

Risk Factors of CLO's and Corporate Bonds ^{*}

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Abstract

Structured products like collateralized loan obligations (CLOs) tend to offer significantly higher yield spreads than corporate bonds with the same rating. At the same time, empirical evidence does not indicate that this higher yield is reduced by higher default losses of CLOs. The evidence thus suggests that CLOs offer higher expected returns compared to corporate bonds with similar credit risk. This study aims to analyze whether this return difference is captured by asset pricing factors. We show that market risk is the predominant risk factor for both corporate bonds and CLOs. CLO investors, however, additionally demand a premium for their risk exposure towards systemic risk. This premium is inversely related to the rating class of the CLO.

Keywords: Structured Finance, Corporate Bond, CLOs, Factor Model, Risk Factors

JEL-Classification: G11, G12

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1 Introduction

Collateralized loan obligations (CLOs) are securitized corporate loans and therefore very similar to financing instruments like corporate bonds (CB). The spread for CLOs, however, is observed to be significantly higher compared to corporate bonds.¹ This study aims to analyze whether this spread difference is due to larger exposure to factor risks and therefore fully explained by asset pricing factors or whether CLOs earn a risk premia due to an unknown component, such as, for example, product complexity. Using the notion of factor investing does not only help in explaining the difference in CLO returns versus CB returns, but further supports the understanding and the decomposing of the sources of realized returns. The objective of this study is thus to provide an intuitive measurement of risk-return characteristics of CLOs and CBs.

The notion of cross-sectional variation in returns of securities is one of the central issues in asset pricing. Factor-based investing originates from the Capital Asset Pricing Model (CAPM), which tries to explain the investment performance of individual assets with a single market risk factor. Further academic research tried to show that a single market risk premium is not the only driver of returns and that it is possible to exploit additional factors to better understand the development of asset returns. Most notably is the seminal work of Fama and French (1992), which has completely changed the landscape of investing. Following Fama and French (1992), a large number of more than 400 additional factors has been found in academic work that has been published in top journals (Fama and French, 2015; Harvey and Liu, 2019). Moreover, factor investing has been extended to multi-asset portfolios and is, in practice, known as the Alternative Risk Premia (ARP) Model. Understanding alternative risk premia is essential for determining sources of returns.

The recent academic research applies asset pricing factors to the field of fixed income, particularly with regards to corporate bond returns. Applying these factors to bond investing, however, resulted in a debate of whether these factors are a reformulation of traditional bond risks and whether the factors used represent an authentic source of risk. Most tests on fixed income factor investing have been carried out using decile analysis. The academic view, however, casts doubt on the approach of decile analysis, as it does not provide a comprehensive assessment of the associated risk factors used in the analysis.

Commonly known risk premia are often derived from structural conditions or market behavior. For example, one well-known factor, the momentum factor, can capture returns when investors exhibit herding behavior, i.e. sell loser assets and chase winner assets. This herding creates a momentum effect in the market that can be identified, priced and rewarded accordingly. An additional example is the volatility factor that identifies periods in which market

¹Note that an active secondary market for CLOs has evolved during the financial crisis, which allows comparing monthly total returns for CLOs and corporate bonds.

volatility spikes. This factor reflects expectations of market crises and tends to create a “run to safety” behavior where safe, low volatility investments tend to outperform. In addition, the empirical finance literature has found small stocks to have higher returns on average. More importantly, size additionally has a moderating effect, as the effect of factors like momentum and value can also be stronger in small stocks (Loughran, 1997). Further insights from asset pricing literature predicts that the current value of a financial asset depends on the distribution of payoffs across different economic states (Arrow, 1964; Debreu, 1959).

In this paper, we use the market factor, the default risk factor, the term factor, and the volatility factor to apply some well-known factors from the asset pricing literature to the universe of corporate bonds and collateralized loan obligations. This allows to see whether and to which extent these factors aim to explain the returns of these two asset classes. We additionally employ a new systemic stress factor to see, whether market participants ask for a premium for their exposure towards systemic stress. We find that the returns of CBs are predominantly explained by a bond market index return, while CLO returns are additionally explained by our systemic risk factor. This finding is particularly strong for CLOs with a non-AAA rating and is increasing the lower the rating of the CLO. These results suggest that CLO investors want to be compensated for the risk of a severe systemic stress event, while investors of corporate bonds do not price this risk.

The remainder of this paper is organized as follows: Section 2 introduces the concept of factor investing and sets out the principle and the evolution of this concept. Introducing the proper theoretical models of asset pricing is helpful in understanding the methodology that was followed in the study. Section 3 explains how factor investing was recently used and applied, both in the academic literature as well as in practitioners’ work related to corporate bond pricing. In Section 4, we discuss the notion of factor investing extension while applying it to CLOs. Section 5 examines the method and the data that we use for the analysis. We provide the results in sections 6. Section 7 summarizes the findings of the study and concludes.

2 Factor Models

Asset pricing models attempt to establish a relationship between the return of an asset and its risk. Testing the strengths of this relationship allows academics and practitioners to make a valid inference and thus be able to make more informed decisions about investing. A significant strand of literature has henceforth emerged that tries to predict asset prices by referring to the intuition of mean-variance optimization. The academic output has resulted in the development of the Capital Asset Pricing Model, which was pioneered by the individual independent contributions of Sharpe (1964) and Lintner (1969). The CAPM elegantly describes the relationship between the return of an asset and its co-movement with the market return, i.e. its volume of systematic risk. More precisely, the CAPM implies that the risk premium on a financial asset is the product

of the risk premium on the market and the asset-specific beta coefficient:

$$E(r_i) = r_f + \beta_i[E(r_M) - r_f], \quad (1)$$

with β_i being defined as the systematic risk component of an asset from the co-movement of the asset with the market,

$$\beta_i = \frac{Cov(R_i, R_M)}{(\sigma^2(R_M))} \quad (2)$$

The basic intuition of a single-index model is that the construction of such a model assumes that all relevant economic forces can be added into one indicator that moves the security market as a whole. Furthermore, the remaining variation is supposed to be idiosyncratic and specific to the asset. Thus, the return specification r_i written as a single index model reads as

$$r_i = E(r_i) + m_i + e_i, \quad (3)$$

where $E(r_i)$ is the expected return on a security at the beginning of the holding period, m_i defines the impact of unexpected macro event, and e_i indicates the impact of an unexpected firm-specific event. Both e_i and m_i have zero expected value such that the unexpected, idiosyncratic events can be fully diversified.

When applying such a model, it is important to emphasize that different assets within the economy have different sensitivities to macroeconomic shocks. The responsiveness of the security to macroeconomic news can be decomposed as a risk factor beta β_i and a price for this risk factor, F , which is constant for all assets. Thus, Equation 3 transforms to

$$r_i = E(r_i) + \beta_i F + e_i. \quad (4)$$

While the single index model allows for capturing a vast universe of securities, it is realistic to contemplate that a more practical application of the model would require more than one factor. This has eventually paved the way to the foundation of the Arbitrage Pricing Theory (Ross, 1976).

Ross (1976) argued that the CAPM empirically fails to explain asset returns primarily due to the absence of a true market portfolio. In his argument for the CAPM revamp, he proposed the well-known model for asset pricing, the Arbitrage Pricing Theory (APT). The theory depends on the assumption that rational expectations of economic agents preclude all opportunities for arbitrage. The APT laid down the foundation for multi-factor models of asset returns.

The primary appeal of the APT is that a rational market will cause pressure to prices whenever they are not in equilibrium so that all arbitrage opportunities will eventually disappear. The expected return relationship is then constructed using a large number of securities, i.e. the APT affirms that the relationship holds true but not for a small number of securities.

Following the APT model, returns on risky assets r_i should thus follow factor intensity and can be expressed in an n-factor model as

$$r_i = a_i + b_{i1}F_1 + b_{i2}F_2 + \dots + b_{in}F_n + e_i, \quad (5)$$

with a_i denoting a constant for the return of asset i , F_k denoting the k^{th} systematic risk factor, b_{ik} indicating the sensitivity of asset i to risk factor k , and e_i denoting an idiosyncratic random shock of risky asset i with a mean of zero. It is vital that the idiosyncratic shock component of the above specification is assumed to be uncorrelated with both the assets and the risk factors.

The APT asset pricing specification states that, if an asset return follows a factor structure, then a relationship between factor sensitivities and returns should exist. This relationship is then expressed as follows:

$$E(r_i) = r_f + b_{i1}RP_1 + b_{i2}RP_2 + \dots + b_{in}RP_n, \quad (6)$$

where RP_n indicates the risk premium of the factor, and r_f denotes the risk-free rate.

Chen et al. (1986) identified variables that could explain systematic risk factors. The factors that they identified were growth in industrial production, changes in expected inflation measured by changes in short-term interest rates (T-bills), unexpected changes in risk premiums measured by the difference between the returns on corporate Baa-rated bonds and long-term government bonds, and unexpected changes in term premium measured by the difference between the returns on long and short-term government bonds. Thus, the general form of APT as described in Equation 6 translates in Chen et al. (1986) into:

$$r_i = a_i + \beta_{iM}r_M + \beta_{iIP}IP + \beta_{iEI}EI + \beta_{iUI}UI + \beta_{iCG}CG + \beta_{iGB}GB, \quad (7)$$

where IP is the growth rate in industrial production, EI is the change in expected inflation, UI is the unexpected inflation (Difference between actual & expectations), CG is the unexpected change in risk premiums (Difference between the returns on corporate Baa bonds and long-term government bonds), and GB is the unexpected changes in the term premium (Difference between returns on long-term and short-term government bonds).

So far, we describe the intuition and shed light on the literature of multi-factor models, which included the Fama and French three factor model. These are, in principle, an extension to the pre-introduced single index models. Fama and French (1993) allow for several systematic components of risk to be tested. Furthermore, like the APT, the following Fama and French methods allow us to quantify and describe the factors that affect returns during a specific time frame. The cross section of average returns on common stocks has shown little relation to the market betas of Sharpe (1964) and Lintner (1969), and this was a major instigator for the work

of Fama and French. Their study uses variables that have no special standing in asset pricing theory but still proved to be a reliable source for explaining the cross section of average returns. The original list of Fama and French’s risk factors included in addition to the market return a size, and a book to market equity factor. The original three factor model by Fama and French was also extended to cover additional factors. An asset pricing model variation of the three-factor model is the Fama and French (2015) five-factor model. The five-factor model added two factors to the original Fama and French (1993) three-factor model. Fama and French (2015) argued that adding profitability and investment to the original Fama and French three-factor model dominates explaining patterns in stock returns. The Fama and French (2015) five factor model reads as follows:

$$r_i - r_f = a_i + b_i(r_M - r_f) + s_iSMB + h_iHML + r_iRWA + c_iCMA + e_i, \quad (8)$$

with r_i indicating the dollar returns on asset i in a specific month, r_f denoting the risk-free rate return (one-month U.S. Treasury bill rate), s_i being the size factor loading and SMB denoting the size factor (return on a diversified portfolio of small and big stocks), h_i being the value factor loading and HML denoting the value factor (return on a diversified portfolio of high and low book-to-market stocks), r_i being the profitability factor loading with the profitability factor RWA (measured as the return on a diversified portfolio of firms that have robust and weak profitability), and c_i being the investment factor loading with the investment factor CMA (defined as return on a diversified portfolio of firms that have conservative and aggressive investment).

Inspired by the path breaking work of factor investing, numerous studies have been devoted to whether systematic risk predicts the cross-sectional differences in stock returns, but little attention has been paid to systematic risk factors in corporate bonds and in other fixed income assets.

3 Risk Factors of Corporate Bonds

Established Factors Academic research demonstrates that alternative premiums exist. Most academic research that has been conducted in this sphere is predominantly focused on equity investments. For risk factors on corporate bonds, however, research has been scarce and little attention has been paid to systematic risk factors in the CB market. Most literature trying to investigate the cross-section of CB returns relies on stock market factors. This is often justified by the point of argument that asset pricing models suggest that risk premiums in equities should be consistent with those in CBs as the two markets are integrated (Chordia et al., 2017). This argument can be supported by several theories in the literature. First, stocks and bonds are contingent claims on the same underlying asset (Merton, 1974). Second, an expected default of a bond changes with equity prices. Additionally, the results of Chordia

et al. (2017) state that size, profitability, and past equity returns are good predictors of CB returns. Nevertheless, despite these valid points of argument, the CB market has its own features and frictions that could violate this predisposition, including credit risk importance in determining returns (bankruptcy costs), sensitivity of bond holders to downside risk, liquidity of the CB markets, nature of bond holders, and finally observed discrepancy in return premiums between bonds and stocks. Thus, it is relevant to identify common risk factors based on the characteristics of CBs rather than only depending on stock market factors. Fama and French (1993) follow this line of argumentation and employ aggregate bond market factors. They extended the use of the original equity factors to include term structure variables (Term, DEF) that are likely to play a role in bond returns. Their goal was to examine whether these variables are important in understanding bond returns, whether they can help explain stock returns and whether risk factors derived from stocks can additionally explain bond returns over and above the term structure variables. The justification of using these two proxies, TERM and DEF, is as follows. It is known that one common risk in bond returns arises from unexpected changes in interest rates. TERM, denoted as the difference between the monthly long-term government bond returns and one-month Treasury bill rate, should proxy the deviation of long-term bond returns from expected returns due to shifts in interest rates. Second, for CBs, shifts in economic conditions change the likelihood of a default. A proxy that can capture this default factor, DEF, is denoted as the difference between the return on the market portfolio of long-term CBs and long-term government bond returns. Fama and French (1993) confirm that TERM and DEF explain the cross-sectional variation of stock returns. Additionally, the two variables were found to dominate the common variation in government bonds and corporate bond returns. Other factors that were found to be of relevance to stock prices, such as momentum, were recently also the subject of further academic scrutiny. However, it was found that CBs are not as sensitive to firm outcomes as is the case for equities. Moreover, past equity returns tend to be positively correlated to CB returns, which is also referred to as equities having a lead to bonds (Collin-Dufresne et al., 2001). Understanding the distribution of bond returns is a critical issue that makes diversification in bonds not easily obtainable. Default risk for CBs refers to a small yet significant probability of a large loss. The distribution of returns is thus said to be negatively skewed. In contrast, equity returns tend to show a much more symmetric distribution.

Newly found Factors The literature provides a list of documented CB factors, which include low volatility (Frazzini and Pedersen, 2014), value (Correia et al., 2012), and size (Houweling and Van Zundert, 2017). Recent literature and academic work on identifying relevant CB factors also support and confirm that carry, momentum, low volatility and value could help explain as much as 15% of the cross-sectional variation in U.S. CB excess return (Alquist et al., 2018). Another work by Bai et al. (2019) investigates the cross-sectional determinant of CB returns and concludes that downside risk is one of the strongest predictors of future bond returns.

Additionally, the study identifies, beside a downside risk factor, liquidity, return reversal, and credit risk as additional risk factors and shows that these factors are statistically and economically significant for determining corporate bond returns. The study, with its proposed four factor model, is one of the most important academic works on what is now being referred to as new bond factors. It is important to point out that a factor can be any characteristic that helps explain an asset return and/or risk. Nevertheless, for a factor to be deemed relevant, it should satisfy certain criteria. First, it should be based on a sound economic rationale and provide ample and significant explanatory power for the cross-sectional returns. Second, the selected factor should exhibit significant premia that persist in the future and across a period of time. Being exposed to alternative risk premia can help achieve the possibility of accessing differentiated exposures and identifying complementary sources of uncorrelated return. The main concept underlying ARP is that investors will be rewarded to bear some form of risk.

4 Applying Factor investing to CLOs

Several studies provide evidence that a change in macroeconomic fundamentals can predict time-series variation in aggregate bond and stock returns. However, no comprehensive academic work has been done so far on the cross-sectional relation between systematic risk factors and CLO returns. The use of a factor-based estimate of economic uncertainty has been used and applied in academia (Jurado et al., 2015). Similar studies chose a rich set of time-series variables that captures a broad set of macroeconomic variation, such as real output and income, manufacturing data, consumer spending, foreign exchange, capacity utilization measures, and price of bond and stock market indexes.

We apply the Fama and French methodology and their multi-factor extension in order to provide a relation between several factor risks and the return of CLOs. More precisely, we choose four risk factors that have been found to explain the cross section of bond returns and applied these to both CBs and CLOs by measuring their exposure to these risk factors. We additionally add a new factor capturing the exposure of CLOs and CBs towards systemic risk. The motivation for this fifth factor emerges from the argumentation in Coval et al. (2009). It is stated that the securitization process substitutes risks that are largely diversifiable for risks that are highly systematic, which implies that CLOs have a lower chance of surviving a systemic crisis compared to traditional corporate bonds of equal rating. If this claim were true, we would expect that a systemic risk factor is priced by CLO investors to a larger degree compared to when it is done by CB investors.

Risk Factors We build our analysis of explaining the returns of corporate bonds and CLOs on four factors that have been found to explain the cross-section of corporate bond returns (Bali et al., 2019). In addition, we add a fifth factor capturing the risk exposure towards a systemic

crisis that is supposed to be particularly relevant for pricing CLOs.

First, we include a market factor, MKT_t , which measures the excess return on the aggregate bond market portfolio. The market factor is proxied by the return of the Merrill Lynch U.S. Aggregate Bond Index. Second, we employ a default risk factor, DEF_t , which aims to capture the default risk in the market. This measure is calculated as the difference between the return on a market portfolio of long-term corporate bonds and the long-term government bond return. The market portfolio of long-term corporate bonds is proxied by the Composite portfolio on the corporate bond module of Ibbotson Associates, and the long-term government bond return is proxied by US government bonds with a 10 year maturity (from Ibbotson Associates). Third, we include the term factor $TERM_t$, which captures the interest rate risk in the market. $TERM$ is calculated as the difference between the monthly long-term government bond return and the one-month Treasury bill rate. Fourth, we use the change in the Volatility Index (VIX) from the Chicago Board Options Exchange (CBOE) from month $t - 1$ to month t , ΔVIX_t , as a proxy for expected future market volatility. The VIX represents the implied volatility of a synthetic at-the-money option contract on the Standard & Poor’s 500 (S&P500) index with a maturity of one month. It is constructed from eight S&P500 index options (puts and calls) and takes into account the American features of the option contracts, discrete cash dividends, and microstructure frictions such as bid-ask spreads.² Finally, we use a measure of systemic stress to capture the risk of a severe stress event. We use $\Delta CISS_t$, the change in the “Composite Indicator of Systemic Stress,” as a proxy for the systemic stress in the economy. CISS is provided by the ECB and it is measured as the aggregation of five market-specific sub-indices created from a total of 15 individual financial stress measures. To ensure that the $CISS$ index provides a valid proxy of systemic stress beyond its region (Europe), we collect information about a similar measure in the US, the “Chicago Fed National Activity Index (CFNAI)”, a monthly index that measures inflationary pressure and economic activity in the U.S.³ Note that these risk factors by nature cannot be diversified away. Therefore, bearing risks from the factors listed above are expected to be compensated with return premiums.

5 Data and Methodology

Data We observe monthly yields on CLOs provided by JP Morgan via Union Investment and calculate total returns in the unit percent per annum using historical spread data and assuming a bond term of 5 years. The time series of CLO returns are available for five different rating classes, AAA, AA, A, BBB, and BB/B, and for the two currencies USD and EUR. In addition, we obtain time series of corporate bond prices from Bank of America Merrill Lynch via Union

²For further details, see Whaley (2000).

³As this measure is highly correlated with the $CISS$ index and as our results qualitatively do not change, we will present results only for the $CISS$ index.

Investment. We transform each time series of corporate bond prices to returns measured in the unit percent per annum as the log difference between the price at time t and the price at time $t - 1$. Corporate bond returns are available for different rating classes (AAA, AA, A, BBB, and BB/B), and different maturities (1-3 years, 3-5 years, 5-7 years, and 7-10 years) for both currencies USD and EUR.⁴ We winsorize all returns with a monthly return larger than 1200 percent per annum with the largest return observation in the sample for the respective instrument below 1200 %. Likewise, we winsorize all negative returns with a monthly return lower than -1200 % pa with the closest return in the sample just over -1200 %pa. Our sample starts in January 2010 with the evolution of a secondary market for CLOs right after the financial crisis and covers the time period until December 2017.

The Fama and French (1993) methodology consists of a two-stage approach. In a first stage, one derives for each asset a risk exposure towards each risk factor using the time series variation within the asset class. In a second stage, one uses at one particular point in time only the cross-sectional variation of returns and risk exposures to determine the price of the risk factor. We will describe the procedure of these two steps in more detail below.

First Stage Regression In a first stage regression, we calculate for each asset class the risk exposure towards our five risk factors based on an OLS regression of the following model using monthly data:

$$r_{it} = \alpha_{it} + \beta_{it1}MKT_t + \beta_{it2}DEF_t + \beta_{it3}TERM_t + \beta_{it4}\Delta VIX_t + \beta_{it5}\Delta CISS_t + \epsilon_{it} \quad (9)$$

$r_{(it)}$ is the return of asset class i at time t , MKT_t is the excess return on the aggregate bond market portfolio proxied by the Merrill Lynch U.S. Aggregate Bond Index at month t , DEF_t is the difference between the return on a market portfolio of long-term corporate bonds (the composite portfolio on the corporate bond module of Ibbotson Associates) and the long-term government bond return, $TERM_t$ is the difference between the monthly long-term government bond return (from Ibbotson Associates) and the one-month Treasury bill rate, ΔVIX_t is the monthly change of the Chicago Board Options Exchange Volatility Index, a measure of the stock market's expectation of volatility implied by S&P 500 index options, and $\Delta CISS_t$ is the monthly change in the 'Composite Indicator of Systemic Stress' by the ECB. The β_{nit} shows the exposure of each asset class to the respective risk factor, and $\alpha_{(it)}$ denotes the abnormal returns that cannot be explained by the used factors.

We calculate the β 's running the regression over a 36 month rolling window so that, for each point in time t and for each asset i , a separate regression is run with $N = 36$ observations. Note again that at this point, one asset class is defined as one time series of returns so that

⁴Note that we exploit different maturities only in order to increase the cross-section when we determine the price for the systemic risk factor, $CISS$. We abstract from a differentiation between various maturities, however, in the later analysis.

we calculate, for example, a separate risk exposure for a AAA-rated corporate bond with a maturity of 1-3 years and for a AAA-rated corporate bond with a maturity of 3-5 years.

Second Stage In the second stage of the Fama and French (1993) methodology, one uses the asset- and time-varying risk exposures determined by Equation 9 as regressors in a cross-sectional regression to explain the expected return at one point in time t , as displayed in Equation 10.

$$E(r_{it}) = \hat{\beta}_{itMKT} \cdot \lambda_{MKT} + \hat{\beta}_{itDEF} \cdot \lambda_{DEF} + \hat{\beta}_{itTERM} \cdot \lambda_{TERM} + \hat{\beta}_{it\Delta VIX} \cdot \lambda_{\Delta VIX} + \hat{\beta}_{it\Delta CISS} \cdot \lambda_{\Delta CISS} \quad (10)$$

This procedure results in a market price for the different risk factors. In order to generate reliable market prices of risk, however, one needs a cross-section that is large enough. However, since in our case, the cross section of assets is limited, we use the market prices for the four risk factors MKT , DEF , $TERM$, and VIX estimated in the paper “The Economic Uncertainty Premium in Corporate Bond Returns” (Bali et al., 2019), and use only the market price for the systemic risk factor $CISS$ determined by our sample.

Return Decomposition Having determined a market price of risk, as well as an asset-specific exposure towards risk, allows us to now decompose returns according to the different risk factors. More precisely, the return that can be attributed to a specific risk factor is determined by $\hat{\beta}_{it} \cdot \lambda$, i.e., for example, the product between β_{MKT} for asset i and λ_{MKT} defines the portion of return of asset i that is explained by the market risk factor. In other words, it is the premium of asset i that compensates investors for bearing the bond market risk. Note again that we do not use the calculated prices of risk λ_{MKT} , λ_{DEF} , λ_{TERM} , and λ_{VIX} from our small sample calculation but rather rely on the market prices determined using a larger sample in Bali et al. (2019). However, as there is no market price for systemic risk, λ_{MKT} , we use the one that we calculated here.

The return of asset i that cannot be attributed to any of the risk factors,

$$Residual_{it} = Alpha_{it} = Return_{it} - ExpectedReturn_{it} \quad (11)$$

is defined as the alpha of the asset. Figure 1 displays the $Alpha_{it}$ for CBs and CLOs separately for different rating classes.

While corporate bonds earn higher returns than what is expected by the five risk factors for all rating classes, CLO returns were only found to be higher than the expected return in the lowest and highest rating categories.

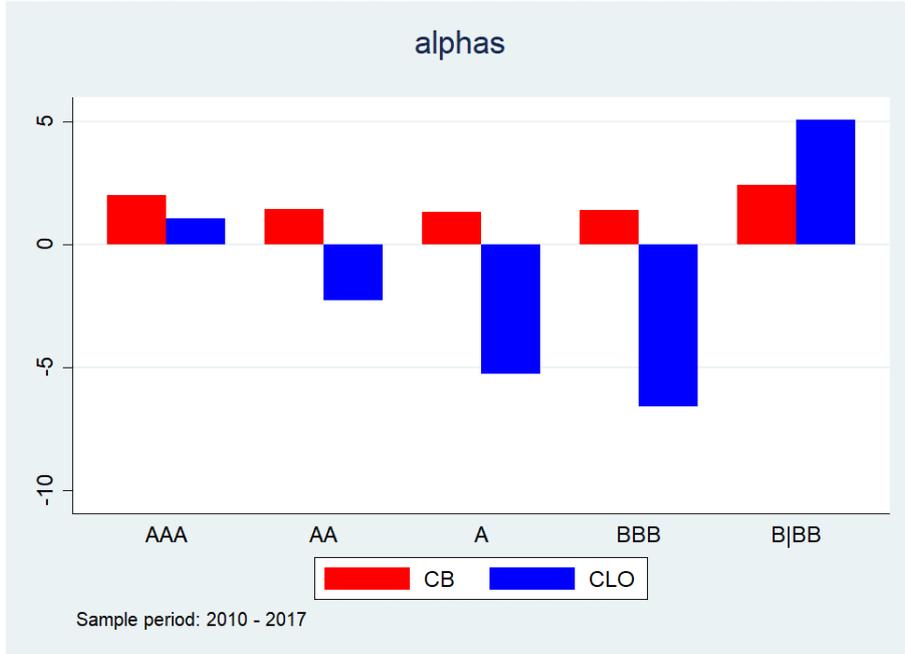


Figure 1: The Difference between realized and expected monthly return p.a. for different rating classes of CLOs and CB

6 Results

We plot the average return of CLOs and CBs in Figure 2. While the average return of CLOs and CBs are very similar for AAA rated investments, one can clearly see a strong divergence of average CLO returns and average CBs returns for lower rating categories. More precisely, for lower ratings of the asset class, CLOs outperform corporate bonds.

However, looking at returns alone for financial securities is not sufficient, as higher returns are usually “bought” by a larger amount of risk. We therefore calculate the Sharpe Ratio of CLOs and CB that relates the average return to its risk. The Sharpe Ratio therefore indicates how much return an investor gets for every unit of risk she accepts and is defined as:

$$SR_i = \frac{\mu_{r_i}}{\sigma_{r_i}} \quad (12)$$

We obtain the average return, μ_{r_i} , and the standard deviation, σ_{r_i} , over a 36-month rolling window, i.e. for each month, we calculate the mean and the standard deviation of the asset return of the previous 36 months. The results of this exercise are depicted in Figure 3, where we show the Sharpe Ratio for both CLOs and CBs over different rating classes. . While CLOs with AAA ratings show a higher Sharpe Ratio than CBs, the picture reverses for lower rating categories.

We decompose the two ingredients of the Sharpe Ratio, return and volatility, and depict them separately in a scatter plot in Figure 4. Return-risk combinations of CLOs are shown

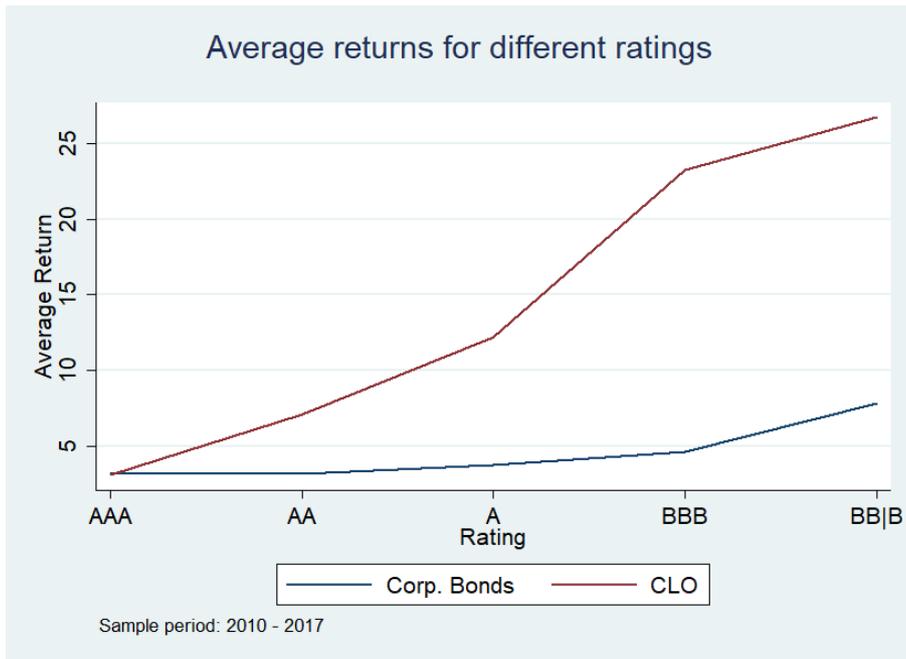


Figure 2: : The spread between the returns of CB & CLOs

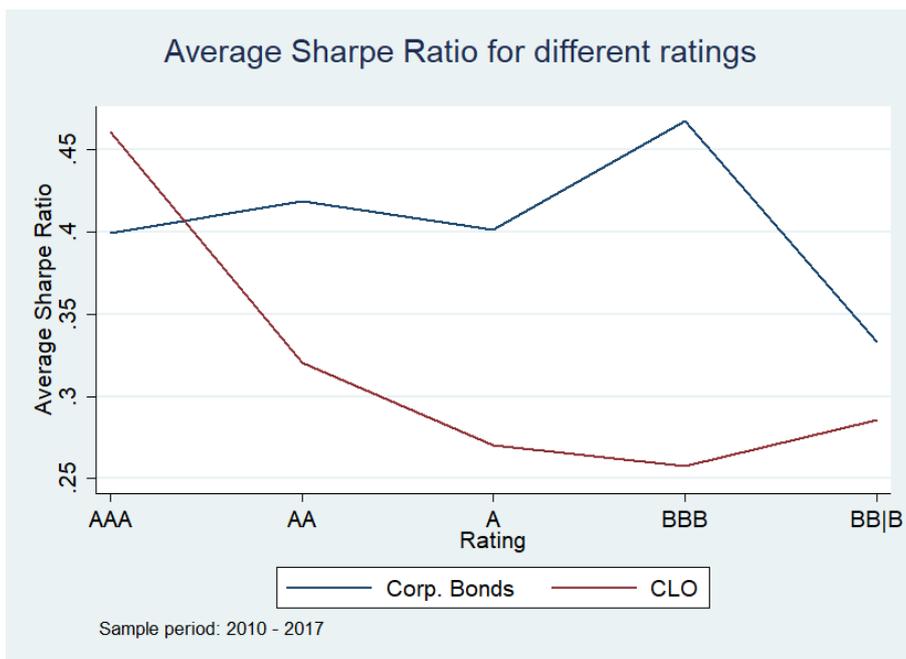


Figure 3: : The differences in Sharpe Ratio across different rating classes for the 2010-2017 period.

in red and are found to be more scattered compared to return-risk combinations of CBs (in blue). Hence, from Figure 2, Figure 3 and Figure 4, one could infer that CLOs generated higher realized returns, but this higher return comes at the cost of carrying higher risk.

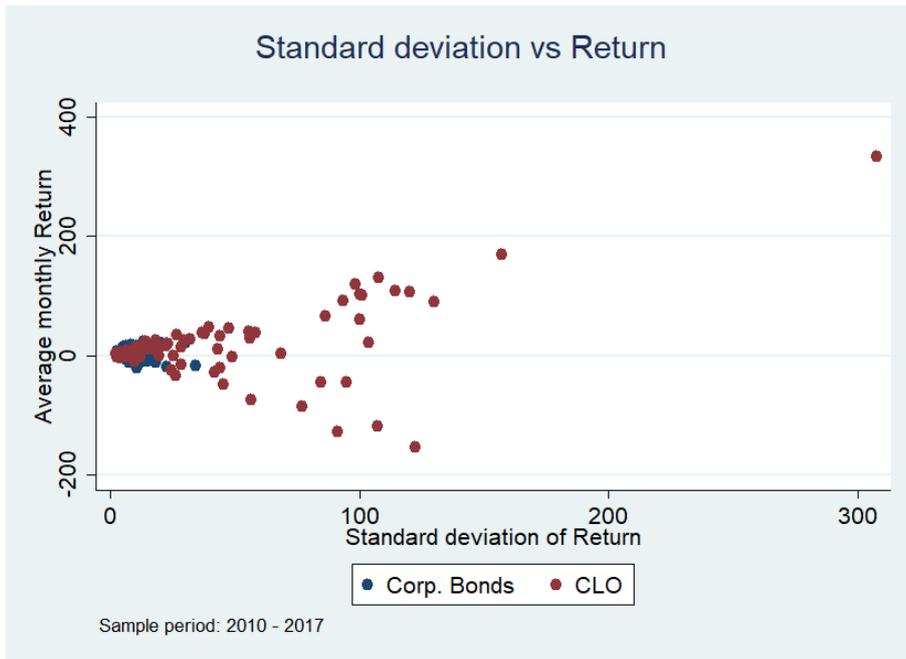


Figure 4: : A scatter plot of risk/returns for both CLOs and CB, sample period: 2010-2017

We finally decompose realized returns of both investment classes CLOs and CBs according to the five different risk factors and a residuum.⁵ The results of this exercise are shown in Figure 5.

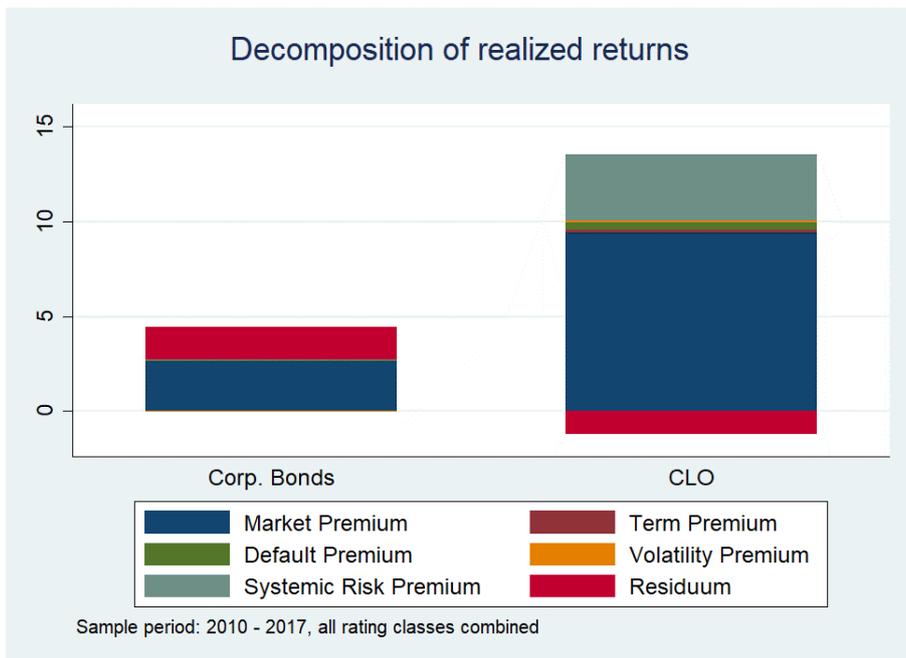


Figure 5: : Return Decomposition of realized returns for Both CLOs and CB, all rating classes included, sample period: 2010-2017

⁵The residuum has also been shown for different rating classes in Figure 1.

We find that CB returns are predominantly explained by the bond market factor, while CLO returns are explained by two main factors: the bond market factor and the systemic risk factor. One of the major observations is that default premia do not seem to play a major role in explaining realized returns. Our findings are supported by the fact that the time frame of the study captures an environment where default of the respective securities hardly occurred.

In the appendix, we additionally provide the return decomposition for CLOs and CBs for different rating classes. In fact, all figures in the appendix show a similar pattern. For all rating classes, the market risk is priced in both CLOs and CBs, while a large component of the realized returns of CLOs is due to a systemic risk premium. Interestingly, the systemic risk premium of CLOs is inversely related to the rating class, i.e. the systemic risk premium is higher for CLOs with the worse rating.

7 Conclusion

Collateralized loan obligations (CLOs) are found to have higher realized returns than corporate bonds despite being assigned an identical rating. But do they earn a risk premium due to larger exposure to factor risks, or does an unknown component, such as instrument complexity, explain the differences in realized returns? Factor investing has been primarily focused so far on analyzing realized returns in equity investment portfolios and became only recently more popular for fixed income instruments. We apply the same factor analysis logic to corporate bonds and CLOs and examine in this study whether traditional bond risk pricing factors can explain the returns of CLOs. This allows us to identify whether the difference in realized returns can be explained by differences in risk exposures. In particular, we emphasize the role of systemic risk in the cross-section of CB and CLO returns.

We find that corporate bond returns are largely explained by a market risk premium, while CLO returns are additionally driven by a systemic risk component. We additionally show that the systemic risk premium of CLOs is inversely related to the rating of the CLO, i.e. the premium increases the worse the rating is.

References

- Alquist, R., Israel, R., and Moskowitz, T. (2018). Fact, fiction, and the size effect. *The Journal of Portfolio Management*, 45(1):34–61.
- Arrow, K. J. (1964). The role of securities in the optimal allocation of risk-bearing. *The Review of Economic Studies*, 31(2):91–96.
- Bai, J., Bali, T. G., and Wen, Q. (2019). Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics*, 131(3):619–642.
- Bali, T. G., Subrahmanyam, A., and Wen, Q. (2019). Economic uncertainty premium in the corporate bond market. Technical report.
- Chen, N.-F., Roll, R., and Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, pages 383–403.
- Chordia, T., Goyal, A., Nozawa, Y., Subrahmanyam, A., and Tong, Q. (2017). Are capital market anomalies common to equity and corporate bond markets? an empirical investigation. *Journal of Financial and Quantitative Analysis*, 52(4):1301–1342.
- Collin-Dufresne, P., Goldstein, R. S., and Martin, J. S. (2001). The determinants of credit spread changes. *The Journal of Finance*, 56(6):2177–2207.
- Correia, M., Richardson, S., and Tuna, İ. (2012). Value investing in credit markets. *Review of Accounting Studies*, 17(3):572–609.
- Coval, J., Jurek, J., and Stafford, E. (2009). The economics of structured finance. *Journal of Economic Perspectives*, 23(1):3–25.
- Debreu, G. (1959). *Theory of value: An axiomatic analysis of economic equilibrium*. Yale University Press.
- Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2):427–465.
- Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.
- Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.
- Frazzini, A. and Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, 111(1):1–25.
- Harvey, C. R. and Liu, Y. (2019). A census of the factor zoo. Technical report.

- Houweling, P. and Van Zundert, J. (2017). Factor investing in the corporate bond market. *Financial Analysts Journal*, 73(2):100–115.
- Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring uncertainty. *American Economic Review*, 105(3):1177–1216.
- Lintner, J. (1969). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets: A reply. *The Review of Economics and Statistics*, pages 222–224.
- Loughran, T. (1997). Book-to-market across firm size, exchange, and seasonality: Is there an effect? *Journal of Financial and Quantitative Analysis*, 32(3):249–268.
- Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2):449–470.
- Ross, S. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory*.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3):425–442.
- Whaley, R. E. (2000). The investor fear gauge. *The Journal of Portfolio Management*, 26(3):12–17.

Appendix

Decomposition of Realized Returns for Different Rating Classes

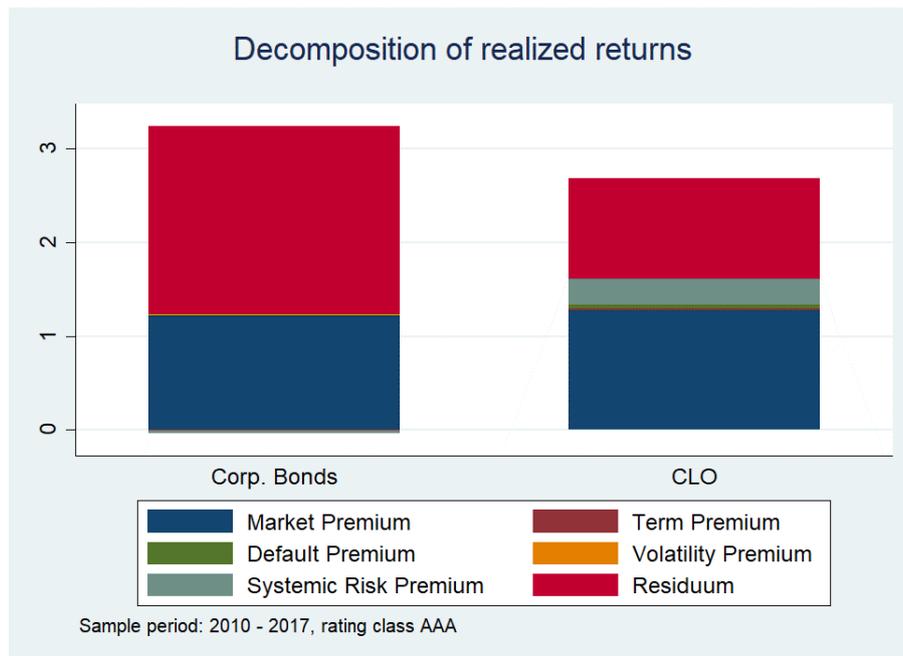


Figure A1: Decomposition of realized returns for rating AAA

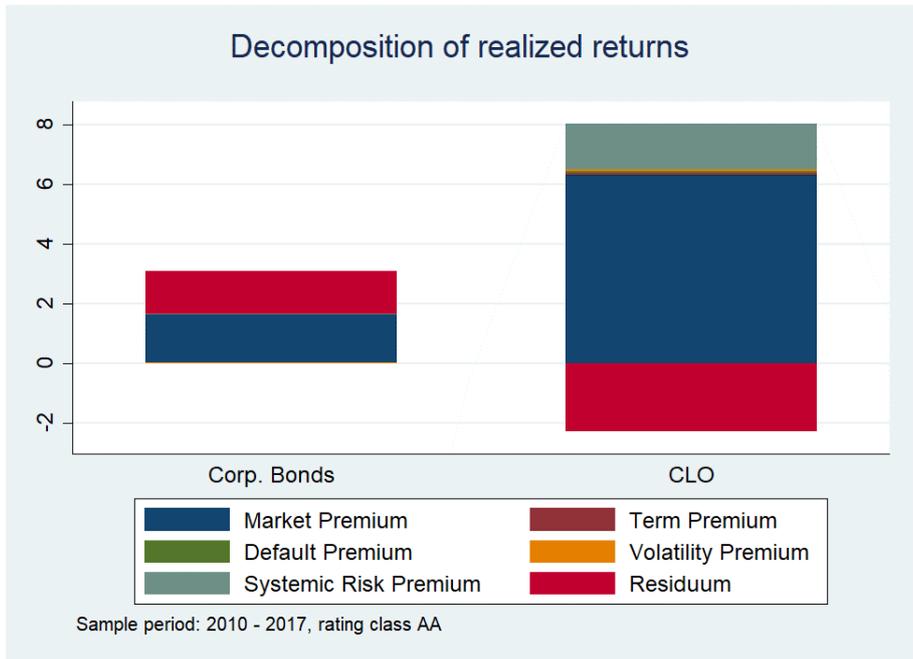


Figure A2: Decomposition of realized returns for rating AA

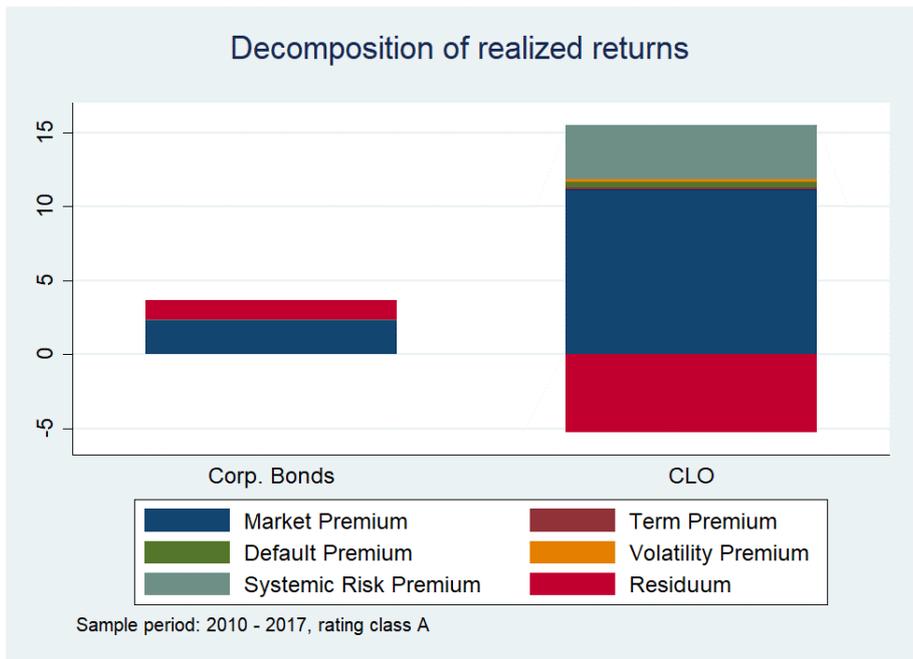


Figure A3: Decomposition of realized returns for rating A

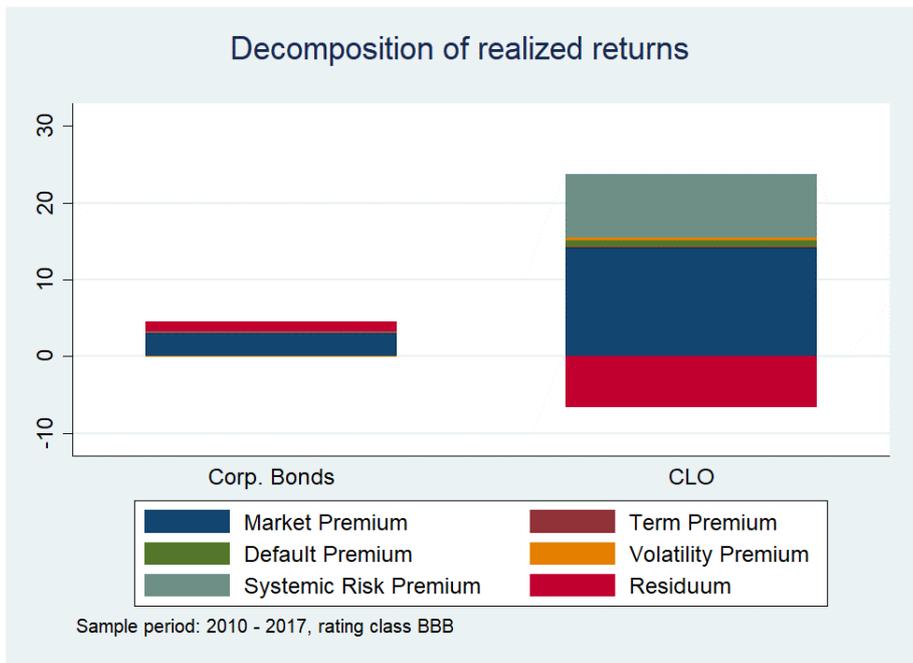


Figure A4: Decomposition of realized returns rating BBB

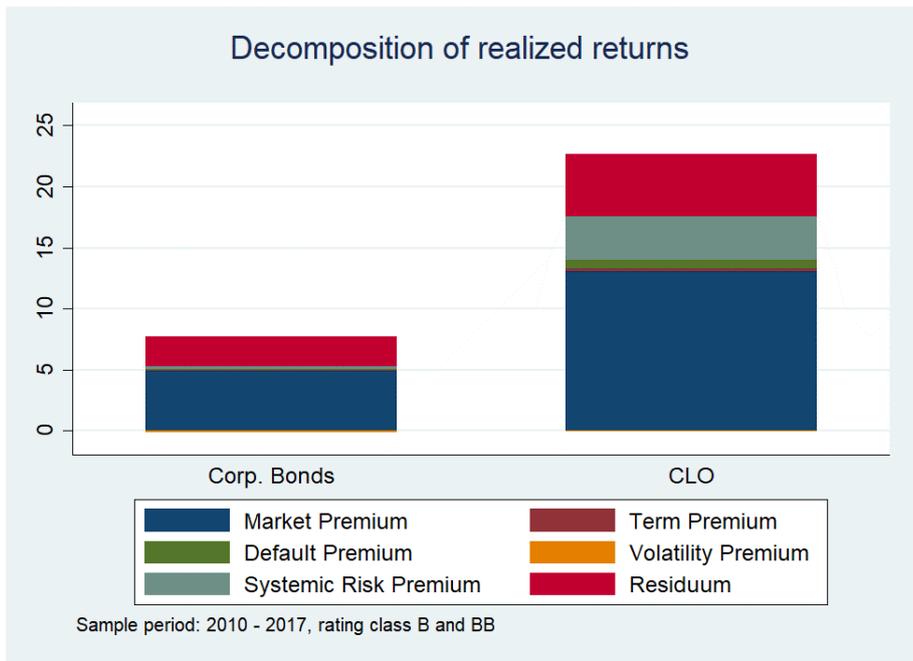


Figure A5: Decomposition of realized returns for rating B/BB