch spreads as the dependent variable fail to reject normality for the residuals, while normality is rejected for regressions using the natural logarithm of launch spreads as the dependent variable. However, the RESET test does not find functional form misspecification for a set of regressions using the natural logarithm as the dependent variable, while it is found for all regressions using launch spreads as the dependent variable.

The choice of which set of regressions to infer on is thus a trade-off between the normality of residuals and functional form misspecification. While the asymptotic properties of the OLS estimators allow

[32]See section 4.2.3.

[33]See appendix 10.6

for inference even when the normality assumption is breached, functional form misspecifications result in biased estimates no matter the number of observations. I thus choose to infer based on the set of regressions using the natural logarithm of launch spreads as the dependent variable, to reduce the impact of functional form misspecification. In this set of regressions, the impact from credit support is statistically insignificant across all regressions. I therefore do not find evidence to accept H5. However, it is noteworthy that the estimates are almost solely positive, in alignment with what to expect if the variable should carry systematic risk.

7.2 Summary of empirical findings and hypotheses

In section 4.1 I used a set of deviation drivers identified in previous literature to formulate the hypothesis (H1) that these factors in conjunction cause a difference in required spreads for structured and unstructured debt. H1 states that the required spreads are significantly different between structured and unstructured debt. It does not make any requirements regarding the sign of the difference. In this thesis, the difference is tested between CLOs and corporate bonds.

Using a joint data set for CLOs and corporate bonds, I find evidence that the required spreads are different between CLOs and corporate bonds. The finding is consistent across regression analyses. Furthermore, I find that the differences are dependent on ratings. For debt rated from AAA to BB, required spreads are found to be higher for CLOs than for corporate bonds, whereas the opposite is found for debt rated B and below. H1 is thus accepted.

A comparable analysis was conducted by Pinto, Marques, and Megginson (2020), which arrived at a similar result when comparing spreads for CDOs and corporate bonds. They inferred that the larger required spreads observed for CDOs were due to investors requiring a risk premia for the larger systematic risk carried by structured debt compared to unstructured debt. I argue that it is difficult assigning the observed difference in spreads between structured and unstructured debt to a particular deviation driver[34]. Instead, I infer that the observed differences in required spreads are caused by the deviation drivers as a group and the effect from each deviation driver is unobservable in my data set. To test whether systematic risk could carry explanatory power in the observed differences in spreads, I extend the methodology of Pinto, Marques, and Megginson (2020) by working from the intuition that if the differences in required spreads identified are to some extent caused by systematic risk, systematic risk should have a significant effect on spreads required for CLO tranches.

Previous literature and the derivations conducted in section 4.2 suggests that a set of measurable SPV characteristics drive the systematic risk of a tranche. Specifically, I derive four measurable systematic risk drivers and test whether they have an impact on the required launch spreads by the market.

[34] See section 4.1 for a discussion.

The second hypothesis tested in this thesis concerns the number of loans in the collateral portfolio (H2). I derive that as the number of loans in the collateral portfolio increases, so do the systematic risk of the tranche. Hence, investors should increase their required spread at launch, as the number of loans in the collateral portfolio increases. However, no evidence is found that the number of loans has a positive impact on spreads. The impact is tested across 24 different regression analyses and the result is consistent across all analyses. H2 is thus not accepted.

The third hypothesis concerns the systematic risk of the underlying loans' obligors (H3). The systematic risk of the collateral portfolio is proxied by the industry beta of the obligors, as described in section 6.3.2. I derive in section 4.2.3 that as the systematic risk of the underlying loans increase, so does the systematic risk of the tranche. However, no robust evidence is found that the collateral portfolio's beta has a positive impact on the investors' required launch spreads across 24 different regression analyses. H3 is thus also not accepted.

H4 concerns the interaction between the number of loans in the collateral portfolio and the beta of the collateral portfolio. In section 4.2.3, I derive that the interaction term should have a positive impact on the required spreads. No evidence is found that the interaction term has a positive impact on required spreads across 12 conducted regression analyses. I thus also do not accept H4.

H5 concerns the final systematic risk driver considered in this thesis. I derive, in section 4.2.4, that systematic risk is higher for senior tranches than for junior tranches. Hence, when real-world probability of default is controlled for, investors should require a higher launch spread for senior tranches than for junior tranches. For a set of regressions, this was indeed shown to be the case. However, the impact is insignificant for the group of regressions where functional form misspecification is not found. I use these regressions for inference. H5 is thus also not accepted.

In conclusion, none of the systematic risk drivers derived in this thesis have been found to have a robust significant positive impact on required launch spreads.

For the hypotheses H2, H3 and H4 the results are very robust to changes in the regression model. A very interesting finding is that H5 is accepted in a subset of the regressions conducted. Furthermore, the estimated coefficient is positive in almost all regressions, as predicted in section 4.2.4. While the hypotheses are not accepted in this thesis, the results raise the question if seniority can be found to be a significant systematic risk driver in future studies with higher statistical power in the analyses conducted.

Credit ratings were consistently highly significant and carried by far the most explanatory power across all regressions conducted. This finding supports the view of Brennan, Hein, and Poon (2009) that rating dependency is a sine qua non in structured debt.

Concluding on these findings, investors are not found to be identifying systematic risk for CLO tranches and, to some extent, requiring risk premia by adjusting their required spreads. The finding is robust across systematic risk drivers and regression analyses. I also infer that systematic risk do not carry explanatory power in the observed differences in required spreads between CLOs.

An overview of hypotheses and the empirical findings is given in the table below.

Table 6: Overview of accepted/rejected hypotheses

Effect tested	Hypothesis	Accepted/Not accepted
Spread differences	*H1: Structured debt has significantly different required spreads than unstructured debt*	**Accepted**
Systematic risk	*H2: Number of loans in the loan portfolio has a positive impact on spread for structured debt tranches*	**Not accepted**
	H3: The systematic risk of the loans in the collateral portfolio has a positive coefficient to the required spreads for structured debt	**Not accepted**
	H4: The effect of systematic risk of the loans in the collateral portfolio increases with the number of loans in the portfolio	**Not accepted**
	H5: Seniority of the tranche has a positive impact on spreads for structured debt tranches when controlling for real-world probability of default	**Not accepted**

The next section provides a discussion of issues with the methodology applied in this thesis and suggestions for future research.

8 Discussion and future studies

Severe problems with most of the OLS assumptions are found across the regression analyses conducted in this thesis. The extent of the issues differs across the different analyses conducted. For a subset of the regressions, no functional form misspecification is found using the RESET test while another subset of regressions has been found to have normally distributed error terms.

For the regressions concerning systematic risk in CLOs, one issue consistent across the regression analyses is severe multicollinearity for some of the systematic risk driver variables. Specifically, the number of loans and the interaction term between beta and the number of loans have particular issues with multicollinearity. The issue is also present for seniority, although not as severe. For the beta variables, multicollinearity is not found to be a major issue when the interaction term between beta and the number of loans in the collateral portfolio is excluded from the analyses. While multicollinearity is not a breach of assumptions, it severely reduces the statistical power of the conducted analyses.

When inferring on systematic risk in CLOs, I have used a set of regressions which showed least evidence of functional form misspecification as the primary basis for my inference. For these tests however, the error terms have been found not to be normally distributed. I cannot with certainty state that the number of observations is large enough to benefit from the large sample properties of the OLS estimators and thus mitigate the issue of breach of normality.

For the regressions testing for spread difference between CLOs and corporate bonds, similar issues with assumptions are found. Normality of residuals is rejected and heteroscedasticity is found across all regressions. Furthermore, the RESET test finds evidence of functional form misspecifications for almost all regressions. However, some regression models are made where no functional form misspecification is found. The issues with multicollinearity are furthermore not severe in this group of regressions.

It is worth noting that the findings in this thesis can only be generalized to CLOs and corporate bonds in Western Europe with floating coupons denominated in EUR and issued from January 2017 to April 2020. This period can be considered as relatively "steady waters" and no inference can thus be made on periods of crisis. There might also exist selection bias as only active corporate bonds at the time of data extraction were available. Furthermore, CLO tranches which were described as heavily exposed to "Industrials" industries had often unavailable industry weightings in the Bloomberg terminal and thus unavailable beta estimates for this thesis. This might suggest biased selection from the population.

An important observation is that some of the systematic risk drivers used in this thesis are intuitively very sensitive to omitted variable bias. For example, the coefficient estimate for the credit support variable can be biased downward if a variable which captures the lower probability of default for seniority within credit ratings is omitted from my analyses. A similar point can be made for the number of loans in the collateral portfolio. If my analyses do not control for the beneficial diversification effect caused by increasing the number of loans, the coefficient estimate could also be downward biased. Investors may require lower spreads for tranches with more diversified collateral portfolios.

The issues of breach of assumptions and low statistical power needs to be taken into account when considering the findings of this thesis. However, a large set of measures have been applied to mitigate these issues and the findings have been found to be highly robust across a large set of analyses with varying degrees of issues with assumptions and statistical power. Based on this, I argue that the finding that systematic risk is not priced into CLO spreads is reliable and an adequate groundwork for further studies.

The finding that deviation drivers as a group causes differences in required spreads between CLOs and corporate bonds encourages further investigation into the effects of the different deviation drivers. For example, future studies could aim to isolate the effect of systematic risk from the effect of other deviation drivers on the differences in required spreads between structured and unstructured debt.

Taking aside the insignificance of the impact of systematic risk drivers on spreads, some indication has been found that the systematic risk drivers might indeed have an impact on required spreads. For example, the sign of the coefficient estimate for seniority is positive for almost all conducted analyses. In the common perception of seniority, this seems counter intuitive. However, the sign of the coefficient might be explained by the systematic risk caused by seniority. This enforces a need for further investigation of the effects on the systematic risk drivers. A natural extension to this thesis is applying a similar approach with inclusion of potentially omitted variables as discussed above and larger statistical power caused by increased sample size. A larger sample size also allows for further sensitivity analyses of the effects of systematic risk across credit ratings. Another natural extension is an application of a similar method on a US data set, where the CLO market is more developed.

9 Conclusion

This thesis explores whether investors require a risk premia for systematic risk when pricing Western European collateralized loan obligations (CLOs) from January 2017 to April 2020. It also provides insights into the set of factors which causes a difference in required spreads between structured and unstructured debt.

In order to test the impact from systematic risk on required spreads for CLOs, a set of systematic risk drivers are derived. Inspired by previous literature, I use a simple model of normally distributed number of loan defaults conditional on an economic state to derive a set of special purpose vehicle (SPV) characteristics which drive the systematic risk of issued tranches. The four systematic risk drivers derived in this thesis are the number of loans in the collateral portfolio, the estimated beta of the collateral portfolio, the interaction term between beta and the number of loans and the seniority of the tranche. If investors require risk premia according to the systematic risk of the tranche, the systematic risk drivers derived are hypothesized to have a significant impact on required launch spreads.

None of the systematic risk drivers are found to have a robust significant impact on launch spreads for CLOs. The number of loans and beta of the collateral portfolio are neither found to have a significant impact on spreads nor meaningful signs of the coefficient estimates if they should carry systematic risk. These findings are consistent across a set of regressions conducted. Seniority is also not found to have a robust significant impact on spreads. In sum no systematic risk drivers are found to influence required spreads for CLOs.

A recent paper tested a similar hypothesis but arrived at a different conclusion for collateralized debt obligations (CDOs). Pinto, Marques, and Megginson (2020) worked from the intuition that if structured debt were found to have larger required spreads than unstructured debt, the spread difference was driven by systematic risk. They did indeed find spreads to be higher for CDOs than corporate bonds and concluded that investors did take systematic risk into account when pricing CDOs as a result. I conduct a similar test and analyze whether required spreads differ between CLOs and corporate bonds. I also find that required spreads are higher for structured than for unstructured debt for all debt instruments rated BB and above. The finding is robust across all conducted regression analyses.

In this thesis, I extend the work of Pinto, Marques, and Megginson (2020) by examining what might cause such a difference in required spreads other than systematic risk. With an offset in previous literature, I suggest a set of factors which could equally explain the differences found between spreads for structured and unstructured debt. This includes information destruction and adverse selection problems in structured debt among others. I argue that the spread difference found between structured and unstructured debt cannot reasonably be assumed to be solely caused by systematic risk, but is a result of the impact from all suggested factors as a group. Instead, I work from the intuition that if systematic risk explains the identified spread differences to some extent, systematic risk should have a significant impact on required spread for structured debt. If systematic risk do not drive spreads for structured debt, it can't drive the differences in spreads between structured and unstructured debt. Based on the finding that systematic risk drivers do not have a significant impact on structured debt, I conclude that systematic risk do not cause the observed difference in spreads between CLOs and corporate bonds. The conclusion is at odds with the findings of Pinto, Marques, and Megginson (2020) despite the use of a similar methodology and similar regression results.

The implication of the results is that investors do not require a risk premia for the systematic risk in CLOs which implies CLO tranches to be overpriced. The complexity of structured debt might be the reason as it leaves investors barred from properly understanding the risk profile of the tranches as suggested by Brennan, Hein, and Poon (2009). Instead, the risk assessment is suspected to be delegated to rating agencies which do not consider systematic risk in their rating methodologies. This is in accordance with the high explanatory power of credit ratings found in this thesis. Further research is suggested to provide insight into the methodologies used by investors for systematic risk assessment in practice.

The mispricing is suggested to increase with the values of the systematic risk drivers. Specifically, tranches with high seniority, large number of loans in the collateral portfolio and loans with high systematic risk in the collateral portfolio are suggested to be the tranches with the largest systematic risk and thus the largest mispricing.

I also conclude that the observed differences in required spreads between CLOs and corporate bonds are not driven by systematic risk. Instead, it is driven by other unidentified factors which cause a difference in spreads between structured and unstructured debt. The exact cause of the identified spread differences observed both in this thesis and in the work of Pinto, Marques, and Megginson (2020) remains unidentified which substantiates the need for further research.

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10 Appendix

10.1 Regression analyses

Table 7: Estimation results - Spread difference between CLOs and corp. bonds

	Launch spreads					Natural logarithm of launch spreads				
	1.1.1	1.1.2	1.1.3	1.1.4	1.1.5	1.2.1	1.2.2	1.2.3	1.2.4	1.2.5
SD	143.3**	-22.1	-462.4**	-460.5**	-456.7**	0.9**	0.1	-2.2**	-2.2**	-2.2**
	(9.9)	(33.0)	(40.5)	(42.5)	(48.5)	(0.1)	(0.2)	(0.2)	(0.3)	(0.3)
SD_AAA			511.9**	548.9**	552.6**			3.3**	3.4**	3.4**
			(42.0)	(45.1)	(50.8)			(0.5)	(0.5)	(0.5)
SD_AA			588.7**	576.7**	578.7**			3.5**	3.4**	3.5**
			(40.5)	(42.0)	(47.7)			(0.3)	(0.3)	(0.3)
SD_A			612.8**	598.0**	592.9**			3.2**	3.1**	3.1**
			(40.7)	(42.5)	(48.5)			(0.2)	(0.3)	(0.3)
SD_BBB			688.0**	665.3**	657.6**			3.3**	3.2**	3.2**
			(41.2)	(43.0)	(49.0)			(0.2)	(0.3)	(0.3)
SD_BB			776.6**	789.9**	784.3**			2.8**	2.8**	2.9**
			(75.2)	(76.5)	(80.4)			(0.4)	(0.4)	(0.5)
SD_B			660.1**	640.9**	630.6**			2.2**	2.1**	2.1**
			(126.9)	(124.7)	(123.7)			(0.4)	(0.4)	(0.4)
SD_WAL				15.7**	16.1**				0.1**	0.1**
				(3.0)	(2.9)				(0.0)	(0.0)
SD_Prin				-0.0**	-0.0**				0.0	0.0
				(0.0)	(0.0)				(0.0)	(0.0)
SD_T_yield					269.0					78.7
					(7790.3)					(105.4)
SD_Diff					111.1					0.6
					(105.3)					(1.2)
SD_imp_vol					0.8 (1.5)					-0.0*
										(0.0)
T_yield	-10600.3	-11121.7	-5433.2	-8735.1	-7778.4	-76.2	-105.5*	-91.2*	-104.8*	-168.5*
	(7754.2)	(5858.6)	(5318.9)	(5104.8)	(6003.2)	(53.8)	(43.5)	(42.5)	(42.6)	(82.8)
Diff	-149.1	-145.6	-43.2	-69.4	-113.6	-0.9	-1.4*	-0.9	-0.9	-1.5
	(113.1)	(87.7)	(79.4)	(79.1)	(83.4)	(0.7)	(0.6)	(0.6)	(0.6)	(0.9)
imp_vol	2.3	2.3*	3.2*	2.8*	3.0**	0.0	0.0**	0.0**	0.0**	0.1**
	(1.6)	(1.2)	(1.3)	(1.2)	(1.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)

Table 7: Estimation results - Spread difference between CLOs and corp. bonds

WAL	8.3**	5.5**	4.7**	1.4	2.0 (1.3)	0.1**	0.1**	0.1**	0.0*	0.0*
	(1.3)	(1.1)	(1.3)	(1.3)		(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Prin	-0.0	0.0*	-0.0	0.0*	0.0*	-0.0*	-0.0	-0.0*	-0.0	-0.0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
D_AAA	-349.6	-415.7**	-510.1**	-528.1**	-526.8**	-1.8**	-2.3**	-3.2**	-3.1**	-3.1**
	**	(73.4)	(37.9)	(36.5)	(36.6)	(0.6)	(0.3)	(0.4)	(0.4)	(0.4)
	(111.9)									
D_AA	-303.6	-334.1**	-533.8**	-522.5**	-518.8**	-1.5*	-1.8**	-3.0**	-2.9**	-2.9**
	**	(74.5)	(36.0)	(33.7)	(33.9)	(0.6)	(0.3)	(0.2)	(0.2)	(0.2)
	(109.7)									
D_A	-254.5**	-293.6**	-498.4**	-495.5**	-486.5**	-1.1	-1.4**	-2.3**	-2.3**	-2.3**
	(109.9)	(73.9)	(36.5)	(34.2)	(34.4)	(0.6)	(0.3)	(0.2)	(0.1)	(0.1)
D_BBB	-185.5	-241.8**	-460.2**	-462.8**	-452.4**	-0.8*	-1.2**	-2.1**	-2.1**	-2.1**
	(110.3)	(73.3)	(36.2)	(34.1)	(34.4)	(0.6)	(0.3)	(0.1)	(0.1)	(0.1)
D_BB	-17.4	-4.8	-364.1**	-382.4**	-377.2**	-0.1	-0.5	-1.2**	-1.2**	-1.2**
	(108.6)	(77.4)	(43.7)	(42.6)	(42.0)	(0.6)	(0.4)	(0.3)	(0.3)	(0.3)
D_B	130.5	68.8	-119.8**	-118.9**	-102.6**	0.7	0.2	-0.5**	-0.5**	-0.4**
	(112.1)	(76.1)	(40.6)	(38.9)	(38.7)	(0.6)	(0.3)	(0.1)	(0.1)	(0.1)
Control-*Dummies*[1]	T	T + G	T	T	T	T	T + G	T	T	T
No. Obs	590	590	590	590	590	479	479	479	479	479
R^2	0.775	0.853	0.868	0.882	0.888	0.718	0.805	0.798	0.809	0.814
Adj. R^2	0.765	0.842	0.860	0.874	0.880	0.702	0.786	0.784	0.794	0.799

Note: *Significant at 5%, **at 1%. Robust White std. errors are reported in brackets.

1: T: Time dummies, G: Geography dummies

Table 8: Estimation results - Systematic risk, composite ratings

	Launch spreads						Natural logarithm of launch spreads					
	2.1.1	2.1.2	2.1.3	2.1.4	2.1.5	2.1.6	2.2.1	2.2.2	2.2.3	2.2.4	2.2.5	2.2.6
N	-0.7	-0.9	0.6	-0.0	-0.0	-0.1	-0.0	-0.0	-0.0	0.0	0.0	0.0
	(0.8)	(0.7)	(1.0)	(0.1)	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
β	-125.3	-168.8	194.0	59.0	263.2**	44.7	-0.6	-0.8	0.3	0.3	0.5*	0.8
	(170.7)	(177.6)	(241.6)	(48.9)	(61.5)	(163.8)	(0.9)	(1.0)	(1.6)	(0.3)	(0.3)	(1.0)
$N\beta$	0.7	0.9	-0.6				0.0	0.0	0.0			
	(0.8)	(0.8)	(1.1)				(0.0)	(0.0)	(0.0)			
CS	5.1*	4.9*	4.4*	4.1*	4.7*	3.6	0.0	0.0	0.0	0.0	0.0	-0.0
	(2.4)	(2.4)	(2.2)	(2.2)	(2.2)	(2.5)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
β_AAA					-349.8**						-0.4*	
					(61.0)						(0.2)	
β_AA					-282.3**						-0.3	
					(55.8)						(0.2)	
β_A					-155.6**						0.1	
					(43.0)						(0.2)	
T_yield	-9413.3*	-9577*	-8120.9	-7666.1	-5209.2	-13472.6	-65.2*	-61.2*	-68.6	-68.7	-65.7	-88.1*
	(4558.9)	(4552.4)	(6404.6)	(6188.0)	(6326.9)	(6982.9)	(25.8)	(24.3)	(38.5)	(36.6)	(37.1)	(42.3)
Diff	-25.5	-30.5	-109.4	-101.3	-58.6	-210.5	-0.4	-0.4	-1.1	-1.1*	-1.0	-1.7*
	(60.5)	(62.1)	(89.5)	(88.8)	(89.0)	(121.4)	(0.3)	(0.4)	(0.5)	(0.5)	(0.5)	(0.7)
imp_vol	0.3	0.1	5.4**	5.4**	5.4**	3.6	0.0	-0.0	0.0**	0.0**	0.0**	0.0
	(0.8)	(1.0)	(1.2)	(1.2)	(1.2)	(2.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
WAL	14.6**	14.7**	13.1**	13.3**	12.5**	11.7**	0.1**	0.1**	0.1**	0.1**	0.1**	0.1**
	(3.0)	(3.0)	(2.2)	(2.3)	(2.1)	(2.6)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Prin	-0.0	-0.0	0.0	-0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Num_B	0.6	0.6	0.7*	0.6*	0.6	0.5	0.0	0.0	0.0	0.0	0.0	0.0
	(0.4)	(0.4)	(0.3)	(0.3)	(0.3)	(0.4)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
D_AAA	-750.2**	-744.8**	-733.8**	-729.3**		-716.2**	-2.6**	-2.5**	-2.3**	-2.3**		-1.8**
	(78.4)	(78.5)	(65.0)	(64.7)		(75.3)	(0.4)	(0.4)	(0.4)	(0.4)		(0.4)

Table 8: Estimation results - Systematic risk, composite ratings

D_AA	-	-	-	-	35.0	-	-1.9**	-1.8**	-1.7**	-1.7**	0.6*	-1.4**
	650.4**	647.4**	639.1**	636.4**	(47.7)	623.1**	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
	(60.8)	(61.3)	(48.3)	(48.2)		(55.5)						
D_A	-	-	-	-	-3.9	-	-1.5**	-1.4**	-1.3**	-1.3**	0.5	-1.1**
	564.0**	562.2**	557.4**	555.7**	(61.5)	545.4**	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.2)
	(49.4)	(49.8)	(38.4)	(38.4)		(43.1)						
D_BBB	-	-	-	-	-35.4	-	-1.0**	-1.0**	-0.9**	-0.9**	1.0**	-0.8**
	442.4**	441.6**	439.5**	438.5**	(77.8)	429.3**	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.2)
	(42.4)	(42.8)	(33.1)	(33.1)		(36.0)						
D_BB	-	-	-	-	229.9*	-	-0.3*	-0.2*	-0.2	-0.2	1.7**	-0.2
	174.8**	175.1**	172.4**	172.4**	(88.7)	166.4**	(0.1)	(0.1)	(0.1)	(0.1)	(0.4)	(0.1)
	(35.4)	(35.7)	(32.3)	(32.3)		(34.2)						
D_B											1.9**	
											(0.4)	
Control-Dummies[1]		G	G+T	G+T	G+T	G+T+S		G	G+T	G+T	G+T	G+T+S
No. Obs	206	206	206	206	206	206	206	206	206	206	206	206
R^2	0.955	0.955	0.967	0.967	0.972	0.969	0.949	0.950	0.963	0.963	0.964	0.969
Adj. R^2	0.951	0.951	0.961	0.961	0.967	0.962	0.945	0.945	0.956	0.956	0.956	0.962

Note: *Significant at 5%, **at 1% (Systematic risk are one-sided tests. Else, two sided). Robust White std. errors are reported in brackets.

1: T: Time dummies, G: Geography dummies, S: Sector dummies

Table 9: Estimation results - Systematic risk, adjusted ratings

	Launch spreads						Natural logarithm of launch spreads					
	2.3.1	2.3.2	2.3.3	2.3.4	2.3.5	2.3.6	2.4.1	2.4.2	2.4.3	2.4.4	2.4.5	2.4.6
N	-1.1	-1.2	0.7	-0.0	-0.0	-0.3	-0.0	-0.0	0.0	0.0	0.0	-0.0
	(0.9)	(0.8)	(1.0)	(0.1)	(0.1)	(0.1)	(0.0)	(.0)	(0.0)	(0.0)	(0.0)	(0.0)
β	-215.5	-226.2	211.4	53.5	261.9	-217.3	-1.2	-1.1	0.4	0.3	0.5	-1.0
	(196.4)	(191.0)	(246.8)	(53.1)	**	(119.5)	(1.1)	(1.1)	(1.6)	(0.3)	(0.3)	(0.7)
					(62.4)							
$N\beta$	1.2	1.2	-0.7				0.0	0.0	-0.0			
	(0.9)	(0.8)	(1.1)				(0.0)	(0.0)	(0.0)			
CS	3.9	3.8	4.3*	4.2*	4.8*	4.6*	0.0	0.0	0.0	0.0	0.0	0.0
	(2.7)	(2.7)	(2.2)	(2.2)	(2.2)	(2.4)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
β_AAA					-						-0.5*	
					360.9**						(0.2)	
					(60.0)							
β_AA					-						-0.3	
					283.6**						(0.2)	
					(55.3)							
β_A					-						0.1	
					158.9**						(0.2)	
					(43.4)							
T_yield	-	-	-	-	-	-	-34.5	-29.1	-64.3	-64.0	-60.7	-48.2
	4573.7	4521.7	7446.5(7096.0)	7[illegible]9.8	4330.1	7774.4	(32.4)	(32.8)	(41.7)	(39.9)	(40.5)	(43.8)
	(5541.0)	(5796.8)		(6894.7)	(6964.2)	(7106.5)						
Diff	37.5	37.3	-88.4	-78.7	-35.8	-103.4	0.0	0.0	-0.9	-0.9	-0.9	-1.0
	(73.8)	(77.0)	(101.7)	(101.5)	(100.7)	(122.0)	(0.4)	(0.5)	(0.6)	(0.6)	(0.6)	(0.7)
imp_vol	0.5	0.5	5.5**	5.5**	5.5**	2.5	0.0	0.0	0.0**	0.0**	0.0**	0.0
	(0.8)	(1.0)	(1.2)	(1.2)	(1.2)	(2.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
WAL	11.5**	11.5**	10.3**	10.6**	9.7**	10.1**	0.1**	0.1**	0.1**	0.1**	0.1**	0.1**
	(3.7)	(3.7)	(3.0)	(3.0)	(2.9)	(2.7)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Prin	0.0	0.0	0.0	0.0	0.0	0.0	0.0*	0.0*	0.0	0.0	0.0*	0.0
	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
Num_B	0.3	0.3(0.4)	0.5	0.4	0.4	1.0**	0.0	0.0	0.0*	0.0	0.0	0.0*
	(0.4)		(0.3)	(0.3)	(0.3)	(0.4)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
D_AAA					-						-2.0**	
					419.6**						(0.4)	
					(97.8)							

Table 9: Estimation results - Systematic risk, adjusted ratings

D_AA	97.3**	96.6**	104.0	101.8	-	108.4	0.7**	0.7**	0.7**	0.7**	-1.4**	0.6**
	(24.5)	(23.0)	**	**	385.5**	**	(0.1)	(0.1)	(0.1)	(0.1)	(0.3)	(0.1)
			(22.2)	(22.1)	(72.8)	(23.1)						
D_A	177.9	176.7	188.5	185.2	-	195.0	1.1**	1.1**	1.1**	1.1**	-1.4**	0.9**
	**	**	**	**	419.8**	**	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
	(40.1)	(38.4)	(36.0)	(35.3)	(58.9)	(37.6)						
D_BBB	293.0	291.5	306.8	302.7	-	316.9	1.5**	1.5**	1.5**	1.5**	-1.0**	1.3**
	**	**	**	**	454.2**	**	(0.3)	(0.3)	(0.3)	(0.3)	(0.2)	(0.3)
	(53.2)	(51.0)	(46.0)	(45.8)	(35.0)	(49.1)						
D_BB	551.9**	549.9	574.2	568.9	-	587.9	2.2**	2.2**	2.2**	2.2**	-0.3*	1.9**
	(72.5)	**	**	**	188.9**	**	(0.4)	(0.4)	(0.3)	(0.3)	(0.1)	(0.3)
		(70.2)	(58.4)	(58.1)	(32.3)	(63.1)						
D_B	727.0	725.1	750.1	744.8		759.6	2.5**	2.4**	2.4**	2.4**		2.2**
	**	**	**	**		**	(0.5)	(0.4)	(0.4)	(0.4)		(0.4)
	(85.2)	(84.0)	(67.2)	(67.0)		(70.0)						
Control-		G	G+T	G+T	G+T	G+T+S		G	G+T	G+T	G+T	G+T+S
Dummies[1]												
No. Obs	209	209	209	209	209	209	209	209	209	209	209	209
R^2	0.952	0.952	0.963	0.963	0.968	0.967	0.944	0.944	0.956	0.956	0.956	0.965
Adj. R^2	0.948	0.947	0.956	0.956	0.962	0.959	0.939	0.939	0.948	0.948	0.948	0.956

Note: *Significant at 5%, **at 1% (Systematic risk are one-sided tests. Else, two sided). Robust White std. errors are reported in brackets.

1: T: Time dummies, G: Geography dummies S: Sector dummies

10.2 Overview of notation

Table 10: Overview of notation in regression analyses

Variable name	Description
For hypothesis testing	
SD	Dummy equaling 1 if the debt is a CLO tranche and equalling 0 if the debt is a corporate bond.
SD_AAA	Interaction term between the debt dummy SD and the rating dummy, which in this example is for AAA rated debt.
N	Number of loans in the collateral portfolio at issue.
β	Estimated beta of the collateral portfolio as described in section 6.3.2.
$N\beta$	Interaction term between the number of loans and the estimated beta of the collateral portfolio as discussed in section 4.2.3.
CS	Credit support as described in section 6.3.3.
Control variables	
Num_B	Number of bonds in the collateral portfolio.
WAL	Weighted average lifetime of the debt as described in section 6.4.1.
Prin	The principal of the debt.
D_AAA	Rating dummy equaling 1 if the debt is rated AAA in this example.
imp_vol	Implied interest rate volatility of a 5 year interest rate cap as described in section 6.4.1.
Diff	Difference between the swap yields for swaps with 2 years and 10 years tenor as described in section 6.4.
T_yield	10 year bond yields from a synthetic EUR denominated government bond as described in section 6.4.
SD_	Interaction term between the structured debt dummy and other control variables.

Table 11: Overview of notation in this thesis

Variable name	Description
ABS	Asset backed security.
BDR	Break-even default rate.
Bps	Basis points.
BSL	Broadly syndicated leveraged bank loan.
CDF	Cumulative distribution function.
CDO	Collateralized debt obligation.
CLO	Collateralized loan obligation.
GFC	Great financial crisis.
I/C tests	Interest coverage tests.
Investment grade	Defined as debt with a BBB rating or higher.
LBO	Leveraged buy-out
M&A	Mergers & acquisitions
MBS	Mortgage-backed securities
NFBI	Non-bank financial institutions
O/C tests	Overcollateralization coverage tests
SDR	Scenario default rate
SPV	Special purpose vehicle
Structured debt	A phrase used in this thesis to define debt backed by a debt portfolio
Unstructured debt	A phrase used in this thesis to define debt not backed by a debt portfolio

10.3 Sector relations applied for beta calculation

Table 12: Overview of applied industry relations to calculate beta

GICS industry	Moody's industry from Bloomberg
Automobiles and components	Automotive
Capital goods	Aerospace & Defense, Capital Equipment, Construction & Building
Commercial & Professional services	Environmental Industries, Services: Business
Consumer durables & Apparel	Consumer Goods: Durable
Consumer services	Hotel, Gaming & Leisure, Services: Consumer
Diversified financials	Banking, Finance, Insurance & Real Estate
Energy	Energy: Oil, Energy: Electricity
Food, beverage & Tobacco	Beverage, Food & Tobacco
Healthcare	Healthcare & Pharmaceuticals
Household & personal products	Consumer Goods: Non-Durable
Information technology	High Tech Industries
Materials	Chemicals, Plastics & Rubber, Containers, Packaging & Glass, Metals & Mining, Forestry products & paper
Media & entertainment	Media: Advertising, Printing & Publishing, Media: Broadcasting & Subscription, Media: Diversified & Production
Retailing	Retail, Wholesale
Telecommunication services	Telecommunications
Transportation	Transportation: Cargo, Transportation: Consumer
Utilities	Utilities: Electric, Utilities: Water, Utilities: Oil & gas

10.4 Descriptive statistics

Table 13: Credit support across composite ratings for CLOs

Rating	Obs	Mean	Max
AAA	268	39.5	56.7
AA	205	29.2	62.0
A	217	22.4	49.3
BBB	178	16.2	31.3
BB	21	11.3	25.0
B	11	7.0	8.9

Note: The credit support variable is the principal of all tranches junior to the tranche in question as a percentage of the principal of the total deal. Given in percentage

Table 14: Collateral portfolio industry weightings for CLOs

Industry	Mean	Standard dev.	Max
Automobiles and components	2.0	2.1	10.1
Capital goods	8.9	6.2	63.3
Commercial & Professional services	10.8	4.4	28.6
Consumer durables & Apparel	1.5	1.9	7.5
Consumer services	9.9	4.6	21.8
Diversified financials	5.0	3.8	16.2
Energy	0.1	0.4	3.2
Food, beverage & Tobacco	4.3	2.7	18.1
Healthcare	15.4	4.8	27.6
Household & personal products	0.5	1.2	5.6
Information technology	8.5	3.8	19.0
Materials	14.3	4.3	29.8
Media & entertainment	5.8	3.3	16.7
Retailing	5.4	3.8	27.5

Table 14: Collateral portfolio industry weightings for CLOs

Telecommunication services	6.6	3.6	20.1
Transportation	0.7	1.5	9.0
Utilities	0.2	1.0	9.3

Note: Used to calculate estimated beta as described in section 6.3.2. Given in percentage.

Table 15: Loan numbers in the collateral portfolio across composite ratings for CLOs

Rating	Obs	Mean	Max
AAA	276	560	71668
AA	210	801	49148
A	220	358	11341
BBB	180	193	441
BB	21	1349	24053
B	11	2919	29763

Note: The credit support variable is the principal of all tranches junior to the tranche in question as a percentage of the principal of the total deal. Given in percentage

Table 16: Spreads across composite ratings for CLOs

Rating	Obs	Mean	Standard dev.	Max
AAA	276	82.2	22.9	150
AA	213	148.8	33.4	217
A	220	212.4	48.3	387
BBB	180	321.8	60.5	480
BB	21	513.2	138.3	682
B	11	694.2	205.8	925

Note: Given in bps

Table 17: Spreads across composite ratings for corporate bonds

Table 17: Spreads across composite ratings for corporate bonds

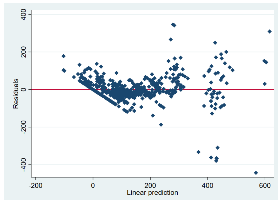
Rating	Obs	Mean	Standard dev.	Max
AAA	10	13.5	23.7	75
AA	108	10.7	22.7	100
A	65	42.0	40.2	150
BBB	83	74.7	39.0	170
BB	6	150	63.2	250
B	33	417.7	117.3	675

Note: Given in bps

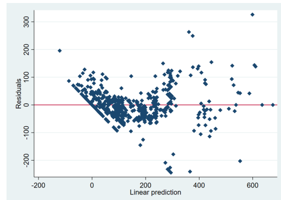
10.5 Residuals versus fitted values scatters

Table 18: Residuals versus fitted values scatters

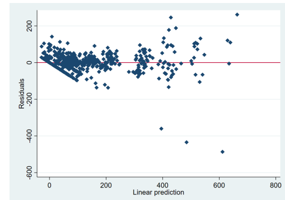
Regression 1.1.1



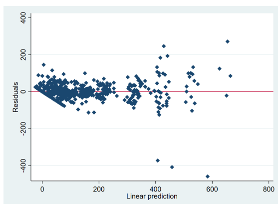
Regression 1.1.2



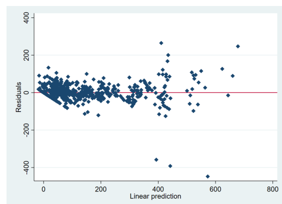
Regression 1.1.3



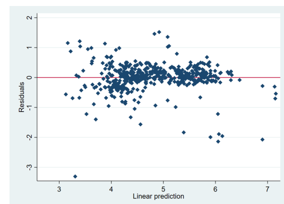
Regression 1.1.4



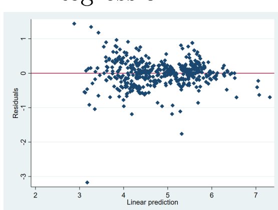
Regression 1.1.5



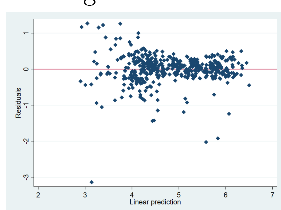
Regression 1.2.1



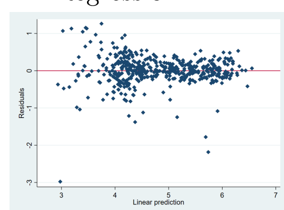
Regression 1.2.2



Regression 1.2.3

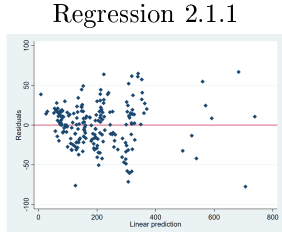


Regression 1.2.4

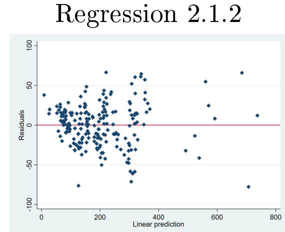


Regression 1.2.5

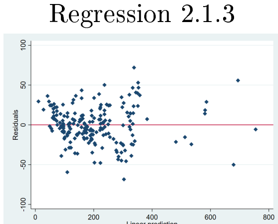
Regression 2.1.1



Regression 2.1.2



Regression 2.1.3



Regression 2.1.4

Regression 2.1.5

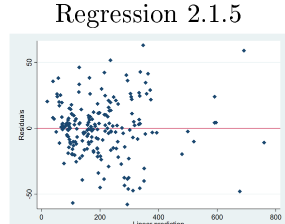
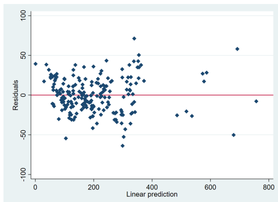
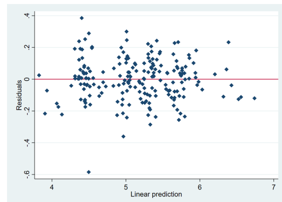


Table 18: Residuals versus fitted values scatters

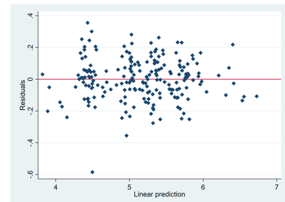
Regression 2.1.6



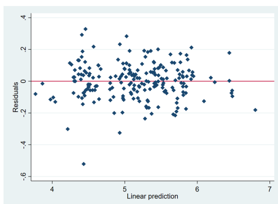
Regression 2.2.1



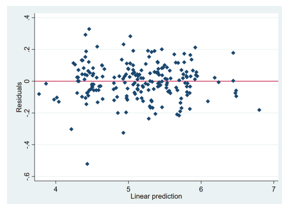
Regression 2.2.2



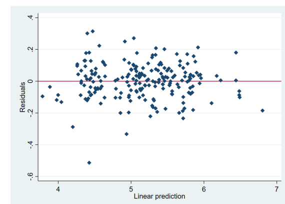
Regression 2.2.3



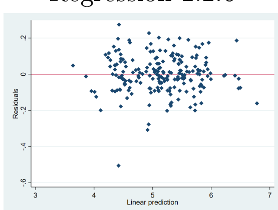
Regression 2.2.4



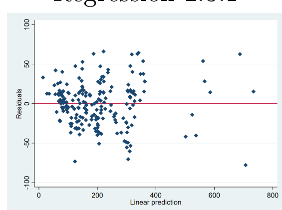
Regression 2.2.5



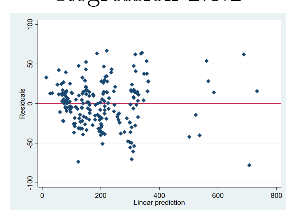
Regression 2.2.6



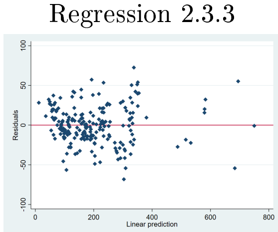
Regression 2.3.1



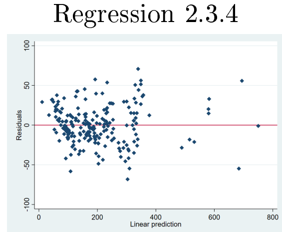
Regression 2.3.2



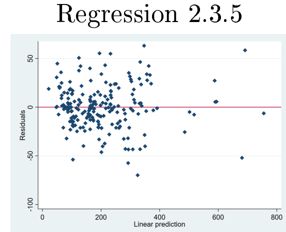
Regression 2.3.3



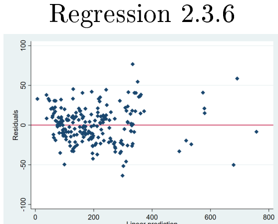
Regression 2.3.4



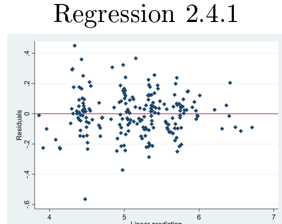
Regression 2.3.5



Regression 2.3.6



Regression 2.4.1



Regression 2.4.2

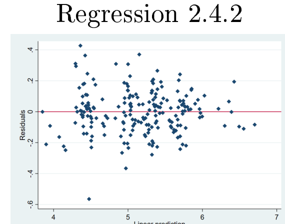
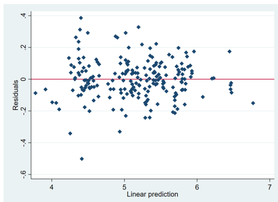
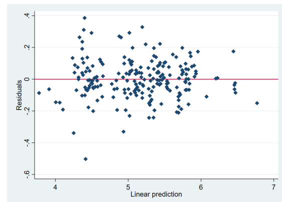


Table 18: Residuals versus fitted values scatters

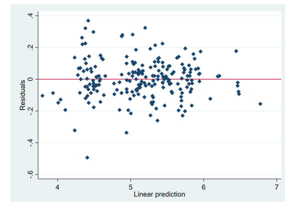
Regression 2.4.3



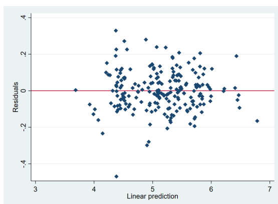
Regression 2.4.4



Regression 2.4.5



Regression 2.4.6



10.6 Testing OLS assumptions

Table 19: Test for heteroskedasticity, normality, correct specification and multicollenarity

		Heteroscedasticity		Ramsey Reset		Multicollenarity	Normality	
		H0: Constant variances		H0: No omitted var.			H0: Normal data	
Study[1]	Regression	χ^2	P-value	F	P-value	Mean VIF	Z	P-value
Differences - S	1.1.1	1875.0	.0000	28.2	.0000	10	10.2	.0000
	1.1.2	987.4	.0000	108.2	.0000	7	8.7	.0000
	1.1.3	1951.7	.0000	70.2	.0000	15	10.5	.0000
	1.1.4	2151.2	.0000	54.9	.0000	15	10.7	.0000
	1.1.5	2139.2	.0000	65,9	.0000	21	10.7	.0000
Differences - LnS	1.2.1	701.4	.0000	13.4	.0000	10	9.2	.0000
	1.2.2	551.6	.0000	3.9	.0087	7	8.1	.0000
	1.2.3	534.1	.0000	0.28	.8408	15	9.2	.0000
	1.2.4	584.3	.0000	4.5	.0039	15	8.9	.0000
	1.2.5	637.3	.0000	3.3	.0204	23	9.1	.0000
Systematic risk - S C	2.1.1	73.4	.0000	14.9	.0000	7641	0.8	.2124
	2.1.2	73.2	.0000	14.8	.0000	8840	0.8	.2091
	2.1.3	70.4	.0001	19.2	.0000	7314	-1.9	.9679
	2.1.4	70.7	.0000	19.8	.0000	78	-1.8	.9639
	2.1.5	72.2	.0005	11.3	.0000	120	1.8	.0325
	2.1.6	84.7	.0001	28.9	.0000	164	-1.2	.8755
Systematic risk - LnS C	2.2.1	102.0	.0000	3.0	.0318	7641	1.7	.0430
	2.2.2	99.5	.0000	2.6	.0523	8840	1.8	.0387
	2.2.3	143.9	.0000	3.9	.0107	7314	2.6	.0046
	2.2.4	142.3	.0000	3.8	.0107	78	2.6	.0047
	2.2.5	150.0	.0000	5.7	.0009	120	2.6	.0042
	2.2.6	194.6	.0000	2.2	.0881	164	3.5	.0002
Systematic risk - S A	2.3.1	65.5	.0000	18.3	.0000	7344	0.4	.3285
	2.3.2	65.8	.0000	18.2	.0000	8719	0.4	.3631
	2.3.3	77.5	.0000	19.4	.0000	7300	-0.9	.8265
	2.3.4	78.1	.0000	20.1	.0000	70	-0.9	.8145
	2.3.5	72.2	.0005	11.2	.0000	126	1.6	.0587
	2.3.6	83.1	.0001	26.2	.0000	133	-0.3	.6066
Systematic risk - LnS A	2.4.1	107.2	.0000	3.0	.0331	7343	1.7	.0424

Table 19: Test for heteroskedasticity, normality, correct specification and multicollenarity

2.4.2	102.9	.0000	2.6	.0555	8719	1.6	.0506
2.4.3	171.0	.0000	2.8	.0397	7300	2.3	.0101
2.4.4	170.8	.0000	2.8	.0411	70	2.3	.0095
2.4.5	150.0	.0000	4.2	.0068	126	2.4	.0084
2.4.6	183.9	.0000	2.3	.0763	133	2.0	.0206

1: S and LnS is spread and the natural logarithm of spreads as the dependent variable, respectively. A and C is adjusted and composite rating dummies, respectively. “Differences” is for studies testing the spread differences between CLOs and corporate bonds. “Systematic risk” is for studies testing systematic risk in CLOs

10.7 Stata code

10.7.1 Generation of data set for CLOs

Data generation - Structured.do - Printed on 10-05-2020 09:08:29

```
**This code is used to generate the CLO data set used to test H2 to H6. The data set is also used as input for generating the data set for testing H1. This section entails importing and appending data from excel, selection steps in stata, variable generation and finally some descriptive statistics.

clear

** Get primary sheet
    import excel "C:\Users\petyde\Desktop\Speciale\Data\Master - Hardcoded v2.xlsx", sheet("Western Europe") firstrow case(lower)
    generate date=issue_date

    **Merge with others
    merge m:1 date using "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\Treasury yield.dta"
    drop if _merge==2
    drop _merge
    *
    merge m:m date using "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\currency swap diff.dta"
    drop if _merge==2
    drop _merge
    *
    merge m:1 date using "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\Implied volatility.dta"
    drop if _merge==2
    drop _merge

** Data cleaning
    **Cleaning of data

    **Kun floating med price 100
    keep if coupon_type=="FLOATING"
    keep if issue_price==100

    **Kun med spreads
    drop if spread==.

    **Drop years which the rating variable is not working
    generate year=yofd(issue_date)
    drop if year<2017

    **Remove other currencies than EUR
    keep if currency=="EUR"

    **Drop meaningless values
    drop if credit_support<0
    drop if credit_support>100 & credit_support<1000

    **Kun callables
    drop if iscallable==0

    **Drop redundant variables
    drop usd10yearyield
    drop gbp10yearyield
    drop coupon
    drop wac
    drop syndicates
    drop syndicates2
    drop syndicates3
    drop exchanges
    drop date

**Variable making
    **Variable making

    **Principal in millions
    generate principalmio=orig_bal/1000000

    ** Interaction term
    generate betaxn=beta*loan_number
    **Year dummies

        **create year dummies
            forvalues i=17/20 {
```

```
                set seed `i'
                generate year_20`i'=(year==20`i')
                }
        **Month dummies
            generate month=month(issue_date)

            **create year dummies
                forvalues i=1/12 {
                set seed `i'
                generate month_`i'=(month==`i')
                }

        **Geography for collateral dummies
            generate col_geo_BE=(country_of_collateral=="BE")
            generate col_geo_ES=(country_of_collateral=="ES")
            generate col_geo_IT=(country_of_collateral=="IT")
            **Mixed as omitted

        **Geography for SPV dummies
            generate spv_geo_BE=(country=="BELGIUM")
            generate spv_geo_IE=(country=="IRELAND")
            generate spv_geo_IT=(country=="ITALY")
            generate spv_geo_LU=(country=="LUXEMBOURG")
            generate spv_geo_ES=(country=="SPAIN")
            *Netherlands as omitted

            **Composite rating dummies
        generate comp_aaa=(composite_rating=="AAA")
        generate comp_nr=(composite_rating=="NR")

            **Gen specifics
            generate s_comp_aap=(composite_rating=="AA+")
            generate s_comp_aa=(composite_rating=="AA")
            generate s_comp_aam=(composite_rating=="AA-")
            generate sum_comp_aa=s_comp_aap+s_comp_aa+s_comp_aam
            generate comp_aa=(sum_comp_aa>0)
            drop sum_comp_aa

            generate s_comp_ap=(composite_rating=="A+")
            generate s_comp_a=(composite_rating=="A")
            generate s_comp_am=(composite_rating=="A-")
            generate sum_comp_a=s_comp_ap+s_comp_a+s_comp_am
            generate comp_a=(sum_comp_a>0)
            drop sum_comp_a

            generate s_comp_bbbp=(composite_rating=="BBB+")
            generate s_comp_bbb=(composite_rating=="BBB")
            generate s_comp_bbbm=(composite_rating=="BBB-")
            generate sum_comp_bbb=s_comp_bbbp+s_comp_bbb+s_comp_bbbm
            generate comp_bbb=(sum_comp_bbb>0)
            drop sum_comp_bbb

            generate s_comp_bbp=(composite_rating=="BB+")
            generate s_comp_bb=(composite_rating=="BB")
            generate s_comp_bbm=(composite_rating=="BB-")
            generate sum_comp_bb=s_comp_bbp+s_comp_bb+s_comp_bbm
            generate comp_bb=(sum_comp_bb>0)
            drop sum_comp_bb

            generate s_comp_bp=(composite_rating=="B+")
            generate s_comp_b=(composite_rating=="B")
            generate s_comp_bm=(composite_rating=="B-")
            generate sum_comp_b=s_comp_bp+s_comp_b+s_comp_bm
            generate comp_b=(sum_comp_b>0)
            drop sum_comp_b

            generate s_comp_cccp=(composite_rating=="CCC+")
            generate s_comp_ccc=(composite_rating=="CCC")
            generate s_comp_cccm=(composite_rating=="CCC-")

            generate s_comp_ccp=(composite_rating=="CC+")
            generate s_comp_cc=(composite_rating=="CC")
            generate s_comp_ccm=(composite_rating=="CC-")

            generate s_comp_cp=(composite_rating=="C+")
```

```
        generate s_comp_c=(composite_rating=="C")
        generate s_comp_cm=(composite_rating=="C-")

**Rating refinement creation
        **Moodys adjustment
        replace moodys_rating="A2" if moodys_rating=="(P)A2"
        replace moodys_rating="Aa2" if moodys_rating=="(P)Aa2"
        replace moodys_rating="Baa2" if moodys_rating=="(P)Baa2"

        **S&P adjustment
        replace sp_rating="AAA" if sp_rating=="(P)AAA"
        replace sp_rating="AA" if sp_rating=="(P)AA"
        replace sp_rating="A" if sp_rating=="(P)A"
        replace sp_rating="BBB" if sp_rating=="(P)BBB"

        generate rating_adj=sp_rating

            **Moodys addition
                **For N.A.
                replace rating_adj="AAA" if sp_rating=="N.A." & moodys_rating=="Aaa"

                replace rating_adj="AA+" if sp_rating=="N.A." & moodys_rating=="Aa1"
                replace rating_adj="AA" if sp_rating=="N.A." & moodys_rating=="Aa2"
                replace rating_adj="AA-" if sp_rating=="N.A." & moodys_rating=="Aa3"

                replace rating_adj="A+" if sp_rating=="N.A." & moodys_rating=="A1"
                replace rating_adj="A" if sp_rating=="N.A." & moodys_rating=="A2"
                replace rating_adj="A-" if sp_rating=="N.A." & moodys_rating=="A3"

                replace rating_adj="BBB+" if sp_rating=="N.A." & moodys_rating=="Baa1"
                replace rating_adj="BBB" if sp_rating=="N.A." & moodys_rating=="Baa2"
                replace rating_adj="BBB-" if sp_rating=="N.A." & moodys_rating=="Baa3"

                replace rating_adj="BB+" if sp_rating=="N.A." & moodys_rating=="Ba1"
                replace rating_adj="BB" if sp_rating=="N.A." & moodys_rating=="Ba2"
                replace rating_adj="BB-" if sp_rating=="N.A." & moodys_rating=="Ba3"

                replace rating_adj="B+" if sp_rating=="N.A." & moodys_rating=="B1"
                replace rating_adj="B" if sp_rating=="N.A." & moodys_rating=="B2"
                replace rating_adj="B-" if sp_rating=="N.A." & moodys_rating=="B3"

                replace rating_adj="CCC+" if sp_rating=="N.A." & moodys_rating=="Caa1"
                replace rating_adj="CCC" if sp_rating=="N.A." & moodys_rating=="Caa2"
                replace rating_adj="CCC-" if sp_rating=="N.A." & moodys_rating=="Caa3"

                replace rating_adj="CC+" if sp_rating=="N.A." & moodys_rating=="Ca1"
                replace rating_adj="CC" if sp_rating=="N.A." & moodys_rating=="Ca2"
                replace rating_adj="CC-" if sp_rating=="N.A." & moodys_rating=="Ca3"

                replace rating_adj="C+" if sp_rating=="N.A." & moodys_rating=="C1"
                replace rating_adj="C" if sp_rating=="N.A." & moodys_rating=="C2"
                replace rating_adj="C-" if sp_rating=="N.A." & moodys_rating=="C3"

                **For NR
                replace rating_adj="AAA" if sp_rating=="NR" & moodys_rating=="Aaa"

                replace rating_adj="AA+" if sp_rating=="NR" & moodys_rating=="Aa1"
                replace rating_adj="AA" if sp_rating=="NR" & moodys_rating=="Aa2"
                replace rating_adj="AA-" if sp_rating=="NR" & moodys_rating=="Aa3"

                replace rating_adj="A+" if sp_rating=="NR" & moodys_rating=="A1"
                replace rating_adj="A" if sp_rating=="NR" & moodys_rating=="A2"
                replace rating_adj="A-" if sp_rating=="NR" & moodys_rating=="A3"

                replace rating_adj="BBB+" if sp_rating=="NR" & moodys_rating=="Baa1"
                replace rating_adj="BBB" if sp_rating=="NR" & moodys_rating=="Baa2"
                replace rating_adj="BBB-" if sp_rating=="NR" & moodys_rating=="Baa3"

                replace rating_adj="BB+" if sp_rating=="NR" & moodys_rating=="Ba1"
                replace rating_adj="BB" if sp_rating=="NR" & moodys_rating=="Ba2"
                replace rating_adj="BB-" if sp_rating=="NR" & moodys_rating=="Ba3"

                replace rating_adj="B+" if sp_rating=="NR" & moodys_rating=="B1"
                replace rating_adj="B" if sp_rating=="NR" & moodys_rating=="B2"
                replace rating_adj="B-" if sp_rating=="NR" & moodys_rating=="B3"
```

```
                replace rating_adj="CCC+" if sp_rating=="NR" & moodys_rating=="Caa1"
                replace rating_adj="CCC" if sp_rating=="NR" & moodys_rating=="Caa2"
                replace rating_adj="CCC-" if sp_rating=="NR" & moodys_rating=="Caa3"

                replace rating_adj="CC+" if sp_rating=="NR" & moodys_rating=="Ca1"
                replace rating_adj="CC" if sp_rating=="NR" & moodys_rating=="Ca2"
                replace rating_adj="CC-" if sp_rating=="NR" & moodys_rating=="Ca3"

                replace rating_adj="C+" if sp_rating=="NR" & moodys_rating=="C1"
                replace rating_adj="C" if sp_rating=="NR" & moodys_rating=="C2"
                replace rating_adj="C-" if sp_rating=="NR" & moodys_rating=="C3"

        **Fitch addition
            **For N.A.
            replace rating_adj="AAA" if fitch_rating=="AAA" & rating_adj=="N.A."

            replace rating_adj="AA+" if fitch_rating=="AA+" & rating_adj=="N.A."
            replace rating_adj="AA" if fitch_rating=="AA" & rating_adj=="N.A."
            replace rating_adj="AA-" if fitch_rating=="AA-" & rating_adj=="N.A."

            replace rating_adj="A+" if fitch_rating=="A+" & rating_adj=="N.A."
            replace rating_adj="A" if fitch_rating=="A" & rating_adj=="N.A."
            replace rating_adj="A-" if fitch_rating=="A-" & rating_adj=="N.A."

            replace rating_adj="BBB+" if fitch_rating=="BBB+" & rating_adj=="N.A."
            replace rating_adj="BBB" if fitch_rating=="BBB" & rating_adj=="N.A."
            replace rating_adj="BBB-" if fitch_rating=="BBB-" & rating_adj=="N.A."

            replace rating_adj="BB+" if fitch_rating=="BB+" & rating_adj=="N.A."
            replace rating_adj="BB" if fitch_rating=="BB" & rating_adj=="N.A."
            replace rating_adj="BB-" if fitch_rating=="BB-" & rating_adj=="N.A."

            replace rating_adj="B+" if fitch_rating=="B+" & rating_adj=="N.A."
            replace rating_adj="B" if fitch_rating=="B" & rating_adj=="N.A."
            replace rating_adj="B-" if fitch_rating=="B-" & rating_adj=="N.A."

            replace rating_adj="CCC+" if fitch_rating=="CCC+" & rating_adj=="N.A."
            replace rating_adj="CCC" if fitch_rating=="CCC" & rating_adj=="N.A."
            replace rating_adj="CCC-" if fitch_rating=="CCC-" & rating_adj=="N.A."

            replace rating_adj="CC+" if fitch_rating=="CC+" & rating_adj=="N.A."
            replace rating_adj="CC" if fitch_rating=="CC" & rating_adj=="N.A."
            replace rating_adj="CC-" if fitch_rating=="CC-" & rating_adj=="N.A."

            replace rating_adj="C+" if fitch_rating=="C+" & rating_adj=="N.A."
            replace rating_adj="C" if fitch_rating=="C" & rating_adj=="N.A."
            replace rating_adj="C-" if fitch_rating=="C-" & rating_adj=="N.A."

            **For NR
            replace rating_adj="AAA" if fitch_rating=="AAA" & rating_adj=="NR"

            replace rating_adj="AA+" if fitch_rating=="AA+" & rating_adj=="NR"
            replace rating_adj="AA" if fitch_rating=="AA" & rating_adj=="NR"
            replace rating_adj="AA-" if fitch_rating=="AA-" & rating_adj=="NR"

            replace rating_adj="A+" if fitch_rating=="A+" & rating_adj=="NR"
            replace rating_adj="A" if fitch_rating=="A" & rating_adj=="NR"
            replace rating_adj="A-" if fitch_rating=="A-" & rating_adj=="NR"

            replace rating_adj="BBB+" if fitch_rating=="BBB+" & rating_adj=="NR"
            replace rating_adj="BBB" if fitch_rating=="BBB" & rating_adj=="NR"
            replace rating_adj="BBB-" if fitch_rating=="BBB-" & rating_adj=="NR"

            replace rating_adj="BB+" if fitch_rating=="BB+" & rating_adj=="NR"
            replace rating_adj="BB" if fitch_rating=="BB" & rating_adj=="NR"
            replace rating_adj="BB-" if fitch_rating=="BB-" & rating_adj=="NR"

            replace rating_adj="B+" if fitch_rating=="B+" & rating_adj=="NR"
            replace rating_adj="B" if fitch_rating=="B" & rating_adj=="NR"
            replace rating_adj="B-" if fitch_rating=="B-" & rating_adj=="NR"

            replace rating_adj="CCC+" if fitch_rating=="CCC+" & rating_adj=="NR"
            replace rating_adj="CCC" if fitch_rating=="CCC" & rating_adj=="NR"
            replace rating_adj="CCC-" if fitch_rating=="CCC-" & rating_adj=="NR"
```

```
            replace rating_adj="CC+" if fitch_rating=="CC+" & rating_adj=="NR"
            replace rating_adj="CC" if fitch_rating=="CC" & rating_adj=="NR"
            replace rating_adj="CC-" if fitch_rating=="CC-" & rating_adj=="NR"

            replace rating_adj="C+" if fitch_rating=="C+" & rating_adj=="NR"
            replace rating_adj="C" if fitch_rating=="C" & rating_adj=="NR"
            replace rating_adj="C-" if fitch_rating=="C-" & rating_adj=="NR"

    **refinement rating dummies
    generate adj_refinement_aaa=(rating_adj=="AAA")

    generate adj_refinement_aap=(rating_adj=="AA+")
    generate adj_refinement_aa=(rating_adj=="AA")
    generate adj_refinement_aam=(rating_adj=="AA-")

    generate adj_refinement_ap=(rating_adj=="A+")
    generate adj_refinement_a=(rating_adj=="A")
    generate adj_refinement_am=(rating_adj=="A-")

    generate adj_refinement_bbbp=(rating_adj=="BBB+")
    generate adj_refinement_bbb=(rating_adj=="BBB")
    generate adj_refinement_bbbm=(rating_adj=="BBB-")

    generate adj_refinement_bbp=(rating_adj=="BB+")
    generate adj_refinement_bb=(rating_adj=="BB")
    generate adj_refinement_bbm=(rating_adj=="BB-")

    generate adj_refinement_bp=(rating_adj=="B+")
    generate adj_refinement_b=(rating_adj=="B")
    generate adj_refinement_bm=(rating_adj=="B-")

    generate adj_refinement_cccp=(rating_adj=="CCC+")
    generate adj_refinement_ccc=(rating_adj=="CCC")
    generate adj_refinement_cccm=(rating_adj=="CCC-")

    generate adj_refinement_ccp=(rating_adj=="CC+")
    generate adj_refinement_cc=(rating_adj=="CC")
    generate adj_refinement_ccm=(rating_adj=="CC-")

    generate adj_refinement_cp=(rating_adj=="C+")
    generate adj_refinement_c=(rating_adj=="C")
    generate adj_refinement_cm=(rating_adj=="C-")


    **Nonrefinement rating dummies

    generate sum_adj_aaa=adj_refinement_aaa
    generate adj_aaa=(sum_adj_aaa>0)
    drop sum_adj_aaa

    generate sum_adj_aa=adj_refinement_aap+adj_refinement_aa+adj_refinement_aam
    generate adj_aa=(sum_adj_aa>0)
    drop sum_adj_aa

    generate sum_adj_a=adj_refinement_ap+adj_refinement_a+adj_refinement_am
    generate adj_a=(sum_adj_a>0)
    drop sum_adj_a

    generate sum_adj_bbb=adj_refinement_bbbp+adj_refinement_bbb+adj_refinement_bbbm
    generate adj_bbb=(sum_adj_bbb>0)
    drop sum_adj_bbb

    generate sum_adj_bb=adj_refinement_bbp+adj_refinement_bb+adj_refinement_bbm
    generate adj_bb=(sum_adj_bb>0)
    drop sum_adj_bb

    generate sum_adj_b=adj_refinement_bp+adj_refinement_b+adj_refinement_bm
    generate adj_b=(sum_adj_b>0)
    drop sum_adj_b

    generate sum_adj_ccc=adj_refinement_cccp+adj_refinement_ccc+adj_refinement_cccm
    generate adj_ccc=(sum_adj_ccc>0)
    drop sum_adj_ccc

```

```
    generate sum_adj_cc=adj_refinement_ccp+adj_refinement_cc+adj_refinement_ccm
    generate adj_cc=(sum_adj_cc>0)
    drop sum_adj_cc

    generate sum_adj_c=adj_refinement_cp+adj_refinement_c+adj_refinement_cm
    generate adj_c=(sum_adj_c>0)
    drop sum_adj_c

    replace adj_aaa=. if rating_adj=="N.A."
    replace adj_aa=. if rating_adj=="N.A."
    replace adj_a=. if rating_adj=="N.A."
    replace adj_bbb=. if rating_adj=="N.A."
    replace adj_bb=. if rating_adj=="N.A."
    replace adj_b=. if rating_adj=="N.A."

    replace adj_aaa=. if rating_adj=="NR"
    replace adj_aa=. if rating_adj=="NR"
    replace adj_a=. if rating_adj=="NR"
    replace adj_bbb=. if rating_adj=="NR"
    replace adj_bb=. if rating_adj=="NR"
    replace adj_b=. if rating_adj=="NR"

    replace comp_aaa=. if composite_rating=="NR"
    replace comp_aa=. if composite_rating=="NR"
    replace comp_a=. if composite_rating=="NR"
    replace comp_bbb=. if composite_rating=="NR"
    replace comp_bb=. if composite_rating=="NR"
    replace comp_b=. if composite_rating=="NR"

    **systematic risk driver interaction terms for composite ratings
        **Loan numbers
        generate nxaaa_comp=loan_number*comp_aaa
        generate nxaa_comp=loan_number*comp_aa
        generate nxa_comp=loan_number*comp_a
        generate nxaaa_adj=loan_number*adj_aaa
        generate nxaa_adj=loan_number*adj_aa
        generate nxa_adj=loan_number*adj_a

        **Beta
        generate betaxaaa_comp=beta*comp_aaa
        generate betaxaa_comp=beta*comp_aa
        generate betaxa_comp=beta*comp_a
        generate betaxaaa_adj=beta*adj_aaa
        generate betaxaa_adj=beta*adj_aa
        generate betaxa_adj=beta*adj_a

        **Credit support
        generate creditsupportxaaa_comp=credit_support*comp_aaa
        generate creditsupportxaa_comp=credit_support*comp_aa
        generate creditsupportxa_comp=credit_support*comp_a
        generate creditsupportxaaa_adj=credit_support*adj_aaa
        generate creditsupportxaa_adj=credit_support*adj_aa
        generate creditsupportxa_adj=credit_support*adj_a

        generate lnspread=ln(spread)

        **Preparing sector weightings
        rename capitalgoods s_capital_goods
        rename householdpersonalproducts s_household_personal_products
        rename commercialprofessionalservic s_professional_services
        rename healthcarelevel1 s_healthcare
        rename informationtechnologylevel1 s_info_tech
        rename consumerservices s_consumer_services
        rename mediaentertainment s_media_entertainment
        rename retailing s_retail
        rename telecommunicationservices s_telecommunication
        rename transportation s_transportation
        rename utilities s_utilities
        rename energy s_energy


**Descriptive statistics
    **Beta
    summarize beta
    histogram beta
```

```

    **Credit support
    summarize credit_support if comp_aaa==1
    summarize credit_support if comp_aa==1
    summarize credit_support if comp_a==1
    summarize credit_support if comp_bbb==1
    summarize credit_support if comp_bb==1
    summarize credit_support if comp_b==1

    **Industry weightings
    summarize s_capital_goods automobilesandcomponents diversifiedfinancials
foodbeveragetobacco materials consumerdurablesapparel consumerdurablesapparel
s_household_personal_products s_professional_services s_healthcare s_info_tech
s_consumer_services s_media_entertainment s_retail s_telecommunication s_transportation
s_utilities s_energy

    **Loan numbers
    summarize loan_number, detail
    summarize loan_number if year==2017, detail
    summarize loan_number if year==2018, detail
    summarize loan_number if year==2019, detail
    summarize loan_number if year==2020, detail
```

10.7.2 Regression analyses for CLOs


```
**This code is used to conduct regression analyses for the CLO data set and to test hypothesis H2 to H6. For each regression analyses conducted, a series of assumption tests are conducted as described in the thesis.

**Regressions - Spreads 1.
eststo clear
    ** Regressions for non-refinement composite rating 1.1
        **
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds, cluster(dealticker)

        **
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b, cluster(dealticker)

        ** 2.1.1 + Systematic risk
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b loan_number beta betaxn credit_support, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_1_3, xb
            predict ur1_1_3, resid
            twoway scatter ur1_1_3 yhat1_1_3, yline(0)

            **Normality of residuals
            swilk ur1_1_3

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Beta*N
            test _b[betaxn]=0
            local sign_betaxn=sign(_b[betaxn])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

            **H7: Total impact
            test loan_number beta betaxn credit_support

            **BP hetero test
            quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b loan_number beta betaxn credit_support
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b loan_number beta betaxn credit_support

        ** 2.1.2 + geo for SPV and underlying loans
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support, cluster(dealticker)

```

```
                **Adjusted R squared
                di e(r2_a)

                **Variance Inflation factor
                vif

                **Ramseys RESET test
                ovtest

                **fitted value and residuals scatter plot
                predict yhat1_1_4, xb
                predict url_1_4, resid
                twoway scatter url_1_4 yhat1_1_4, yline(0)

                **Normality of residuals
                swilk url_1_4

                **H4: Loan number
                test _b[loan_number]=0
                local sign_n=sign(_b[loan_number])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

                **H5: Beta
                test _b[beta]=0
                local sign_beta=sign(_b[beta])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

                **H6: Beta*N
                test _b[betaxn]=0
                local sign_betaxn=sign(_b[betaxn])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

                **H6: Seniority
                test _b[credit_support]=0
                local sign_credit_support=sign(_b[credit_support])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

                **H7: Total impact
                test loan_number beta betaxn credit_support

                **BP hetero test
                quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support
                hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support

        ** 2.1.3 + time dummies
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support, cluster(dealticker)

                **Adjusted R squared
                di e(r2_a)

                **Variance Inflation factor
                vif

                **Ramseys RESET test
                ovtest

                **fitted value and residuals scatter plot
                predict yhat1_1_5, xb
                predict url_1_5, resid
                twoway scatter url_1_5 yhat1_1_5, yline(0)

                **Normality of residuals
                swilk url_1_5

```

```
		**H4: Loan number
		test _b[loan_number]=0
		local sign_n=sign(_b[loan_number])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

		**H5: Beta
		test _b[beta]=0
		local sign_beta=sign(_b[beta])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

		**H6: Beta*N
		test _b[betaxn]=0
		local sign_betaxn=sign(_b[betaxn])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

		**H6: Seniority
		test _b[credit_support]=0
		local sign_credit_support=sign(_b[credit_support])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

		**H7: Total impact
		test loan_number beta betaxn credit_support

		**BP hetero test
		quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support
		hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support

	** 2.1.4 - betaxn
	eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support, cluster(dealticker)

		**Adjusted R squared
		di e(r2_a)

		**Variance Inflation factor
		vif

		**Ramseys RESET test
		ovtest

		**fitted value and residuals scatter plot
		predict yhat1_1_6, xb
		predict ur1_1_6, resid
		twoway scatter ur1_1_6 yhat1_1_6, yline(0)

		**Normality of residuals
		swilk ur1_1_6

		**H4: Loan number
		test _b[loan_number]=0
		local sign_n=sign(_b[loan_number])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

		**H5: Beta
		test _b[beta]=0
		local sign_beta=sign(_b[beta])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

		**H6: Seniority
		test _b[credit_support]=0
		local sign_credit_support=sign(_b[credit_support])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))
```

```

			**H7: Total impact
			test loan_number beta credit_support

			**BP hetero test
			quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support
			hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support


		** 2.1.5 (6) + beta/rating interaction terms
		eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support betaxaaa_comp betaxaa_comp betaxa_comp, cluster(dealticker)

			**Adjusted R squared
			di e(r2_a)

			**Variance Inflation factor
			vif

			**Ramseys RESET test
			ovtest

			**fitted value and residuals scatter plot
			predict yhat1_1_7, xb
			predict ur1_1_7, resid
			twoway scatter ur1_1_7 yhat1_1_7, yline(0)

			**Normality of residuals
			swilk ur1_1_7

			**H4: Loan number
			test _b[loan_number]=0
			local sign_n=sign(_b[loan_number])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

			**H5: Beta
			test _b[beta]=0
			local sign_beta=sign(_b[beta])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

			**H6: Seniority
			test _b[credit_support]=0
			local sign_credit_support=sign(_b[credit_support])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

			**H7: Total impact
			test loan_number beta credit_support

			**BP hetero test
			quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa nxaaa nxaa nxa
			hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa nxaaa nxaa nxa

		** 2.1.6 (6) + sector weightings
```

```
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support s_capital_goods s_household_personal_products s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_1_8, xb
            predict ur1_1_8, resid
            twoway scatter ur1_1_8 yhat1_1_8, yline(0)

            **Normality of residuals
            swilk ur1_1_8

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

            **H7: Total impact
            test loan_number beta credit_support

            **BP hetero test
            quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support s_capital_goods s_household_personal_products s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support s_capital_goods s_household_personal_products s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy


    ** Regressions for adjusted rating 1.2.
        **
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds, cluster(dealticker)

        **
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b, cluster(dealticker)

        ** 2.3.1
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b loan_number beta betaxn credit_support, cluster(dealticker)
```

```

		**Adjusted R squared
		di e(r2_a)

		**Variance Inflation factor
		vif

		**Ramseys RESET test
		ovtest

		**fitted value and residuals scatter plot
		predict yhat1_2_3, xb
		predict ur1_2_3, resid
		twoway scatter ur1_2_3 yhat1_2_3, yline(0)

		**Normality of residuals
		swilk ur1_2_3

		**H4: Loan number
		test _b[loan_number]=0
		local sign_n=sign(_b[loan_number])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

		**H5: Beta
		test _b[beta]=0
		local sign_beta=sign(_b[beta])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

		**H6: Beta*N
		test _b[betaxn]=0
		local sign_betaxn=sign(_b[betaxn])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

		**H6: Seniority
		test _b[credit_support]=0
		local sign_credit_support=sign(_b[credit_support])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

		**H7: Total impact
		test loan_number beta betaxn credit_support

		**BP hetero test
		quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b loan_number beta betaxn credit_support
		hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b loan_number beta betaxn credit_support

	** 2.3.2
	eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support, cluster(dealticker)

		**Adjusted R squared
		di e(r2_a)

		**Variance Inflation factor
		vif

		**Ramseys RESET test
		ovtest

		**fitted value and residuals scatter plot
		predict yhat1_2_4, xb
		predict ur1_2_4, resid
		twoway scatter ur1_2_4 yhat1_2_4, yline(0)

		**Normality of residuals
		swilk ur1_2_4

		**H4: Loan number
		test _b[loan_number]=0
		local sign_n=sign(_b[loan_number])
```

```
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Beta*N
            test _b[betaxn]=0
            local sign_betaxn=sign(_b[betaxn])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

            **H7: Total impact
            test loan_number beta betaxn credit_support

            **BP hetero test
            quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support

        ** 2.3.3
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_2_5, xb
            predict ur1_2_5, resid
            twoway scatter ur1_2_5 yhat1_2_5, yline(0)

            **Normality of residuals
            swilk ur1_2_5

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Beta*N
            test _b[betaxn]=0
            local sign_betaxn=sign(_b[betaxn])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))
```

```

		**H7: Total impact
		test loan_number beta betaxn credit_support

		**BP hetero test
		quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support
		hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support

	** 2.3.4
	eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support, cluster(dealticker)

		**Adjusted R squared
		di e(r2_a)

		**Variance Inflation factor
		vif

		**Ramseys RESET test
		ovtest

		**fitted value and residuals scatter plot
		predict yhat1_2_6, xb
		predict ur1_2_6, resid
		twoway scatter ur1_2_6 yhat1_2_6, yline(0)

		**Normality of residuals
		swilk ur1_2_6

		**H4: Loan number
		test _b[loan_number]=0
		local sign_n=sign(_b[loan_number])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

		**H5: Beta
		test _b[beta]=0
		local sign_beta=sign(_b[beta])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

		**H6: Seniority
		test _b[credit_support]=0
		local sign_credit_support=sign(_b[credit_support])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

		**H7: Total impact
		test loan_number beta credit_support

		**BP hetero test
		quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support
		hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support

	** 2.3.5
	eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
```

```
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta credit_support betaxaaa_adj betaxaa_adj betaxa_adj,
cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_2_7, xb
            predict ur1_2_7, resid
            twoway scatter ur1_2_7 yhat1_2_7, yline(0)

            **Normality of residuals
            swilk ur1_2_7

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
)))

            **H7: Total impact
            test loan_number beta credit_support

            **BP hetero test
            quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES
col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa nxaaa
nxaa nxa
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT
spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020
month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa nxaaa nxaa nxa

        ** 2.3.6
        eststo: regress spread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES
col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta credit_support s_capital_goods
s_household_personal_products s_professional_services s_info_tech s_consumer_services
s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy,
cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_2_8, xb
            predict ur1_2_8, resid
```

```
		twoway scatter ur1_2_8 yhat1_2_8, yline(0)

		**Normality of residuals
		swilk ur1_2_8

		**H4: Loan number
		test _b[loan_number]=0
		local sign_n=sign(_b[loan_number])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

		**H5: Beta
		test _b[beta]=0
		local sign_beta=sign(_b[beta])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

		**H6: Seniority
		test _b[credit_support]=0
		local sign_credit_support=sign(_b[credit_support])
		display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
)))

		**H7: Total impact
		test loan_number beta credit_support

		**BP hetero test
		quietly regress spread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES
col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta credit_support s_capital_goods
s_household_personal_products s_professional_services s_info_tech s_consumer_services
s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy
		hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT
spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020
month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
 loan_number beta credit_support s_capital_goods s_household_personal_products
s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail
s_telecommunication s_transportation s_utilities s_energy


**Regressions - lnSpreads 2.
eststo clear
    ** Regressions for non-refinement composite rating 2.1.
	**
	eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds, cluster(dealticker)

	**
	eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b, cluster(dealticker)

	** 2.2.1
	eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b loan_number beta
betaxn credit_support, cluster(dealticker)

		**Adjusted R squared
		di e(r2_a)

		**Variance Inflation factor
		vif

		**Ramseys RESET test
		ovtest

		**fitted value and residuals scatter plot
		predict yhat2_1_3, xb
		predict ur2_1_3, resid
		twoway scatter ur2_1_3 yhat2_1_3, yline(0)

		**Normality of residuals
		swilk ur2_1_3

		**H4: Loan number
```

```
                test _b[loan_number]=0
                local sign_n=sign(_b[loan_number])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

                **H5: Beta
                test _b[beta]=0
                local sign_beta=sign(_b[beta])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

                **H6: Beta*N
                test _b[betaxn]=0
                local sign_betaxn=sign(_b[betaxn])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

                **H6: Seniority
                test _b[credit_support]=0
                local sign_credit_support=sign(_b[credit_support])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
)))

                **H7: Total impact
                test loan_number beta betaxn credit_support

                **BP hetero test
                quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b loan_number beta
betaxn credit_support
                hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b loan_number beta betaxn
credit_support

        ** 2.2.2
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number
beta betaxn credit_support, cluster(dealticker)

                **Adjusted R squared
                di e(r2_a)

                **Variance Inflation factor
                vif

                **Ramseys RESET test
                ovtest

                **fitted value and residuals scatter plot
                predict yhat2_1_4, xb
                predict ur2_1_4, resid
                twoway scatter ur2_1_4 yhat2_1_4, yline(0)

                **Normality of residuals
                swilk ur2_1_4

                **H4: Loan number
                test _b[loan_number]=0
                local sign_n=sign(_b[loan_number])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

                **H5: Beta
                test _b[beta]=0
                local sign_beta=sign(_b[beta])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

                **H6: Beta*N
                test _b[betaxn]=0
                local sign_betaxn=sign(_b[betaxn])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

                **H6: Seniority
                test _b[credit_support]=0
                local sign_credit_support=sign(_b[credit_support])
                display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
)))

```

```
			**H7: Total impact
			test loan_number beta betaxn credit_support

			**BP hetero test
			quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
	principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
	col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number
	beta betaxn credit_support
			hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
	numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT
	spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn
	credit_support


		** 2.2.3
		eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
	principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
	col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018
	year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9
	month_10 month_11 month_12 loan_number beta betaxn credit_support, cluster(dealticker)

			**Adjusted R squared
			di e(r2_a)

			**Variance Inflation factor
			vif

			**Ramseys RESET test
			ovtest

			**fitted value and residuals scatter plot
			predict yhat2_1_5, xb
			predict ur2_1_5, resid
			twoway scatter ur2_1_5 yhat2_1_5, yline(0)

			**Normality of residuals
			swilk ur2_1_5

			**H4: Loan number
			test _b[loan_number]=0
			local sign_n=sign(_b[loan_number])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

			**H5: Beta
			test _b[beta]=0
			local sign_beta=sign(_b[beta])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

			**H6: Beta*N
			test _b[betaxn]=0
			local sign_betaxn=sign(_b[betaxn])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

			**H6: Seniority
			test _b[credit_support]=0
			local sign_credit_support=sign(_b[credit_support])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
	)))

			**H7: Total impact
			test loan_number beta betaxn credit_support

			**BP hetero test
			quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
	principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
	col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018
	year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9
	month_10 month_11 month_12 loan_number beta betaxn credit_support
			hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
	numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT
	spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020
	month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
	 loan_number beta betaxn credit_support

		** 2.2.4
```

```
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018
year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9
month_10 month_11 month_12 loan_number beta credit_support, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_1_6, xb
            predict ur2_1_6, resid
            twoway scatter ur2_1_6 yhat2_1_6, yline(0)

            **Normality of residuals
            swilk ur2_1_6

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
)))

            **H7: Total impact
            test loan_number beta credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018
year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9
month_10 month_11 month_12 loan_number beta credit_support
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT
spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020
month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
 loan_number beta credit_support


        ** 2.2.5
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018
year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9
month_10 month_11 month_12 loan_number beta credit_support betaxaaa_comp betaxaa_comp
betaxa_comp, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_1_7, xb
            predict ur2_1_7, resid
```

```
            twoway scatter ur2_1_7 yhat2_1_7, yline(0)

            **Normality of residuals
            swilk ur2_1_7

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

            **H7: Total impact
            test loan_number beta credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa nxaaa nxaa nxa
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa nxaaa nxaa nxa


        ** 2.2.6
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support s_capital_goods s_household_personal_products s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_1_8, xb
            predict ur2_1_8, resid
            twoway scatter ur2_1_8 yhat2_1_8, yline(0)

            **Normality of residuals
            swilk ur2_1_8

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

```

```
            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

            **H7: Total impact
            test loan_number beta credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support s_capital_goods s_household_personal_products s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support s_capital_goods s_household_personal_products s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy


    ** Regressions for adjusted rating 2.2.
        **
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds, cluster(dealticker)

        **
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b, cluster(dealticker)

        ** 2.4.1
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b loan_number beta betaxn credit_support, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_2_3, xb
            predict ur2_2_3, resid
            twoway scatter ur2_2_3 yhat2_2_3, yline(0)

            **Normality of residuals
            swilk ur2_2_3

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Beta*N
            test _b[betaxn]=0
            local sign_betaxn=sign(_b[betaxn])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
```

```
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

            **H7: Total impact
            test loan_number beta betaxn credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b loan_number beta betaxn credit_support
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b loan_number beta betaxn credit_support

        ** 2.4.2
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_2_4, xb
            predict ur2_2_4, resid
            twoway scatter ur2_2_4 yhat2_2_4, yline(0)

            **Normality of residuals
            swilk ur2_2_4

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Beta*N
            test _b[betaxn]=0
            local sign_betaxn=sign(_b[betaxn])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

            **H7: Total impact
            test loan_number beta betaxn credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES loan_number beta betaxn credit_support

        ** 2.4.3
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
```

```
month_11 month_12 loan_number beta betaxn credit_support, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_2_5, xb
            predict ur2_2_5, resid
            twoway scatter ur2_2_5 yhat2_2_5, yline(0)

            **Normality of residuals
            swilk ur2_2_5

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Beta*N
            test _b[betaxn]=0
            local sign_betaxn=sign(_b[betaxn])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_betaxn'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
)))

            **H7: Total impact
            test loan_number beta betaxn credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES
col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta betaxn credit_support
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT
spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020
month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
 loan_number beta betaxn credit_support

        ** 2.4.4
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES
col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta credit_support, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_2_6, xb
            predict ur2_2_6, resid
            twoway scatter ur2_2_6 yhat2_2_6, yline(0)
```

```
			**Normality of residuals
			swilk ur2_2_6

			**H4: Loan number
			test _b[loan_number]=0
			local sign_n=sign(_b[loan_number])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

			**H5: Beta
			test _b[beta]=0
			local sign_beta=sign(_b[beta])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

			**H6: Seniority
			test _b[credit_support]=0
			local sign_credit_support=sign(_b[credit_support])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F)))

			**H7: Total impact
			test loan_number beta credit_support

			**BP hetero test
			quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support
			hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support


		** 2.4.5
		eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12 loan_number beta credit_support betaxaaa_adj betaxaa_adj betaxa_adj, cluster(dealticker)

			**Adjusted R squared
			di e(r2_a)

			**Variance Inflation factor
			vif

			**Ramseys RESET test
			ovtest

			**fitted value and residuals scatter plot
			predict yhat2_2_7, xb
			predict ur2_2_7, resid
			twoway scatter ur2_2_7 yhat2_2_7, yline(0)

			**Normality of residuals
			swilk ur2_2_7

			**H4: Loan number
			test _b[loan_number]=0
			local sign_n=sign(_b[loan_number])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

			**H5: Beta
			test _b[beta]=0
			local sign_beta=sign(_b[beta])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

			**H6: Seniority
			test _b[credit_support]=0
			local sign_credit_support=sign(_b[credit_support])
			display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
```

```
)))

            **H7: Total impact
            test loan_number beta credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE
col_geo_ES col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018
year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9
month_10 month_11 month_12 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa
nxaaa nxaa nxa
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
numbonds comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b col_geo_BE col_geo_ES col_geo_IT
spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020
month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
 loan_number beta betaxn credit_support betaxaaa betaxaa betaxa nxaaa nxaa nxa

        ** 2.4.6
        eststo: regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES
col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta credit_support s_capital_goods
s_household_personal_products s_professional_services s_info_tech s_consumer_services
s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy,
cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_2_8, xb
            predict ur2_2_8, resid
            twoway scatter ur2_2_8 yhat2_2_8, yline(0)

            **Normality of residuals
            swilk ur2_2_8

            **H4: Loan number
            test _b[loan_number]=0
            local sign_n=sign(_b[loan_number])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_n'*sqrt(r(F)))

            **H5: Beta
            test _b[beta]=0
            local sign_beta=sign(_b[beta])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_beta'*sqrt(r(F)))

            **H6: Seniority
            test _b[credit_support]=0
            local sign_credit_support=sign(_b[credit_support])
            display "H0: coef <=0 p-value = " ttail(r(df_r),`sign_credit_support'*sqrt(r(F
)))

            **H7: Total impact
            test loan_number beta credit_support

            **BP hetero test
            quietly regress lnspread eur10yearyield diff10 impliedvolatility wal_at_issue
principalmio numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES
col_geo_IT spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019
year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10
month_11 month_12 loan_number beta credit_support s_capital_goods
s_household_personal_products s_professional_services s_info_tech s_consumer_services
s_media_entertainment s_retail s_telecommunication s_transportation s_utilities s_energy
            hettest eur10yearyield diff10 impliedvolatility wal_at_issue principalmio
numbonds adj_aaa adj_aa adj_a adj_bbb adj_bb adj_b col_geo_BE col_geo_ES col_geo_IT
spv_geo_BE spv_geo_IE spv_geo_IT spv_geo_LU spv_geo_ES year_2018 year_2019 year_2020
```

```
month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
 loan_number beta credit_support s_capital_goods s_household_personal_products
s_professional_services s_info_tech s_consumer_services s_media_entertainment s_retail
s_telecommunication s_transportation s_utilities s_energy
```

10.7.3 Generation of data set for CBs and CLOs


```
**This code is used for generating the data set containing both CLOs and corporate bonds to test H1. This section entails importing and appending data from excel, selection steps in stata, variable generation and finally some descriptive statistics.

clear

    **Adjust structured debt data
    use "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\Structured debt\Structured debt.dta"

        **Create structured dummy
        generate structured=1

            **Create geogrpahy dummies
            rename spv_geo_IT geo_IT
            rename spv_geo_ES geo_ES
            rename spv_geo_LU geo_LU
            rename spv_geo_BE geo_BE
            rename spv_geo_IE geo_IE
            generate geo_NL=0
            generate geo_FR=0
            generate geo_DE=0
            generate geo_GB=0
            generate geo_CH=0
            generate geo_NO=0
            generate geo_SE=0
            generate geo_DK=0
            generate geo_US=0
            generate geo_FI=0
            generate geo_GR=0
            generate geo_PT=0
            generate geo_AT=0

        **Delete redundant variables
        drop currency
        drop issue_date
        drop coupon_type
        drop loan_number
        drop country_of_collateral
        drop credit_support
        drop sp_rating
        drop moodys_rating
        drop fitch_rating
        drop issue_price
        drop mostsenior
        drop leadmgr
        drop iscallable
        drop numbonds
        drop currencyfromtheloans
        drop currencyrisk
        drop betaxn
        drop col_geo_BE
        drop col_geo_ES
        drop col_geo_IT
        drop adj_refinement_aaa
        drop adj_refinement_aap
        drop adj_refinement_aa
        drop adj_refinement_aam
        drop adj_refinement_ap
        drop adj_refinement_a
        drop adj_refinement_am
        drop adj_refinement_bbbp
        drop adj_refinement_bbb
        drop adj_refinement_bbbm
        drop adj_refinement_bbp
        drop adj_refinement_bb
        drop adj_refinement_bbm
        drop adj_refinement_bp
        drop adj_refinement_b
        drop adj_refinement_bm
        drop adj_refinement_cccp
        drop adj_refinement_ccc
        drop adj_refinement_cccm
        drop adj_refinement_ccp
        drop adj_refinement_cc
```

```
        drop adj_refinement_ccm
        drop adj_refinement_cp
        drop adj_refinement_c
        drop adj_refinement_cm
        drop adj_aaa
        drop adj_aa
        drop adj_a
        drop adj_bbb
        drop adj_bb
        drop adj_b
        drop adj_ccc
        drop adj_cc
        drop adj_c
        drop rating_adj

    save "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\Difference in structured and unstructured debt\Structured.dta"

    **Prepare unstructured debt data
    clear
    import excel "C:\Users\petyde\Desktop\Speciale\Data\Corporate debt - 20-04 hardcoded.xlsx", sheet("Pure") cellrange(A2:K314) firstrow case(lower)

    rename issue_dtvalue date

    **Merge with others
    merge m:1 date using "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\Treasury yield.dta"
    drop if _merge==2
    drop _merge
    *
    merge m:m date using "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\currency swap diff.dta"
    drop if _merge==2
    drop _merge
    *
    merge m:1 date using "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\Implied volatility.dta"
    drop if _merge==2
    drop _merge

    **Create structured dummy
    generate structured=0

    **Allign names
    rename idvalue name
    rename rating composite_rating
    rename yearstoaveragelife wal_at_issue

    **drop redundant variables
    drop column1
    drop classification_nameclassificati
    drop classificationlevel
    drop usd10yearyield
    drop gbp10yearyield

    **Create same variables
        **Principal in millions
        generate principalmio=orig_bal/1000000

        **Year dummies
            generate year=yofd(date)
            **create year dummies
            forvalues i=17/20 {
            set seed `i'
            generate year_20`i'=(year==20`i')
            }
        **Month dummies
            generate month=month(date)

            **create month dummies
            forvalues i=1/12 {
            set seed `i'
            generate month_`i'=(month==`i')
            }
```

```

        **Composite rating dummies
        generate comp_aaa=(composite_rating=="AAA")
        generate comp_nr=(composite_rating=="NR")

        **Gen specifics
        generate s_comp_aap=(composite_rating=="AA+")
        generate s_comp_aa=(composite_rating=="AA")
        generate s_comp_aam=(composite_rating=="AA-")
        generate sum_comp_aa=s_comp_aap+s_comp_aa+s_comp_aam
        generate comp_aa=(sum_comp_aa>0)
        drop sum_comp_aa

        generate s_comp_ap=(composite_rating=="A+")
        generate s_comp_a=(composite_rating=="A")
        generate s_comp_am=(composite_rating=="A-")
        generate sum_comp_a=s_comp_ap+s_comp_a+s_comp_am
        generate comp_a=(sum_comp_a>0)
        drop sum_comp_a

        generate s_comp_bbbp=(composite_rating=="BBB+")
        generate s_comp_bbb=(composite_rating=="BBB")
        generate s_comp_bbbm=(composite_rating=="BBB-")
        generate sum_comp_bbb=s_comp_bbbp+s_comp_bbb+s_comp_bbbm
        generate comp_bbb=(sum_comp_bbb>0)
        drop sum_comp_bbb

        generate s_comp_bbp=(composite_rating=="BB+")
        generate s_comp_bb=(composite_rating=="BB")
        generate s_comp_bbm=(composite_rating=="BB-")
        generate sum_comp_bb=s_comp_bbp+s_comp_bb+s_comp_bbm
        generate comp_bb=(sum_comp_bb>0)
        drop sum_comp_bb

        generate s_comp_bp=(composite_rating=="B+")
        generate s_comp_b=(composite_rating=="B")
        generate s_comp_bm=(composite_rating=="B-")
        generate sum_comp_b=s_comp_bp+s_comp_b+s_comp_bm
        generate comp_b=(sum_comp_b>0)
        drop sum_comp_b

        generate s_comp_cccp=(composite_rating=="CCC+")
        generate s_comp_ccc=(composite_rating=="CCC")
        generate s_comp_cccm=(composite_rating=="CCC-")

        generate s_comp_ccp=(composite_rating=="CC+")
        generate s_comp_cc=(composite_rating=="CC")
        generate s_comp_ccm=(composite_rating=="CC-")

        generate s_comp_cp=(composite_rating=="C+")
        generate s_comp_c=(composite_rating=="C")
        generate s_comp_cm=(composite_rating=="C-")

        generate dav=_n
        generate dealticker=10000+dav
        drop dav


        **Create geogrpahy dummies
        generate geo_NL=(country=="NL")
        generate geo_FR=(country=="FR")
        generate geo_IT=(country=="IT")
        generate geo_DE=(country=="DE")
        generate geo_ES=(country=="ES")
        generate geo_GB=(country=="GB")
        generate geo_CH=(country=="CH")
        generate geo_NO=(country=="NO")
        generate geo_SE=(country=="SE")
        generate geo_DK=(country=="DK")
        generate geo_LU=(country=="LU")
        generate geo_BE=(country=="BE")
        generate geo_US=(country=="US")
        generate geo_FI=(country=="FI")
        generate geo_GR=(country=="GR")
        generate geo_PT=(country=="PT")
```

```
            generate geo_AT=(country=="AT")
            generate geo_IE=0

        **Append with structured debt
        append using "C:\Users\petyde\Desktop\Speciale\Data\Ready to use data\Difference in structured and unstructured debt\Structured dealticker.dta"

        **drop meaningless spreads
        drop if spread<0

        **Mean deviating - To ifer on intercepts
            ** wal
                summarize wal_at_issue
                return list
                generate dev_wal_at_issue=wal_at_issue-r(mean)

            ** principalmio
                summarize principalmio
                return list
                generate dev_principalmio=principalmio-r(mean)

            ** Treasury yield
                summarize eur10yearyield
                return list
                generate dev_eur10yearyield=eur10yearyield-r(mean)

            **Difference in swaps
                summarize diff10
                return list
                generate dev_diff10=diff10-r(mean)

            **Volatility
                summarize impliedvolatility
                return list
                generate dev_impliedvolatility=impliedvolatility-r(mean)

        **Interaction terms
        generate devwalxstructured=dev_wal_at_issue*structured
        generate aaaxstructured=comp_aaa*structured
        generate aaxstructured=comp_aa*structured
        generate axstructured=comp_a*structured
        generate bbbxstructured=comp_bbb*structured
        generate bbxstructured=comp_bb*structured
        generate bxstructured=comp_b*structured
        generate devprinxstructured=dev_principalmio*structured

        generate geo_NLxstructured=geo_NL*structured
        generate geo_FRxstructured=geo_FR*structured
        generate geo_ITxstructured=geo_IT*structured
        generate geo_DExstructured=geo_DE*structured
        generate geo_ESxstructured=geo_ES*structured
        generate geo_GBxstructured=geo_GB*structured
        generate geo_CHxstructured=geo_CH*structured
        generate geo_NOxstructured=geo_NO*structured
        generate geo_SExstructured=geo_SE*structured
        generate geo_DKxstructured=geo_DK*structured
        generate geo_LUxstructured=geo_LU*structured
        generate geo_BExstructured=geo_BE*structured
        generate geo_USxstructured=geo_US*structured
        generate geo_FIxstructured=geo_FI*structured
        generate geo_GRxstructured=geo_GR*structured
        generate geo_PTxstructured=geo_PT*structured
        generate geo_ATxstructured=geo_AT*structured
        generate geo_IExstructured=geo_IE*structured

        generate dev_eur10yearyieldxstructured=dev_eur10yearyield*structured
        generate dev_diff10xstructured=dev_diff10*structured
        generate dev_impliedvolatilityxstructured=dev_impliedvolatility*structured

        **Adjust ratings
        replace comp_aaa=. if composite_rating=="NR"
        replace comp_aa=. if composite_rating=="NR"
        replace comp_a=. if composite_rating=="NR"
        replace comp_bbb=. if composite_rating=="NR"
        replace comp_bb=. if composite_rating=="NR"
```

```
    replace comp_b=. if composite_rating=="NR"

    **lnspread
    drop lnspread
    generate lnspread=ln(spread)

    **Country adjustments
    replace country="BE" if country=="BELGIUM"
    replace country="IE" if country=="IRELAND"
    replace country="IT" if country=="ITALY"
    replace country="LU" if country=="LUXEMBOURG"
    replace country="NL" if country=="NETHERLANDS"
    replace country="ES" if country=="SPAIN"

**Descriptive statistics
    ** Spread across years and asset type
    estpost summarize spread if year==2017 & structured==1
    est store spread_17_1
    estpost summarize spread if year==2018 & structured==1
    est store spread_18_1
    estpost summarize spread if year==2019 & structured==1
    est store spread_19_1
    estpost summarize spread if year==2020 & structured==1
    est store spread_20_1

    esttab spread_17_1 spread_18_1 spread_19_1 spread_20_1 using table2.pdf, replace

    summarize spread if year==2017 & structured==0
    summarize spread if year==2018 & structured==0
    summarize spread if year==2019 & structured==0
    summarize spread if year==2020 & structured==0

    **Ratings across years and asset type
    tabulate composite_rating if structured==1 & year==2017
    tabulate composite_rating if structured==1 & year==2018
    tabulate composite_rating if structured==1 & year==2019
    tabulate composite_rating if structured==1 & year==2020

    tabulate composite_rating if structured==0 & year==2017
    tabulate composite_rating if structured==0 & year==2018
    tabulate composite_rating if structured==0 & year==2019
    tabulate composite_rating if structured==0 & year==2020

    **Geographic exposure across years and asset type
    tabulate country if structured==1 & year==2017
    tabulate country if structured==1 & year==2018
    tabulate country if structured==1 & year==2019
    tabulate country if structured==1 & year==2020

    tabulate country if structured==0 & year==2017
    tabulate country if structured==0 & year==2018
    tabulate country if structured==0 & year==2019
    tabulate country if structured==0 & year==2020

**Descriptive statistics per variable
    **Spreads
    summarize spread if structured==1, detail
    summarize spread if structured==0, detail
```

10.7.4 Regression analyses for CBs and CLOs

Regressions - Differences.do - Printed on 10-05-2020 10:01:30

```
**Regressions - Spreads 1.
eststo clear
    ** Regressions for spreads 1.
        **
        eststo: regress spread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio, cluster(dealticker)

        **
        eststo: regress spread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b, cluster(dealticker)

        ** 1.1.1 + Time dummies
        eststo: regress spread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_3, xb
            predict ur1_3, resid
            twoway scatter ur1_3 yhat1_3, yline(0)

            **Normality of residuals
            sktest ur1_3

            **BP hetero test
            quietly regress spread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12


        ** 1.1.2 + Geo dummies
        eststo: regress spread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b geo_NL geo_FR geo_IT geo_DE geo_ES geo_GB geo_CH geo_NO geo_SE geo_DK geo_LU geo_BE geo_US geo_FI geo_GR geo_PT geo_AT year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_4, xb
            predict ur1_4, resid
            twoway scatter ur1_4 yhat1_4, yline(0)

            **Normality of residuals
            sktest ur1_4

            **BP hetero test
            quietly regress spread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b geo_NL geo_FR geo_IT geo_DE geo_ES geo_GB geo_CH geo_NO geo_SE geo_DK
```

```
geo_LU geo_BE geo_US geo_FI geo_GR geo_PT geo_AT year_2018 year_2019 year_2020 month_2
month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured dev_eur10yearyield dev_diff10 dev_impliedvolatility
dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b geo_NL
geo_FR geo_IT geo_DE geo_ES geo_GB geo_CH geo_NO geo_SE geo_DK geo_LU geo_BE geo_US geo_FI
 geo_GR geo_PT geo_AT year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5
month_6 month_7 month_8 month_9 month_10 month_11 month_12


        ** 1.1.3 (3) + Rating/structured interactions
        eststo: regress spread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured dev_eur10yearyield dev_diff10
dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb
comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6
month_7 month_8 month_9 month_10 month_11 month_12, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_5, xb
            predict ur1_1_5, resid
            twoway scatter ur1_5 yhat1_5, yline(0)

            **Normality of residuals
            sktest ur1_5

            **BP hetero test
            quietly regress spread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured dev_eur10yearyield dev_diff10
dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb
comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6
month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured aaaxstructured aaxstructured axstructured bbbxstructured
bbxstructured bxstructured dev_eur10yearyield dev_diff10 dev_impliedvolatility
dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b
year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8
month_9 month_10 month_11 month_12


        ** 1.1.4 (5) + WAL principal interactions
        eststo: regress spread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio
comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2
month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12,
cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_6, xb
            predict ur1_6, resid
            twoway scatter ur1_6 yhat1_6, yline(0)

            **Normality of residuals
            sktest ur1_6

            **BP hetero test
            quietly regress spread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio
```

```
comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2
month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured aaaxstructured aaxstructured axstructured bbbxstructured
bbxstructured bxstructured devwalxstructured devprinxstructured dev_eur10yearyield
dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a
 comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5
month_6 month_7 month_8 month_9 month_10 month_11 month_12


        ** 1.1.5 (6) + yield interactions
        eststo: regress spread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyieldxstructured dev_diff10xstructured dev_impliedvolatilityxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility wal_at_issue principalmio comp_aaa
comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3
month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12, cluster(
dealticker)

        test dev_eur10yearyieldxstructured dev_diff10xstructured
dev_impliedvolatilityxstructured

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat1_7, xb
            predict ur1_7, resid
            twoway scatter ur1_7 yhat1_7, yline(0)

            **Normality of residuals
            sktest ur1_7

            **BP hetero test
            quietly regress spread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyieldxstructured dev_diff10xstructured dev_impliedvolatilityxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility wal_at_issue principalmio comp_aaa
comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3
month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured aaaxstructured aaxstructured axstructured bbbxstructured
bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyieldxstructured dev_diff10xstructured dev_impliedvolatilityxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility wal_at_issue principalmio comp_aaa
comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3
month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12

** Regressions for lnspreads 2.
        **
        eststo: regress lnspread structured dev_eur10yearyield dev_diff10
dev_impliedvolatility dev_wal_at_issue dev_principalmio, cluster(dealticker)

        **  + ratings
        eststo: regress lnspread structured dev_eur10yearyield dev_diff10
dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb
comp_bb comp_b, cluster(dealticker)

        ** 1.2.1 + Time dummies
        eststo: regress lnspread structured dev_eur10yearyield dev_diff10
dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb
comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6
month_7 month_8 month_9 month_10 month_11 month_12, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
```

```
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_3, xb
            predict ur2_3, resid
            twoway scatter ur2_3 yhat2_3, yline(0)

            **Normality of residuals
            sktest ur2_3

            **BP hetero test
            quietly regress lnspread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12


        ** 1.2.2 + Geo dummies
        eststo: regress lnspread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b geo_NL geo_FR geo_IT geo_DE geo_ES geo_GB geo_CH geo_NO geo_SE geo_DK geo_LU geo_BE geo_US geo_FI geo_GR geo_PT geo_AT year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_4, xb
            predict ur2_4, resid
            twoway scatter ur2_4 yhat2_4, yline(0)

            **Normality of residuals
            sktest ur2_4

            **BP hetero test
            quietly regress lnspread structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b geo_NL geo_FR geo_IT geo_DE geo_ES geo_GB geo_CH geo_NO geo_SE geo_DK geo_LU geo_BE geo_US geo_FI geo_GR geo_PT geo_AT year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b geo_NL geo_FR geo_IT geo_DE geo_ES geo_GB geo_CH geo_NO geo_SE geo_DK geo_LU geo_BE geo_US geo_FI geo_GR geo_PT geo_AT year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12


        ** 1.2.3 (3) + Rating/structured interactions
        eststo: regress lnspread structured aaaxstructured aaxstructured axstructured bbbxstructured bbxstructured bxstructured dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12, cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

```

```
            **fitted value and residuals scatter plot
            predict yhat2_5, xb
            predict ur2_5, resid
            twoway scatter ur2_5 yhat2_5, yline(0)

            **Normality of residuals
            sktest ur2_5

            **BP hetero test
            quietly regress lnspread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured dev_eur10yearyield dev_diff10
dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb
comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6
month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured aaaxstructured aaxstructured axstructured bbbxstructured
bbxstructured bxstructured dev_eur10yearyield dev_diff10 dev_impliedvolatility
dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b
year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5 month_6 month_7 month_8
month_9 month_10 month_11 month_12


        ** 1.2.4 (5) + WAL principal interactions
        eststo: regress lnspread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio
comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2
month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12,
cluster(dealticker)

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_6, xb
            predict ur2_6, resid
            twoway scatter ur2_6 yhat2_6, yline(0)

            **Normality of residuals
            sktest ur2_6

            **BP hetero test
            quietly regress lnspread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio
comp_aaa comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2
month_3 month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured aaaxstructured aaxstructured axstructured bbbxstructured
bbxstructured bxstructured devwalxstructured devprinxstructured dev_eur10yearyield
dev_diff10 dev_impliedvolatility dev_wal_at_issue dev_principalmio comp_aaa comp_aa comp_a
 comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3 month_4 month_5
month_6 month_7 month_8 month_9 month_10 month_11 month_12


        ** 1.2.5 (6) + yield interactions
        eststo: regress lnspread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyieldxstructured dev_diff10xstructured dev_impliedvolatilityxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility wal_at_issue principalmio comp_aaa
comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3
month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12, cluster(
dealticker)

        test dev_eur10yearyieldxstructured dev_diff10xstructured
dev_impliedvolatilityxstructured

            **Adjusted R squared
            di e(r2_a)

            **Variance Inflation factor
```

```
            vif

            **Ramseys RESET test
            ovtest

            **fitted value and residuals scatter plot
            predict yhat2_7, xb
            predict ur2_7, resid
            twoway scatter ur2_7 yhat2_7, yline(0)

            **Normality of residuals
            sktest ur2_7

            **BP hetero test
            quietly regress lnspread structured aaaxstructured aaxstructured axstructured
bbbxstructured bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyieldxstructured dev_diff10xstructured dev_impliedvolatilityxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility wal_at_issue principalmio comp_aaa
comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3
month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
            hettest structured aaaxstructured aaxstructured axstructured bbbxstructured
bbxstructured bxstructured devwalxstructured devprinxstructured
dev_eur10yearyieldxstructured dev_diff10xstructured dev_impliedvolatilityxstructured
dev_eur10yearyield dev_diff10 dev_impliedvolatility wal_at_issue principalmio comp_aaa
comp_aa comp_a comp_bbb comp_bb comp_b year_2018 year_2019 year_2020 month_2 month_3
month_4 month_5 month_6 month_7 month_8 month_9 month_10 month_11 month_12
```