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Understanding the performance of CDS indices compared with bond indices:

Higher returns with lower risk?

Thesis for the Master's degree in Econometrics and Management Science with the specialization Quantitative Finance

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Abstract

CDS indices have generated higher returns than bond indices, and the return difference is especially large in the high yield universe. The outperformance is surprising because CDS and bond indices are similar instruments to hedge or invest in corporate credit risk. This study therefore investigates the return difference between CDS and bond indices for the investment grade and high yield universe from 2005-2017. The higher return of CDS indices cannot be explained by a higher volatility or differences in exposure to well-documented risk factors, such as size and momentum. For high yield, differences in weighting schemes and roll-down (a component of carry) are the main drivers behind the outperformance of the CDS indices. The return difference between investment grade CDS and bond indices is much smaller and may even be negative depending on the chosen sample period. For both universes, using geometric compounding instead of arithmetic compounding is more beneficial for CDS indices which is driven by the substantially lower volatility of CDS indices.

Keywords: credit default swaps, corporate bonds, compounding, roll-down, factor portfolios, risk factors

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1 Introduction

With a size of more than $40 trillion, the U.S bond market is even larger than the U.S. equity market. The bond derivatives market is also tremendous with another $10 trillion in notional (Joia et al., 2018). Issuing bonds is one of the most common ways for companies of raising finance. The bond issuer pays an interest rate to the bond holder which can be split in a risk-free component and an issuer-specific credit component. The credit component can be traded directly via a derivative: a credit default swap (CDS) contract. The CDS contract resembles a fire insurance contract in which the protection buyer pays a periodic fee and receives a single compensation in case of default. This illustrates that selling a CDS contract on a bond yields the same credit risk exposure as holding a bond (ignoring the risk-free component).

Fixed income investors can thus invest in bonds directly or use credit derivatives to obtain or hedge credit exposure. While the notional of individual credit default swaps halved following the financial crisis in 2008, credit default swaps bundled into an index have become an increasingly popular instrument to trade credit risk (Joia et al., 2018). As the credit risk of investing in a corporate bond and a CDS contract is identical, the return of investing in these instruments should therefore also be similar. However, CDS and bond indices have shown return differences of which the magnitude differs per credit universe: investment grade (rated BBB- and above) and high yield (rated BB+ and below) based on the Standard & Poor's and Fitch scale. The two largest investment grade CDS and bond indices, located in the U.S. and Europe, have shown a small return difference from 2005-2017 that fluctuates over time. However, the two largest high yield CDS indices, also located in the U.S. and Europe, outperformed bond indices with more than 2% higher annual returns with lower risk over the period 2005-2017. Understanding the difference in historical performance, and in particular being able to make a prediction about future performance, is therefore essential for portfolio managers who want to invest in credit instruments or hedge their credit positions.

In this paper, I investigate the drivers behind the returns of corporate CDS and bond indices to explain past performance differences and to make a prediction about future performance. I use monthly observations for the constituents of the North-American CDX and European iTraxx indices from October 2005 to September 2017 and the respective Bloomberg Barclays Corporate Indices as reference bond indices. I investigate the investment grade and high yield universes separately because of the large return differences between the two universes. This approach is in line with the approaches of players in financial markets and academic researchers, who often treat the two universes as separate classes (Houweling and Van Zundert, 2017). The attribution of the return difference between CDS and bond indices is based on three different elements: compounding, roll-down[1], and risk factors. I calculate the effect of geometric compounding (as opposed to arithmetic compounding) and differences in roll-down as a constant term. I analyse the difference in exposure to risk factors using time-series regressions.

The bond index that is used as a reference index does not match the constituents of the CDS index and uses a different weighting scheme. Therefore, to make a more precise attribution of the CDS-bond index return differences to risk factors, I use a three-fold decomposition to distinguish three different effects. (1) Composition effects: firstly, because the entities in a CDS index are a subset of the entities in the bond index, I study the return difference between the original bond index and an issuer-matched bond portfolio. (2) Weighting effects: secondly, I adjust the bond portfolio to match the weighting scheme of the CDS index. The return difference between the market value weighted and equally weighted matched bond portfolios can be attributed to differences in weighting schemes. (3) CDS-bond specific effects: thirdly, I study the return differences between the equally weighted matched bond portfolio and the CDS index, that is the remainder of the total return difference. Each of the three steps generates a return series. I attribute the returns of these steps, as well as the total return difference between the CDS and bond indices, to the risk factors for each of the steps separately.

To measure the return of a risk factor, I create factor portfolios with techniques from empirical asset pricing literature. The approach is similar to the methods of Fama and French (1993), who expand the CAPM-model with different risk factors to explain the common variation in stock and bond returns. They create risk factors such as size (for equity markets) and maturity (for bond markets) and create return series for each factor based on factor portfolios. The factor portfolios are generally constructed as long-short portfolios and the returns are calculated in excess of the market. I construct factor portfolios and use their returns to attribute the total return series, and the decomposed return series, to the risk factors. Furthermore, I test whether the factor betas of two universes (investment grade compared with high yield, and U.S. compared with Europe) are equal to each other using seemingly unrelated regression (SUR) models.

The relevance on the link between CDSs and bonds is reflected by the vast amount of literature on the difference between the CDS spread and bond credit spread on the individual level. Even though no-arbitrage arguments imply that the two spreads should be equal, several studies find deviations from this equilibrium (Blanco et al., 2005; Zhu, 2006). However, little research has

[1] Roll-down is a part of carry return. It is the return attributed to the price change of a CDS or bond as it rolls down into a shorter maturity over time assuming that the yield curve does not change (Koijen et al., 2018). In general, yield curves are upward slowing resulting in a price appreciation as the holding period progresses.

been conducted on actual return differences between CDS and bond indices. Exceptions are the non-public studies by Desclée and Polbennikov (2015, 2016). They show that a large part of the return difference of the investment grade CDS indices is explained by (1) composition effects, whereas the outperformance of the high yield CDS indices is explained by (3) CDS-bond specific effects. They do not explicitly quantify the effects of the different weighting schemes.

To the best of my knowledge, this is the first academic study that explains return differences between CDS and bond indices. I extend the analysis of Desclée and Polbennikov (2015, 2016) by analysing the effects of compounding and weighting scheme differences. Furthermore, I improve their methodology by creating decomposing portfolios and testing the exposure of the decomposed return series to risk factors directly using time series regressions. I create a set of risk factors based on literature, such as size and value. I also create specific factors based on differences in characteristics between CDS and bond indices: a financial sector, maturity (specific to the maturity of a CDS index), and call factor. I explicitly test hypotheses regarding bonds embedded with a call option whereas most studies exclude callable bonds from their sample. Given the high prevalence of callable bonds, this can impact more than 50% of the observations. To isolate the effect of a call option on returns, I need to control for the effect of other characteristics, such as sector and rating, on the returns. Therefore, I construct portfolios that goes long in callable and short in non-callable bonds from the same issuer. Furthermore, I extend the research by Chen et al. (2018) on equities, who test the correlation between the factor loading of a security and its rank on the underlying factor, to the bond market. Finally, this study uses data from 2005 to 2017 and therefore covers different economic cycles. This allows me to investigate whether the performance difference between CDS and bond indices depends on market-wide economic conditions.

The results show that the outperformance of high yield indices is mainly driven by differences in weighting scheme and roll-down. The returns attributed to roll-down are fairly constant over time and have an annualized contribution of 3.08% and 1.24% for the U.S. and Europe respectively. This finding is in line with the results of Desclée and Polbennikov (2016). Contrary to the findings of Desclée and Polbennikov (2015), who use a slightly shorter sample period, I do not find a consistent outperformance of CDS indices in the investment grade universe. Geometric compounding (reinvesting the money) instead of arithmetic compounding favors CDS indices over bond indices due to lower volatility. This finding is consistent across all universes. CDS indices have a consistently lower exposure to the bond market. Because the bond markets have generated positive returns on average over the sample period, this yields negative CDS-bond return differences attributed to the market. The findings confirm the existence of a size effect in the bond market, as documented by Houweling and Van Zundert (2017), but there is no significant overall effect of size on CDS-bond return differences.

Altogether, this study shows that the return difference between CDS and bond indices cannot be fully explained by differences in composition or weighting scheme between the two indices. This means that there are differences between the two credit products, whether it be fundamental (such as contract specifities) or technical (such as liquidity differences) in nature. These differences tend to be the most prevalent and persistent in the high yield universe. One consistent result across all universes, however, is the lower volatility of CDS indices compared to bond indices. Lower volatility of CDS indices is especially prevalent during the financial crisis in 2008 when CDS indices remained relatively liquid whereas bonds' liquidity deteriorated. Altogether this implies that, in particular for long-term credit risk investors, synthetic credit risk may be an attractive alternative for corporate bonds.

This paper is organized in the following way. Section 2 provides the reader with a basic understanding of CDS contracts and highlights differences between CDS and bond indices. Section 3 describes the data set used in this study. In Section 4, I present the methodology. I first explain the computation of compounding and roll-down terms. Next, I describe the construction of risk factors and decomposing portfolios. I discuss the main results and robustness checks in Section 5. In Section 6, I investigate some of the findings in greater detail. Finally, I provide a conclusion and suggest some directions for future research.

2 Theoretical background

This section gives a basic understanding of the relationship between CDS contracts and their reference bonds and describes the basics of CDS and bond indices. For a more detailed understanding of credit default swaps and a formal proof of the no-arbitrage relationship between a CDS and its reference bond, I refer to Section A.1 in the Appendix.

2.1 CDS-bond basis

Theoretically, there is a strong link between the value of a CDS contract and the value of its underlying bond (Duffie, 1999). Consider a bond that trades at a yield, hereafter denoted by the spread S_{bond}, of which S_{credit} compensates for the credit risk entailed. An investor can hedge his credit risk by entering into a CDS contract with the same payment dates and maturity T. Buying credit risk protection using a CDS yields opposite cash flows, both in case of default and at maturity, compared to buying this particular bond. Therefore, a portfolio consisting of a bond and protection in the form of a CDS mimics a risk-free bond. Hence, based on no-arbitrage arguments, the spread of the CDS, S_{CDS} should intuitively be equal to the credit spread of the bond. Duffie (1999) has shown formally that the CDS spread and bond spread should be the same, that is $S_{CDS} = S_{bond} - r_f = S_{credit}$ with r_f denoting the risk-free rate, under suitable conditions.

The deviation between the CDS spread and bond credit spread, $S_{CDS} - S_{credit}$, is often referred to as the CDS-bond basis. In a frictionless market with the absence of counterparty risk (a CDS is a bilateral contract), a non-zero basis suggests arbitrage possibilities. If the basis is positive, the credit risk entailed in the CDS is overpaid compared to the underlying bond and vice versa. In practice, the basis may be non-zero for several reasons in the absence of true arbitrage opportunities. For example, the products may not reflect the same risk because of differences in contractual terms[2] or liquidity. Moreover, even if there would be a theoretical arbitrage opportunity, it may not be executable because of difficulties with shorting in the bond market or transaction costs that exceed the anticipated gain.

2.2 CDS and bond indices

Investors may also hold a portfolio of credit contracts. In this study, I compare the performance of the CDS indices with bond indices that serve as a benchmark. CDS indices consist of a fixed number of equally weighted CDS contracts, selected (mainly) based on liquidity, and are rebalanced semiannually. In contrast, the reference bond indices have no restriction on the number of constituents, are market-value weighted, and are rebalanced monthly. For the CDS indices considered in this study, a new on-the-run contract has a 5.25 year to maturity which declines to 4.75 years to maturity resulting in an average of 5 years to maturity for the CDS index. The reference bond indices allow any time to maturity above 1 year which implies that the average time to maturity of the bond indices is generally not equal to 5 years.

The no-arbitrage relationship between individual CDSs and bonds can easily be extended to the aggregate level: CDS and bond indices. The pay-off of a long position in a CDS index can be replicated by taking an equally weighted long position in all constituents. Therefore, using no-arbitrage arguments, an index should trade as the (equally weighted) average of its constituents. A similar argument holds for the bond index but with market value weights.

The aforementioned differences in construction rules of the CDS and bond indices may lead to a different composition between a CDS and its reference bond index. To understand the return

[2] For example, bonds may be embedded with a call option whereas this is never the case for a CDS.

differences between CDS and bond indices, it is therefore important to decompose them into a component that is due to composition differences, and a component that is due to deviations from the CDS-bond parity. This will be explained in further detail in Section 4.

3 Data

I use data for four CDS indices and their reference bond indices. The CDS indices for the U.S. are CDX IG (investment grade) and CDX HY (high yield). The CDS indices for Europe are iTraxx Main (investment grade) and iTraxx Crossover (high yield, sometimes also referred to as "iTraxx XO"). The respective reference bond indices are Bloomberg Barclays U.S. Corporate Index, Bloomberg Barclays U.S. HY Corporate Index, Bloomberg Barclays Euro Corporate Index, and Bloomberg Barclays Euro HY Corporate Index. The data set consists of monthly observations, the highest frequency available, from March 2005 to September 2017 resulting in 150 observations.

I obtain information on the CDS index constituents from Bloomberg. This data set contains the constituent identifiers, their issuer names, and reference bond identifier (if applicable). Moreover, the set contains the monthly returns of the CDS index which are calculated using equal weights. I select the 5-year maturity CDS indices because trading in both CDS and CDS index contracts is generally concentrated in 5-year maturity. Therefore, this choice should minimize the impact of liquidity in the CDS market on the returns. Bond and issuer-specific information is also sourced from Bloomberg. This data set contains individual characteristics, such as seniority, maturity, and rating, and provides the monthly credit spread and return. Unlike many other studies, I do not delete callable bonds from my sample. Instead, I explicitly test the effect of the call option on the returns.

Total returns of a bond can be decomposed into the term premium, driven by changes in the risk-free interest rate, and the credit premium, driven by changes in the creditworthiness of the issuer. CDS returns, on the other hand, are solely driven by changes in the creditworthiness of the issuer. Therefore, to effectively compare the return differences between CDSs and bonds, I remove the term premium from the total bond returns. I follow the approach of Houweling and Van Zundert (2017) and calculate the excess return of the bonds as the returns in excess of investing in government bonds. The government bonds are the duration-matched Treasuries (issued by the U.S. federal government) for the U.S. and the duration-matched Bunds (issued by Germany's federal government) for Europe. Finally, the monthly index excess returns are calculated using market value weights.

3.1 Descriptive statistics

The investment grade CDS indices consist of 125 constituents. The high yield CDS indices are slightly smaller with 100 (U.S.) and 75 (Europe) constituents. For both universes, the number of constituents has increased over time. The investment grade bond indices contain 4,064 (U.S.) and 1,410 (Europe) bonds on average. For the high yield bond indices, the average number of bonds is 1,858 and 427 respectively.

Table 1 presents summary statistics and characteristics for the CDS and bond indices. I calculate the returns using two compounding methods, geometric and arithmetic, and calculate the annualized mean return accordingly. Geometrically compounded mean returns are generally smaller than arithmetically compounded mean returns. This difference is driven by volatility: geometric returns compound the disturbances from the arithmetic mean. I calculate the volatility of the series using the arithmetic return series. I use the information ratio, calculated as ratio of the annualized arithmetic return and the volatility, as a measure of risk-adjusted return. The weights for the characteristics are calculated using equal weights for the CDS indices and using market value weights for the bond indices in line with the official weighting schemes of the indices. I calculate the weights cross-sectionally for each month and then average them over the entire sample period.

CDS indices generated higher average cumulative returns with less volatility than the bond indices with U.S. investment grade as an exception. The information ratios show that the risk-adjusted returns are higher for all four indices. Moreover, CDS indices generally have more weight in senior contracts than bond indices. The average weights attributed to the different sectors differ between the CDS and bond indices. In particular, CDS indices generally have little to no weight in financial companies due to construction rules of the CDS indices. For all indices except Europe high yield, the average rating of the CDS indices is lower compared to the average rating of the reference bond indices. This could be driven by the selection rules of CDS indices, that mainly select on liquidity. Oehmke and Zawadowski (2016) show that the hedging and speculating demand in the CDS market increases following a rating downgrade. This leads to increased liquidity in less creditworthy names which in turn leads to a bias in lower rated names compared to the bond indices. The time to maturity and age for the CDS indices are fixed and both are generally lower than for the bond indices. Finally, high yield indices have a high prevalence of callable bonds, and issuing callable bonds is becoming increasingly popular for investment grade issuers as well. On the other hand, individual CDS contracts and CDS indices do not have a call option.

Table 1: Summary statistics and characteristics for the CDS and bond universes from 2005-2017

	Investment grade				**High yield**			
	U.S.		Europe		U.S.		Europe	
	CDS	*Bond*	*CDS*	*Bond*	*CDS*	*Bond*	*CDS*	*Bond*
Statistics (ann.)								
Arithmetic returns (%)	0.94	1.08	1.16	0.74	6.21	4.41	7.14	5.90
Geometric returns (%)	0.92	0.94	1.14	0.68	6.00	3.84	7.01	5.28
Volatility (std. dev.) (%)	2.17	5.44	2.32	3.73	8.65	11.11	8.24	12.08
Information ratio	0.43	0.20	0.50	0.20	0.72	0.40	0.87	0.49
Weights (%)								
Senior	100	92	100	83	95	90	93	80
Subordinate	0	8	0	17	5	10	7	20
Fin. w/o banking	13	15	8	11	6	7	2	5
Banking	1	21	9	39	0	2	0	13
Basic industry	9	4	10	4	10	9	17	9
Consumers cycl.	18	7	14	7	27	18	20	21
Consumers non-cycl	17	13	17	9	10	12	7	9
Energy	10	7	3	3	7	9	1	1
Technology	7	5	1	1	11	6	4	2
Communication	7	11	18	10	14	18	23	16
Industrial (other)	11	7	9	8	9	11	24	19
Utility	6	10	12	9	5	8	2	3
Callable	0	14	0	15	0	64	0	46
Averages (weighted)								
Rating	BBB+	A-	A-	A	BB-	B+	BB-	BB-
Maturity (years)	5.00	10.36	5.00	5.39	5.00	6.95	5.00	5.40
Age (years)	0.25	5.31	0.25	5.53	0.25	5.27	0.25	5.44

Notes: These figures present the summary statistics and characteristics of the investment grade and high yield CDS and bond indices from 2005-2017. Annualized average returns are calculated both using arithmetic (simple) compounding and using geometric compounding. The volatility (standard deviation) is calculated based on the arithmetic return series. The information ratio is used as a measure of risk-adjusted return. In line with the official weighting schemes of the indices, the weights and averages are calculated using equal weights for CDS indices and using market-value weights for bond indices. Rating is based on Standard & Poor's and Fitch rating scales.

4 Methodology

I attribute the return differences between CDS and bond indices in three steps: compounding, roll-down, and risk factor attribution. An overview of the steps can be found in Figure 1. Here, dots indicate individual bonds and squares indicate individual CDSs. In Table 3, I provide an overview of findings in literature for the elements that I include in my research. Moreover, a more complete overview of potential drivers of CDS and bond return differences can be found in Table 19 in the Appendix. This table also contains drivers that I do not include in my research, for example due to lack of data, that have been studied in previous literature.

4.1 Compounding

A practitioner invests an x amount of money in a product at $t = 0$ and withdraws the accumulated amount of money in his account at time $t = T$. Therefore, from a practitioner's point of view, it is important to calculate the returns over a sample period using geometrically compounded returns. Consequently, I decide to explain the total return difference between CDS and bond indices calculated using geometric compounding. However, as part of my analysis I estimate the effects of roll-down and risk factor attribution. These elements require arithmetic returns to make sure that the measured contribution of roll-down and risk factors is not contaminated by returns attributed to geometric compounding.

To be able to explain the total return difference calculated using geometric compounding, but also use arithmetic returns for the roll-down and risk factor analysis, I calculate a term that captures the difference between geometric and arithmetic compounding over this sample period.

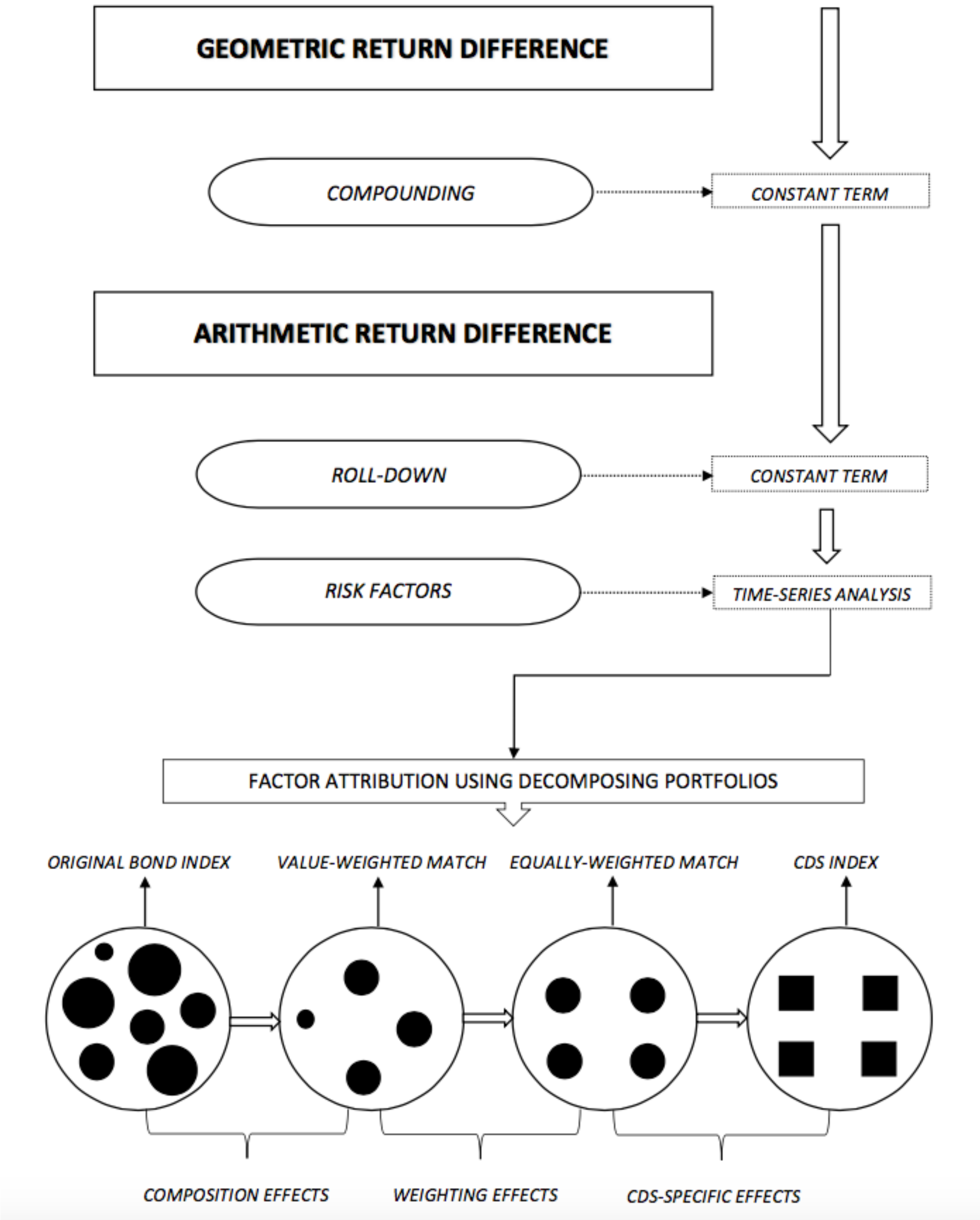
Assume that an investor invests \$1 at time $t = 0$ in index h. Let $h \in \{1, 2, 3, 4\}$ which corresponds to the universes U.S. investment grade, Europe investment grade, U.S. high yield, and Europe high yield respectively. Denote the price return at time t by $R_{h,t}$. Then at time $t = T$, the arithmetically and geometrically compounded returns of the portfolios over the entire sample period are as follows

$$P_{h,arithmetic,T} = \sum_{t=1}^{t=T} R_{h,t}, \tag{1}$$

$$P_{h,geometric,T} = \prod_{t=1}^{T} (1 + R_{h,t}) - 1, \tag{2}$$

where $P_{h,i,T}$ denotes the total compounded return of the portfolio at the end of the sample

Figure 1: Road map of methodology: the order of compounding, roll-down and risk factor analysis



Notes: I start with a CDS-bond index return difference based on geometric compounding. The return attributed to geometric compounding instead of arithmetic compounding is referred to as 'compounding'. Next, I continue with arithmetic returns and calculate the difference in roll-down returns between the CDS and bond index. This term is referred to as 'roll-down'. Then, I attribute the monthly simple return difference based on time-series analysis using risk factor attribution. To understand the source of differences in exposure to risk factors, I create decomposing portfolios. I start with the original bond index which uses market value weighting. The first step is a market value weighted bond portfolio that matches the issuers of the CDS index. The next step is an equally weighted bond portfolio that matches the issuers of the CDS index. The final step is the original CDS index. The return differences that follow from these steps are referred to as 'composition effects', 'weighting effects', and 'CDS-specific effects' respectively.
Dots () indicate individual bonds, squares (■) indicate individual CDSs.

period with $i \in \{\text{arithmetic, geometric}\}$.

The value of arithmetically and geometrically compounded portfolios may differ because arithmetic compounding relatively overweighs gains and underweighs losses. I illustrate this using an example. Consider a portfolio that has a value of \$1 at time $t = 0$, a value of \$0.50 at time $t = 1$ and a value of \$0.75 at time $t = 2$. Using arithmetic compounding, we have

$$P_{h,arithmetic,2} = \sum_{t=1}^{t=2} R_{h,t} = -50\% + 50\% = 0\%, \tag{3}$$

and using geometric compounding, we have

$$P_{h,geometric,2} = \sum_{t=2}^{t=T} R_{h,t} = (1 - 50\%) \cdot (1 + 50\%) - 1 = 0.50 \cdot 1.50 - 1 = -0.25 = -25\%. \tag{4}$$

Hence, the return using geometric compounding is negative whereas it is positive for arithmetic compounding which shows the asymmetry of gains and losses between the different methods.

I calculate the geometrically compounded CDS-bond return difference, in excess of the arithmetically compounded CDS-bond return difference, for universe h as follows:

1. Calculate the difference between the geometrically and arithmetically compounded portfolio return for the CDS and bond index separately with

$$P^{CDS}_{h,compounding,T} = P^{CDS}_{h,geometric,T} - P^{CDS}_{h,arithmetic,T}, \tag{5}$$

$$P^{Bond}_{h,compounding,T} = P^{Bond}_{h,geometric,T} - P^{Bond}_{h,arithmetic,T}. \tag{6}$$

2. Obtain the CDS-bond compounding term, which is the difference in the compounding term between the CDS and bond index, by subtracting the bond compounding term from the CDS compounding term

$$P_{h,compounding,T} = P^{CDS}_{h,compounding,T} - P^{h,Bond}_{h,compounding,T}. \tag{7}$$

   $P_{h,compounding,T}$ is the total contribution of geometric compounding (in excess of arithmetic compounding over the entire sample period) to the total return difference.

I link the total compounding term, $P_{h,compounding,T}$ to the original dependent variable, $P_{h,CDS,T} - P_{h,Bond,T}$, in the following way

$$P_{h,CDS,T} - P_{h,Bond,T} = P_{h,compounding,T} + P^{CDS}_{h,arithmetic,T} - P^{Bond}_{h,arithmetic,T} \tag{8}$$

$$= P_{h,compounding,T} + \sum_{t=1}^{T} \left(R_{h,CDS,t} - r_{h,Bond,t}\right), \tag{9}$$

where $R_{h,CDS,t}$ and $R_{h,Bond,t}$ denote the price returns of the indices at time t. This shows that the total portfolio return difference between CDS and bond indices can be written as the compounding term plus the arithmetically compounded return differences. After quantifying the attribution of geometric compounding (compared with arithmetic compounding) on the total CDS-bond index return difference, I continue my analysis using arithmetic returns.

4.2 Roll-down

Roll-down is the return that is earned from rolling down the spread curve, assuming that the curve does not change (Koijen et al., 2018; Desclée and Polbennikov, 2016). Generally, the spreads of bond and CDS contracts decline with the time to maturity which results in upward sloping spread curves. Because price and yield are inversely related, this implies that the price of the contract increases as time passes.

Roll-down returns depend on the slope of the spread curve and therefore calculating the roll-down returns requires multiple points of the spread curve. To calculate the roll-down of the CDS index, I use the spreads of the on-the-run[3] CDS index (with approximately 5 years to maturity) and the most recently issued off-the-run CDS index (with approximately 4.5 years to maturity) to capture the relevant time-to-maturity range of the spread curve. The CDS index roll-down is approximated by

$$R^{Roll-down}_{h,CDS,t} = \left(S^{On}_{h,CDS,t} - S^{Off}_{h,CDS,t}\right) \cdot SD^{On}_{h,CDS,t}, \tag{10}$$

where S denotes the spread and SD denotes the spread-duration of a CDS index, which is a measure of the price sensitivity to a change in the spread, and h denotes the universe with $h \in \{1,2,3,4\}$. Because roll-down is relatively constant over time, it does not explain time-variation of the CDS-bond returns difference. Therefore, I cannot use it as a regressor in time-series analysis. Instead, I calculate the roll-down return as the average of the monthly roll-down returns over the sample period. This roll-down term is used as a constant that is part of the monthly arithmetic returns.

To measure the roll-down of the bond index, I cannot use the same approach as in Eq. (11) because there are no on-the-run and off-the-run versions of the reference bond indices. Alternatively, estimating the yield curve for the bond index would require estimating the yield

[3] An on-the-run index is the most recently issued index, and an off-the-run index has been issued before the on-the-run index but is still traded.

curve for all its constituents which is beyond the scope of this paper. Therefore I use an estimation based on the results of a study by Desclée and Polbennikov (2016) with an almost identical sample period. I assume that the bond index roll-down return is approximately 24% of the roll-down return of the CDS index. This ratio has also been fairly consistent over time. Using this assumption I obtain a roll-down return difference between the CDS and the bond index for universe h ($h \in \{1, 2, 3, 4\}$) of

$$R^{Roll-down}_{h,CDS-bond} = 0.76 \frac{1}{T} \sum_{t}^{T} (S^{On}_{h,CDS,t} - S^{Off}_{h,CDS,t}) \cdot SD^{On}_{h,CDS,t}, \tag{11}$$

where 0.76 is obtained by subtracting 24% from 1. The final term, $R^{h,Roll-down}_{CDS-bond}$, is used as an explanatory variable for the total arithmetic CDS-bond return difference.

4.3 Factors

This sector describes the construction and definition of the risk factor used in this analysis. I present an overview in Table 2. In Table 3, I summarize which driving elements (i.e. compounding, roll-down and the factors) have been documented in previous literature and show the direction of the effect (if applicable).

4.3.1 Construction

Risk factor portfolios are constructed as an equally weighted long-short portfolio that goes long in bonds with high exposure to a particular factor and short in bonds with low exposure to the same factor.

I distinguish $H = 4$ universes based on each segment (investment grade and high yield) and location (U.S. and Europe) separately following Houweling and Van Zundert (2017). For each of the four universes, I create separate factor portfolios. The portfolios are rebalanced monthly. Moreover, for factors that are created based on percentiles such as size of an issuer, I recalculate the buckets each month. This ensures that the attribution of bonds to, for example, the size buckets is independent of the change in size of issuers over the sample period.

Because factor portfolios are constructed such that they carry a premium on top of the premium of the market, I calculate the return of a portfolio in excess of the market return for that universe. That is, I residualize the returns of the portfolio for factor i of index h (with $h \in \{1, 2, 3, 4\}$) by taking the constant and the residuals that result from regressing the bond returns on the market such that

$$F_{h,i,t}^{original} = \alpha_{h,i} + \beta_{h,i,M} F_{h,M,t} + \epsilon_{h,i,t}^{original}, \tag{12}$$

$$F_{h,i,t} = F_{h,i,t}^{original} - \beta_{h,i,M} F_{h,M,t} \tag{13}$$

$$= \alpha_{h,i} + \epsilon_{h,i,t}^{original}, \tag{14}$$

where $F_{h,i,t}^{original}$ is the original return for factor portfolio i at time t and $\epsilon_{h,i,t}^{original}$ denotes the residual. Furthermore $\beta_{h,i,M}$ is the exposure of the factor portfolio to the market which is also denoted by the market-beta. $F_{h,M,t}$ denotes the corporate bond market excess returns and $F_{h,i,t}$ denotes the residualized factor portfolio returns at time t. In asset pricing literature, $\alpha_{h,i}$ is often referred to as the CAPM-alpha of risk factor i. Because the original factor returns $F_{h,i,t}^{original}$ differ per index h (i.e. U.S. investment grade, Europe investment grade, U.S. high yield, Europe high yield), the corresponding CAPM-alpha and market-beta are also allowed to differ between the four indices.

The factors are constructed within issuer if possible. For example, consider the factor portfolio for index h with $h \in \{1, 2, 3, 4\}$ that goes long in subordinated bonds and short in senior bonds. Assume there are N issuers in index h that have both senior and subordinated bonds outstanding at time t. Furthermore assume that issuer $i \in N$ has L_i subordinated bonds outstanding and S_i senior bonds outstanding at time t with $L_i, S_i > 0$ but not necessarily $L_i = S_i$. Then the within issuer seniority factor return at time t for universe h is calculated as

$$F_{h,sensub,t} = \frac{1}{n} \sum_{i=1}^{N} \left(\frac{1}{L_i} \sum_{j=1}^{L_i} F_{h,i,t}^{L_j} - \frac{1}{S_i} \sum_{g=1}^{S_i} F_{h,i,t}^{S_g} \right) \tag{15}$$

where $F_{h,i,t}^{L_j}$ denotes the excess return of the j^{th} subordinate bond of company i at time t and $F_{h,i,t}^{S_g}$ denotes the excess return of the g^{th} senior bond of the company respectively.

4.3.2 Definitions

I include eleven factors in my analysis. The factors are solely based on bond characteristics and therefore the construction of the factor portfolios requires data neither on returns of individual CDS contracts (which is scarcely available) nor on equity market information (which would exclude the bonds of companies that are not publicly traded). This allows me to use the entire data set on bonds for my analysis. Below, I specify the definitions of the eleven factor portfolios.

(1) Seniority

Because claims of subordinated bonds are ranked after senior bonds, the probability of their

Table 2: Construction of bond factor portfolios

Reference	*Long - short*	*Within issuer*	*Notes*
Seniority	Subordinate - senior	Yes	
Financials	Other financials - banks	No	
Rating	Low rating - high rating	No	Three buckets
Maturity	Short TTM - long TTM	Yes	Long $\leq$ 4-6 years, short others
Size	Small - large	No	Decile
Age	Old - young	Yes	Decile
Value	High - low	No	Decile
Callability	Non-callable - callable	Yes	Make-whole bonds excluded
Low risk	Low risk - high risk	No	Decile, double on rating and age
Momentum	High - low	No	Decile
Market	Long only	Not applicable	Universe-specific market

Notes: This table shows the constructon of bond factor portfolios per factor. The 'Long-short' column shows the characteristics of the bonds in that are overweighted and underweighted respectively. 'Within issuer' indicates whether the factors are constructed based on issuers that have bonds both in the 'long part' of the portfolio and in the 'short part' of the portfolio. I added notes for further specifications if applicable.

pay-out is generally lower. Therefore, subordinated bonds are expected to carry a risk premium and have higher expected returns Desclée and Polbennikov (2015). The portfolio therefore goes long in subordinated bonds and short in senior bonds. The factor is constructed within issuer.

(2) Financials

Due to constitution rules of the indices, CDS indices attribute significantly less weight to banks than bond indices do. To control for the effect of the financial industry as a whole, the portfolio goes long in bonds from other financials and short in bonds from banks.

(3) Rating

The characteristics of CDS and bond indices as presented in Section 3 show that CDS indices generally have relatively more weight in lower rated issuers than bond indices do. Lower rated issuers are perceived less creditworthy and therefore their bonds are expected to carry a risk premium (Desclée and Polbennikov, 2015). Bonds are put in three buckets according to their issuer's rating (low, medium, and high). The buckets for investment grade are: BBB+ or below, A- to A+, and AA- or above respectively. For high yield, the buckets are CCC+ or below, B- to B+, and BB- or above respectively. The factor is constructed as going long in the bucket with the lowest rating and short in the bucket with the highest rating. The factor is constructed within issuer.

(4) Maturity

CDS indices have a fixed time to maturity whereas for bond indices there is no such restriction. Bonds are put in four buckets according to their time to maturity (<4 years, 4-6 years, 6-10 years, >10 years). Since the CDS index has 5.25 years to maturity at the time of issuance, and 4.75 years to maturity at the time of renewal, the on-the-run CDS index has 100% weight in the 4-6 years bucket. I therefore construct a maturity factor that goes long in CDS-matched maturities (4-6 years) and short in the other maturities (all other buckets). The factor is constructed within issuer.

(5) Size

I calculate the size of bonds based on issuers: issuers are ranked on size using the sum of the market weights of their issued bonds. Houweling and Van Zundert (2017) show that bonds of companies that are small-sized according to this measure carry a risk premium. Moreover, they claim that small bond issuers tend to be small firms which is in line with the well-documented size effect in equity markets. Issuers are placed into ten buckets based on size. I construct the factor as going long in the decile with lowest-sized issuers and short in the decile with largest-sized issuers.

(6) Age

Warga (1992) argues that older bonds are relatively illiquid and are therefore expected to pick-up a liquidity premium. I place the bonds in ten buckets according to their age. The factor is constructed as going long in the oldest decile bond returns and short in the youngest decile bond returns[4]. The factor is constructed within issuer.

(7) Value

Similar to the value effect in equity markets, where cheap stocks (based on a fundamental measure) tend to outperform and expensive stocks tend to underperform, an analogy can be found in the bond market. Following Correia et al. (2012) and Houweling and Van Zundert (2017), I consider a bond to be cheap if the actual spread is higher than a fitted spread based on three risk measures. These risk measures are: maturity (M), rating (R), and 3-month spread change (ΔS). The fitted spread for bond i is calculated as

$$S_{i,t} = \alpha + \sum_{r=1}^{R} \beta_R I_{i,r} + \gamma M_i + \delta \Delta S_{i,t} + \epsilon_{i,t}, \tag{16}$$

where $\epsilon_{i,t}$ denotes the error term at time t such that $\mathrm{E}[\epsilon_{i,t}] = 0$. The portfolio goes long in the 10% bonds with the largest spread compared to the fitted spread, and short in the 10% bonds with the lowest spread compared to the fitted spread.

(8) Callability.

Callable bonds carry the risk of being executed before the maturity date. In that case, the investor misses out on future coupon payments. Therefore, callable bonds are expected to pay a premium (Jen and Wert, 1967). In case of declining interest rates, the probability of call execution becomes higher and therefore callable bonds become less valuable. Because interest

[4] In case this leads to less than 10 issuers in a given month, I replace the factor portfolio returns for that month with the quintile portfolio returns.

rates have primarily been declining during our sample period, I construct the factor as going long in non-callable bonds and short in callable bonds. This isolates the effect of the call option from effects of issuer, rating, and sector. I exclude make-whole bonds, callable bonds of which the issuer compensates the investor when the call is executed, because they are neither purely callable nor non-callable. The factor is constructed within issuer.

(9) Low-risk

Similar to the low-volatility factor in equity markets, previous studies have shown evidence that bonds with lower risk generate higher risk-adjusted returns. Houweling and Van Zundert (2017) show that bonds with a high rating earn higher risk-adjusted than bond with a lower rating, and Ilmanen et al. (2004) show that bonds with a short time to maturity earn lower risk-adjusted returns than bonds with a longer time to maturity. Studies by Ilmanen (2011) and Houweling and Van Zundert (2017) combine the two characteristics into a double-sorted low-risk factor. I follow their approach. For the top portfolio, select all high-rated bonds[5]. From these bonds, select the X youngest bonds on a monthly basis such that the selected bonds make up 10% of the total bond universe. For the bottom portfolio, select all low-rated bonds[6]. From these bonds, select the Y oldest bonds on a monthly basis such that the selected bonds make up 10% of the total bond universe. The low-risk factor portfolio takes a long position in the top portfolio and short position in the bottom portfolio.

(10) Momentum

Momentum is a well-documented equity factor (Jegadeesh and Titman, 1993). Several researchers also studied the prevalence of momentum in bond markets and found significant results for the high yield universe (Jostova et al., 2013). I use the momentum factor of Houweling and Van Zundert (2017), who calculate the momentum factor based on the past semi-annual returns with one lag. The portfolio goes long in the top 10% with highest past returns and low in the top 10% with lowest past returns.

(11) Market

The final factor is the market return. To obtain the difference in exposure on the market for CDS and bond indices, I also regress the CDS-bond return difference on the value-weighted bond market return. Therefore, by definition the returns of the bond index have an exposure of 1.00 to the market factor.

[5] Rating A- or higher for investment grade, rating B- or higher for high yield.

[6] Rating below AA- for investment grade, rated below BB- for high yield.

Table 3: Overview of literature on driving elements

Reference	*Effect*	*CDS-bond*	*Literature*
Constant terms			
Compounding			Not documented
Roll-down	0 (IG), + (HY)	✓	Desclée and Polbennikov (2016)
Bond factor portfolios			
Seniority	+ (IG), - (HY)	✓	Desclée and Polbennikov (2015)
Financials			Not documented
Rating	+	✓	Desclée and Polbennikov (2015)
Maturity	+	✓	Desclée and Polbennikov (2015)
Size	+	×	Houweling and Van Zundert (2017)
Age	+	×	Warga (1992)
Value	+	×	Correia et al. (2012)
Callability			Not documented
Low risk	+	×	Ilmanen (2011)
Momentum	0 (IG), + (HY)	×	Jostova et al. (2013)
Market	+	✓	Desclée and Polbennikov (2015)

Notes: This table provides an overview of the documented results for the driving elements that I consider in my study. For the 'Effect column', '+' indicates a positive effect on CDS-bond return differences, '-' indicates a negative effect, and '0' indicates no effect. An empty entry indicates that the element has not been documented in literature in this form. Moreover, the effects are indicated with (IG) or (HY) if the results differ between investment grade (IG) and high yield (HY). The 'CDS-bond' column indicates if the element has been documented in CDS-bond specific literature (✓) or only in bond literature (×).

4.4 Decomposing portfolios

I attribute the return difference to risk factors in several steps. I create decomposing portfolios to measure the composition, weighting scheme, and CDS-bond specific effects. I first have to create a bond portfolio that matches the constituents of the CDS index. Because Bloomberg does not provide a link between the issuers of CDSs and issuers of bonds, I create this link myself.

First, I clean the data set by manually merging the names of issuers that do not match due to a small difference[7]. Hereby, care is taken to assure that I do not merge issuer names that have a different liability structure[8]. Next, I try to match the issuer names from the CDS database with the issuer names from the bond database. If there is no direct match, I look up the specific case and try to manually find a matching issuer name. In on average less than 5% of the cases, there is no issuer name in the bond index for the CDS index constituents.

To create a CDS index-matched bond portfolio, I continue working with the issuers for which I found a match between both data sets. For each issuer in the CDS index at a time t, I want to select a bond that is traded in the same month t. If there is a bond available in the same period

[7]For example, one entry for an issuer name contains N.V. and the other entry is exactly the same except it contains NV without the dots.

[8]For example, a holding company that cannot be held liable for defaults of its subsidiary.

Table 4: Overview of the differences between the decomposed portfolios

	Bond index	Step (1) Composition	Step (2) Weighting scheme	Step (3) CDS-specific **CDS index**
Issuers (#)	Original	75 to 125	75 to 125	75 to 125
Weights	Market value	Market value	Equal	Equal
Seniority	Original	Mapped to CDS	Mapped to CDS	Mainly senior
Maturity (y)	Original	Closest to 5	Closest to 5	4.75 to 5.25

Notes: This table shows the different the steps of creating the decomposing portfolios. In Step (1), I adjust the bond portfolio to match the CDS index in terms of issuers, seniority, and maturity. These effects are labelled as 'Composition'. Next, I adjust the weighting of the portfolio from market value weights to equal weights to match the weighting scheme of the CDS index. These effects are labelled as 'Weighting scheme' in Step (2). Finally, the difference between the equally weighted matched bond portfolio and the CDS index, i.e. the remainder, are labelled in Step (3) as 'CDS-specific' effects.

that is also specified as the reference bond in the CDS contract, I automatically select that bond. Else if there is a bond of the same issuer with the same seniority, I select the bond with the maturity closest to the CDS index. In case there is no bond that meets the requirements, I created an algorithm to find the most appropriate bond which can be found in Section A.2 in the Appendix. Using this algorithm, the majority of the CDS constituents can be matched with a bond. The coverage ratio is larger for more recent observations with approximately 90% matched CDS constituents.

The decomposition consists of three steps. In the first step, I create an issuer-matched bond portfolio using market value weights. In the second step, I keep the matched bonds but use equal weights instead to align with the rules of the CDS index. In the third step, the portfolio consists of the original CDS index. Table 4 presents an overview of the most important steps in the decomposition of the original bond index. Step (1) captures the composition effects, step (2) captures the weighting scheme effects and step (3) captures the CDS-bond specific effects. Based on the construction of the portfolios, I can decompose the total CDS-bond return difference into return series for composition, weighting scheme, and CDS-specific effects. I use these series, as well as the total CDS-bond return difference series, for risk factor attribution.

4.4.1 Decomposing portfolios attribution

To explain the return difference between CDS indices and bond indices, I attribute different return series to the risk factors. Using the decomposing portfolios, I have four return time series: one total return differences series and three decomposing series. The total return difference (sometimes abbreviated to CDS-bond returns) for index h is

$$R^*_{h,Total,t} = R_{h,CDS,t} - R_{h,Bond,t}, \tag{17}$$

which is the monthly arithmetic return difference between a CDS index and its reference bond index at time t. I subtract the roll-down term from the arithmetic series to obtain the total series that I use for risk factor attribution such that

$$R_{h,Total,t} = R_{h,CDS,t} - R_{h,Bond,t} - R^{Roll-down}_{h,CDS-bond}, \tag{18}$$

where $R^{Roll-down}_{h,CDS-bond}$ follows from Eq. (4.2). The other three series are created as the return differences between the decomposing portfolios

$$R_{h,Composition,t} = R_{h,MarketValue,t} - R_{h,Bond,t}, \tag{19}$$

$$R_{h,Weights,t} = R_{h,Equal,t} - R_{h,MarketValue,t}, \tag{20}$$

$$R_{h,CDS-specific,t} = R_{h,CDS,t} - R_{h,Equal,t}, \tag{21}$$

which are the CDS-specific, weighting, and composition effects at time t respectively. Hence for each of these return series $R_{h,j,t}$ with $j \in$ {Composition, Weights, CDS-specific, Total} I run the following time-series regression

$$R_{h,j,t} = c_h + \sum_{i=1}^{I} \beta_{h,i} F_{h,i,t} + \epsilon_{h,j,t}, \tag{22}$$

where $\beta_{h,i}$ denotes the exposure to a factor, $F_{h,i,t}$ denotes the residualized return of factor portfolio i at time t (with a total of $I = 11$ factor portfolios) and $\epsilon_{h,j,t}$ denotes the error term with $E[\epsilon_{h,j,t}] = 0$. The attribution of a factor i to the return $R_{h,j,t}$ at time t can then be calculated as $\beta_{h,i} F_{h,i,t}$.

4.4.2 Testing equality factor betas

As discussed before, the investment grade universe and high yield universe are often treated as separate asset classes by practitioners and academics. Therefore I investigate whether there is a difference in factor beta between investment grade and high yield when I regress the total CDS-bond return difference (see Eq. (18)) on the factor returns (see Eq. (22)). That means, I test differences in factor betas between U.S. investment grade and U.S. high yield, and between Europe investment grade and Europe high yield. In addition, I perform the same analysis between the locations (U.S. and Europe) keeping the credit universe fixed. Table 5 shows the four different combinations for which I test differences in factor betas. In general terms, I am interested in the differences between $\beta_{i,1}$ and $\beta_{i,2}$ provided by

$$y_{1,t} = R_{1,total,t} = c_1 + \sum_{i=1}^{I} \beta_{1,i} F_{1,i,t} + \epsilon_{1,t}, \tag{23}$$

Table 5: Four different index combinations for factor beta equality tests

	Index 1	Index 2
Credit	U.S. investment grade	U.S. high yield
	Europe investment grade	Europe high yield
Location	U.S. investment grade	Europe investment grade
	U.S. high yield	Europe high yield

$$y_{2,t} = R_{2,total,t} = c_2 + \sum_{i=1}^{I} \beta_{2,i} F_{2,i,t} + \epsilon_{2,t}, \tag{24}$$

where subscripts 1 and 2 refer to index 1 and 2 respectively and i refers to factor i with $i \in \{1, \cdots, I\}$. Moreover $\epsilon_{1,t}$ and $\epsilon_{2,t}$ denote the error terms at time t with expectation zero.

Because the factor return series for factor i, denoted by $F_{h,i,t}$, are different for each of the four universes, I model the regressions of index 1 and index 2 together in a seemingly unrelated regression (SUR) model. In a SUR model, the regressions are only correlated via the covariance terms (Woodland, 1986; Heij et al., 2004). The general form of the model is given by

$$\mathbf{y}_t = \mathbf{B}'\mathbf{x}_t + \boldsymbol{\epsilon}_t, \tag{25}$$

where $\mathrm{E}[\boldsymbol{\epsilon}_t] = \mathbf{0}_2$ where $\mathbf{0}_2$ denotes a 2×1 vector with zeroes (Srivastava and Giles, 1987). Here, $\mathbf{y}_t$ is the 2×1 vector of observations for the total return difference for the two universes at time t, and $\mathbf{x}_t$ is the $M \times 1$ vector of explanatory variables at time t. The model contains an intercept and hence the first row is equal to 1. We have $M = 1 + 2 * I$, where I denotes the number of factors per index. The $M \times 2$ matrix $\mathbf{B}$ contains the regression coefficients and $\boldsymbol{\epsilon}_t$ is the 2×1 vector with errors at time t for the two universes. To ensure that the regressions are only correlated via the covariance terms, I have

$$\mathbf{B} = \begin{pmatrix} \mathbf{b}_1 & \mathbf{b}_2 \end{pmatrix} = \begin{pmatrix} c_1 & c_2 \\ \boldsymbol{\beta}_1 & \mathbf{0}_I \\ \mathbf{0}_I & \boldsymbol{\beta}_2 \end{pmatrix}, \tag{26}$$

where $\mathbf{0}_I$ denotes a $I \times 1$ vector with I zeros. Moreover, c_1 and c_2 denote the constants for index 1 and 2 respectively and where $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ are $I \times 1$ vectors such that entry i is the beta corresponding with factor i.

To perform inference on the factor betas, I rewrite Eq. (25) in matrix form. Gather all observations for the total return difference, $y_{1,t}$ and $y_{2,t}$, in the $T \times 1$ vector $\mathbf{y}_1$ and $\mathbf{y}_2$ for index 1 and 2 respectively. Combine these vectors in the $T \times 2$ matrix $\mathbf{Y}$. The explanatory variables are the $T \times 1$ matrix $\mathbf{I}_T$ for the intercept, the $T \times I$ matrix $\mathbf{F}_1$ for the factor returns of index 1, and the $T \times I$ matrix $\mathbf{F}_2$ for the factor returns of index 2. Gather all observations for the explanatory variables in the $T \times M$ matrix $\mathbf{X}$. Gather all error terms in the $T \times 2$ matrix $\mathbf{E}$. The SUR model can be written as

$$\underset{T\times 2}{\mathbf{Y}} = \underset{T\times M}{\mathbf{X}}\underset{M\times 2}{\mathbf{B}} + \underset{T\times 2}{\mathbf{E}}, \tag{27}$$

with

$$\mathbf{Y} = \begin{pmatrix} \mathbf{y}_1 & \mathbf{y}_2 \end{pmatrix}, \tag{28}$$

$$\mathbf{X} = \begin{pmatrix} \mathbf{1}_T & \mathbf{F}_1 & \mathbf{F}_2 \end{pmatrix}, \tag{29}$$

$$\mathbf{B} = \begin{pmatrix} \mathbf{b}_1 & \mathbf{b}_2 \end{pmatrix}, \tag{30}$$

$$\mathbf{E} = \begin{pmatrix} \boldsymbol{\epsilon}_1 & \boldsymbol{\epsilon}_2 \end{pmatrix}, \tag{31}$$

where T denotes the number of observations (150).

To investigate whether the factor beta for factor i is the same for index 1 and index 2, I test whether any of the restrictions $\beta_{1,i} = \beta_{2,i}$ for $i \in \{1, 2, ..., I\}$ is true. I estimate the variance-covariance matrix of the model parameters by the variance of the estimators $\hat{\mathbf{B}}$, where $\hat{\mathbf{B}}$ is the generalized least squares estimator. To do so, I first stack the columns of $\hat{\mathbf{B}}$, that is

$$vec(\hat{\mathbf{B}}) = \begin{pmatrix} \hat{\mathbf{b}}_1 \\ \hat{\mathbf{b}}_2 \end{pmatrix} = \begin{pmatrix} c_1 \\ \hat{\beta}_1 \\ \mathbf{0}_I \\ c_2 \\ \mathbf{0}_I \\ \hat{\boldsymbol{\beta}}_2 \end{pmatrix}. \tag{32}$$

I use the results from Zivot and Wang (2006) that $vec(\hat{\mathbf{B}})$ is consistent and asymptotically normally distributed with covariance matrix

$$\widehat{avar}(vec(\hat{\mathbf{B}})) = \hat{\boldsymbol{\Sigma}} \otimes (\mathbf{X}'\mathbf{X})^{-1}, \tag{33}$$

where $\otimes$ denotes the Kronecker product. Furthermore $\hat{\Sigma}$ denotes the estimated variance matrix of the error terms such that

$$\hat{\Sigma} = \frac{1}{T-m}\hat{\mathbf{E}}'\hat{\mathbf{E}}, \tag{34}$$

with $\hat{\mathbf{E}} = \mathbf{Y} - \hat{\mathbf{B}}\mathbf{X}$, i.e. the $T \times 2$ matrix with residuals.

After deriving the distribution of the elements of $vec(\hat{\mathbf{B}})$, I can test hypotheses on the values of the parameters. I conduct a Wald test to compare the restricted model ($\beta_{1,i} = \beta_{2,i}$ with

$i \in \{1, 2, ..., I\}$) with the unrestricted model (Zivot and Wang, 2006).

The model parameters are denoted by

$$\begin{aligned} \boldsymbol{\theta} &= vec(\mathbf{B}) \\ &= \begin{pmatrix} c_1 & \beta_{1,1} & \dots & \beta_{1,I} & \mathbf{0}'_I & c_2 & \mathbf{0}'_I & \beta_{1,I} & \dots & \beta_{2,I} \end{pmatrix}' \\ &= \begin{pmatrix} \theta_1 \cdots \theta_Z \end{pmatrix}', \end{aligned} \tag{35}$$

with $Z = 2 * M = 2 + 4 * I$.

The restriction function for the Wald test for equality of betas for factor i, denoted by rf_i, is given by

$$rf_i = \beta_{i,1} - \beta_{i,2}, \tag{36}$$

where $rf_i = 0$ if $\beta_{i,1} = \beta_{i,2}$ with $i = 1, ..., I$. For a restriction on factor i, the restriction function Jacobian $\mathbf{RM}_i$ is given by

$$\mathbf{RM}_i = \begin{pmatrix} \frac{\delta rf_i}{\delta \theta_1} & \frac{\delta rf_i}{\delta \theta_2} & \dots & \frac{\delta rf_i}{\delta \theta_Z} \end{pmatrix}. \tag{37}$$

For example, for testing $\beta_{1,1} = \beta_{2,1}$ we get

$$rf_1 = \beta_{1,1} - \beta_{2,1}, \tag{38}$$

$$\mathbf{RM}_1 = \begin{pmatrix} 0 & 1 & 0 & \dots & 0 & -1 & 0 & \dots & 0 \end{pmatrix}, \tag{39}$$

since $\frac{\delta rf_1}{\delta \theta_j} = 0$ for $j \neq \{2, I+2\}$. The Wald statistic for testing $\beta_{1,i} = \beta_{2,i}$ is then given by

$$Wald_i = \left(\mathbf{RM}_i \cdot vec(\hat{\mathbf{B}}) - rf_i\right)' \left(\mathbf{RM}_i \left[\widehat{avar}(vec(\hat{\boldsymbol{B}}))\right]^{-1} \mathbf{RM}_i\right) \left(\mathbf{RM}_i \cdot vec(\hat{\boldsymbol{B}}) - rf_i\right), \tag{40}$$

which has a limiting $\chi^2(q)$ distribution under the restricted model with q equal to the rank of $\mathbf{RM}_I$ (Zivot and Wang, 2006). In this case, $q = 1$. I set the critical value to $\alpha = 0.05$ such that if the p-value of $Wald_i$, denoted by p is smaller than 0.05, I reject the restricted model and conclude that $\beta_{i,1} \neq \beta_{i,2}$. If $p \geq 0.05$, I cannot reject that the betas for factor i are the same for index 1 and index 1.

4.4.3 Factor beta vs. characteristics

Several studies investigate whether characteristics of a firm, rather than exposure to a risk factor, actually drive equity returns. Daniel and Titman (1997) show that when controlling for the underlying characteristic of a company (such as book-to-market ratio for the equity value factor), differences in exposure to the risk factor (factor beta) do not explain differences in returns. Moreover, Chen et al. (2018) show that the cross-sectional correlation between the factor beta and underlying characteristics is only 17% for size, value and 4% for momentum in the equity market. I investigate whether there is a similar pattern for bonds.

To investigate the cross-sectional correlation, I consider the factors seniority, financials, rating, maturity, size, call, and age[9]. For each factor, I rank each bond based on the underlying characteristics (see Section (4.3.1). Beta exposures and characteristics values have the same direction. That is, the highest possible value for a characteristic is associated with the 'long part' of the factor portfolio definition, and the lowest possible value is associated with the 'short' part of the factor definition.

For each of the individual factors in universe h with $h \in \{1, 2, 3, 4\}$, I estimate the individual bond's factor beta as follows

$$R_{h,j,t} = \alpha + \beta_{h,i,j} F_{h,i,t} + \epsilon_{h,j,t}, \quad (41)$$

where $R_{j,t}$ denotes the bond's return at time t, α denotes the intercept and $\beta_{j,i}$ denotes the factor beta of bond j to factor i and $F_{i,t}$ denotes the return of factor i at time t. Moreover, $\epsilon_{j,t}$ denotes the innovation at time t such that $E[\epsilon_{j,t}] = 0$. I follow Chen et al. (2018) and set the minimum number of observations required to calculate factor betas for a bond to 36.

For each factor, I aggregate the betas of the individual bonds and calculate the deciles that split the betas in ten equal parts. Each bond is then ranked with a value of $b \in \{1, 2, \cdots, 10\}$ according to their factor beta, where a higher value of b corresponds with a higher value of $\beta_{i,j}$. Next, using the data of an entire bond index I calculate the Pearson correlation coefficient between the underlying characteristic and the factor betas. I first calculate the correlation coefficient cross-sectionally. Then, I average the coefficients over time to obtain the mean cross-sectional correlation coefficient.

4.5 Decomposing variance

In the previous section, I attribute the return differences between CDS and bond indices using decomposing portfolios. Now, I also investigate the explanatory power of each of the decomposing portfolios for the variability of CDS-bond return differences.

For each universe h, I run three time-series regressions with the total CDS-bond index return difference at time t, $R_{h,Total,t}$, as dependent variable. As independent variables, I use different

[9] I exclude the factors value, low risk, and momentum because I do not have individual underlying characteristics data. I exclude the market factor because it is not a characteristic of a firm.

combinations of two of the three return series from the different steps. The three return series are based on the composition effects, weighting scheme effects, and CDS-specific effects. Next, I use the sum of squared residuals of the regressions as a measure of the explained variability. I will illustrate this approach using decomposing step (1), composition effects, as an example. To consider the explanatory contribution of step (1) to the variability of the CDS-bond return difference, I exclude the return series $R_{h,Composition}$ as explanatory variable and regress

$$R_{h,Total,t} = \alpha R_{h,Weighting,t} + \beta R_{h,CDS-specific,t} + \epsilon_{h,t}, \tag{42}$$

and I obtain

$$SSR_{h,1} = \sum_{t=1}^{T} \epsilon_{ht}^2, \tag{43}$$

where ϵ_t denotes the error term. The larger $SSR_{h,1}$ compared to $SSR_{h,2}$ and $SSR_{h,3}$, the greater the explained variability by step (1), composition effects, compared to step (2) and step (3), weighting effects and CDS-specific effects respectively. The relative contribution of step (1), $RC_{h,1}$, is measured as

$$RC_{h,1} = \frac{SSR_{h,1}}{SSR_{h,1} + SSR_{h,2} + SSR_{h,3}}. \tag{44}$$

5 Results return attribution

Below, I discuss the effect of compounding, roll-down and risk factors on CDS-bond return differences in detail. I present a complete overview of the results in Table 8 (U.S.) and Table 9 (Europe) for investment grade, and Table 10 (U.S.) and Table 11 (Europe) for high yield.

5.1 Compounding and roll-down

Using geometric compounding instead of arithmetic compounding is in favor of CDS indices. CDS indices are less volatile than bond indices which leads to an outperformance attributed to geometric returns[10]. The geometric compounding term explains an annual return difference of 0.10% and 0.11% in the investment grade universe for the U.S. and Europe respectively. For the high yield universe, I attribute 1.45% (U.S.) and 0.03% (Europe) of the total CDS-bond index return difference to compounding. Due to the consistently lower volatility of the CDS index compared to the bond index over the sample period, I expect the effect of compounding on CDS-bond index return differences to remain positive in the future.

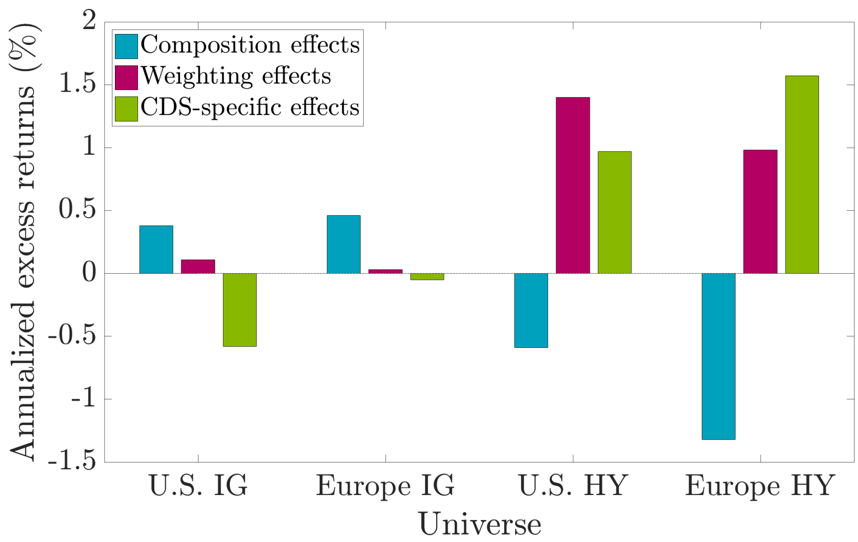
[10] To illustrate why lower volatility is favorable when using geometric compounding, remember the asymmetry of gains and losses from Section 4.

The results for roll-down are different for the investment grade and high yield universes. For both investment grade indices, the contribution from roll-down is negligible. However, with an annual contribution of 3.08% and 1.24% for the U.S. and Europe respectively, it is one of the most important drivers for high yield indices. This finding heavily relies on the assumption that the bond index roll-down is 24% of the CDS-index roll-down that I assumed based on the results of Desclée and Polbennikov (2016). Their explanations for the larger roll-down of CDS indices include differences in supply demand dynamics and the callability of bonds. This is further discussed in Section 6. Because roll-down has generated returns that are fairly constant over time, I expect this driver to remain a driver of CDS-bond outperformance in the high yield universe.

5.2 Decomposing portfolios

In this section, I provide a high-level overview of the contribution of composition, weighting scheme, and CDS-specific effects to the overall CDS-bond index return difference. Figure 2

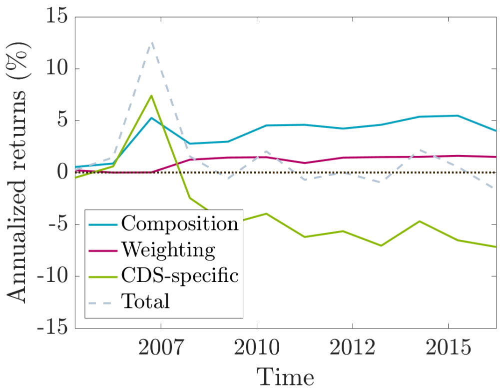
Figure 2: Annualized performance of the decomposing portfolios for each universe



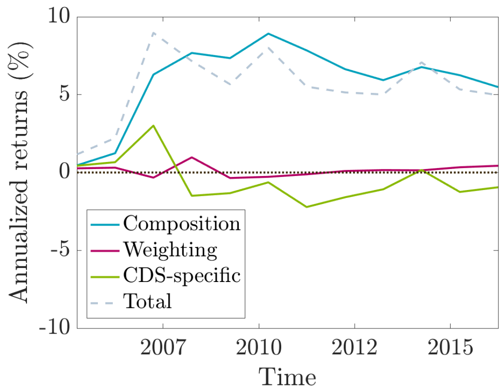
Notes: The graphs show the returns of the decomposing portfolios for investment grade (left) and high yield (right). The returns are calculated for each of the tree decomposing portfolios using arithmetic returns.

shows the attribution of the return differences between CDS and bond indices to the different decomposing portfolios (as summarized in Table 4). In line with results of Desclée and Polbennikov (2015), differences in composition are in favor of CDS indices in the investment grade universe. The opposite is true for the high yield universe: the differences in composition (step (1)) contribute negatively to the CDS-bond returns, and the outperformance of CDS indices is mainly explained by step (3) CDS-bond specific effects. For both universes, using equal weights (step (2)) improves the return of the matched portfolio compared to market value weights. This implies that smaller issuers outperform larger issuers which is in line with the size effect (Houweling and Van Zundert, 2017). As a result of the decomposing steps, the CDS-bond specific effects is the remainder that also captures other effects. For example, error terms that are the result from an incomplete match between CDS constituents and their reference bonds end up in this term. This may have an impact on the accuracy of the size and direction of the term.

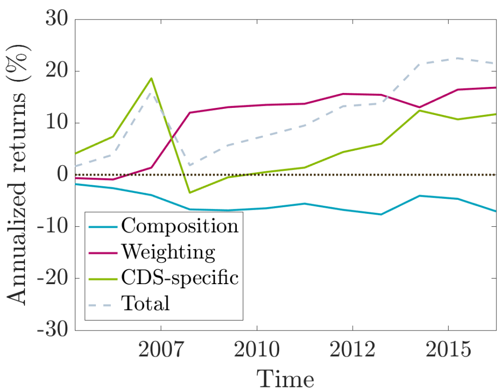
Figure 3: Annualized return series for 'Composition effects', 'Weighting effects', and 'CDS-specific effects' over 2005 - 2017



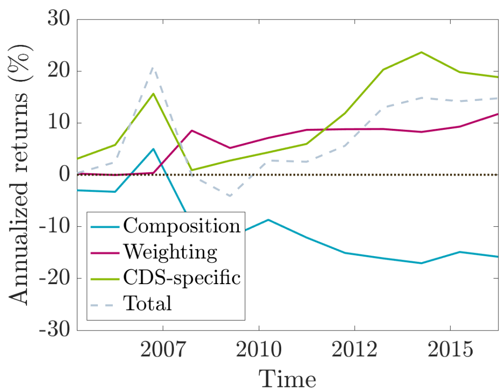
(a) U.S. investment grade



(b) Europe investment grade



(c) U.S. high yield



(d) Europe high yield

Notes: The graphs show the returns of the decomposing portfolios for the investment grade and high yield universes over the sample period. 'Total' denotes the total return difference and is the sum of the three decomposing portfolio returns (arithmetically compounded).

Figure 3 shows the annualized performance of the decomposing portfolios over time. The labels and colors match Figure 2. 'Total' denotes the total return difference and is the sum of the three decomposed returns. The weighting scheme effect is generally positive, except for the financial crisis in 2008. This indicates that bonds with a lower market value experienced a larger drawdown than bonds with a higher market value. Moreover, even though the cumulative effect of

CDS-bond specific effects is of opposite signs for investment grade and high yield, CDS-bond specific effects explained a large part of the outperformance during the financial crisis for both universes.

5.3 Factor attribution

5.3.1 Performance factor portfolios

Table 6 and Table 7 show the annualized CAPM-alpha for the different factor portfolios for each of the four universes. The mean CAPM-alphas of the factor portfolios are generally positive with seniority, call, and momentum as main exceptions. The CAPM-alpha for the size factor portfolio is relatively high with 1.54% for U.S. investment grade and 4.47% for U.S. high yield. These numbers are in line with previous studies such as Houweling and Van Zundert (2017). The market-beta is statistically significant ($\alpha = 0.05$) for all factors except maturity in Europe investment grade, financials, age and momentum in U.S. high yield, and Size in Europe high yield. This confirms the relevance of using residualized factor portfolio returns, that is factor portfolio returns in excess of the market returns. Table 20 and 21 in Section A.4 in the Appendix show the pairwise correlation between the factor portfolio returns. The absolute values of the correlations between the CAPM-alphas are generally well below 30%. This implies that the different factors are able to capture different sources of risk.

5.3.2 Factor return attribution

In this section, I highlight the most important drivers of CDS-bond return differences. I hereby focus on the significant factors and illustrate the differences between investment grade and high yield. Table 8 (U.S.) and Table 9 (Europe) show the return difference attribution for geometric returns (based on compounding) and the arithmetic returns (based on roll-down and risk factors) for investment grade. I provide the same results for the high yield universe in Table 10 (U.S.) and Table 11 (Europe). I show the annual return attribution per decomposing step and for the total return difference (these entries are in italics). I calculated the roll-down term and compounding term as a constant and therefore do not test them for statistical significance in the time-series regression.

For each of the four universes, there is a significant negative contribution resulting from the market. The investment grade CDS indices have a market beta of 0.30 for the U.S. and 0.48 for Europe. The high yield CDS indices have a market beta of 0.39 and 0.52 respectively. By definition, all bond indices have a market beta of 1.0 to the market. Therefore, when considering

Table 6: Annualized CAPM-alpha and Market-beta (%) of the factor portfolios for the investment grade indices from 2005-2017

	Investment grade			
	U.S.		Europe	
	CAPM-alpha	Market-beta	CAPM-alpha	Market-beta
Seniority	-0.32	0.80$^{(***)}$	-0.02	1.80$^{(***)}$
	(0.99)	(0.05)	(1.16)	(0.09)
Financials	0.05	0.46$^{(***)}$	0.66	0.69$^{(***)}$
	(1.03)	(0.06)	(0.96)	(0.08)
Maturity	0.58$^{(***)}$	-0.25$^{(***)}$	0.22	-0.04
	(0.21)	(0.01)	(0.30)	(0.02)
Rating	0.86	0.46$^{(***)}$	1.25	0.79$^{(***)}$
	(0.81)	(0.04)	(0.66)	(0.05)
Size	1.54	-0.30$^{(***)}$	0.65	0.51$^{(***)}$
	(0.89)	(0.05)	(1.46)	(0.12)
Call	-0.59$^{(***)}$	-0.01$^{(**)}$	0.32$^{(***)}$	-0.05$^{(***)}$
	(0.05)	(0.00)	(0.09)	(0.01)
Age	1.14$^{(***)}$	0.08$^{(***)}$	1.40	-0.25$^{(***)}$
	(0.37)	(0.02)	(1.00)	(0.08)
Value	0.28	1.02$^{(***)}$	-0.05	2.27$^{(***)}$
	(0.86)	(0.05)	(1.43)	(0.11)
Momentum	-1.09	-0.45$^{(***)}$	0.70	-1.47$^{(***)}$
	(1.70)	(0.09)	(2.84)	(0.22)
Low-risk	1.40	-1.27$^{(***)}$	1.71$^{(***)}$	-1.51$^{(***)}$
	(0.98)	(0.05)	(0.44)	(0.03)
Market	1.01		0.72	

Notes: The table shows the annualized performance of the factor portfolios for the investment grade indices in the U.S and Europe. The annualized return of the market is presented below the factor portfolios.
Portfolios are constructed as decile portfolios (if applicable). Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses.

the exposure of CDS-bond returns, i.e. the net exposure to the market, this leads to a net market beta of -0.70, -0.52, -0.61 and -0.48 respectively. Due to the low market beta of the CDS indices compared to the bond indices over the sample period, I expect the market contribution to remain negative in the future.

For the investment grade universe only, the results show a positive and significant annual contribution (0.27% for U.S. and 0.29% for Europe) from the rating factor in the composition step (1). This indicates that the CDS index indeed generally has lower rated names in the index than the original bond index. For Europe investment grade, the overall effect of rating is also significant (0.49% annual contribution) whereas it is insignificant for the U.S.

The results confirm the existence of the size factor in the bond market for the high yield universe. The annual returns attributed to the size factor in step (2) weighting effects, in which market value weights of the matched bond portfolio are replaced by equal weights, are positive (0.27% for U.S. and 0.07% for Europe) and significant. This is in line with the expectations as the weighting step gives relatively high weight to small bond issuers, and little weight to large bond issuers. Moreover, the effect is significant for both high yield universes. As long as the construction rules of the CDS and bond indices do not change, this effect is expected to persist in the future. The total attribution to size, however, is not significant at the overall CDS-bond index return difference. One explanation could be that the CDS index contains relatively larger issuers than the bond index, but this is contradicted by the significant positive attribution in the composition step for the European investment grade index. This suggests that the negative attribution to size comes from the CDS-specific effects, which is confirmed by the significantly negative attribution for Europe investment grade for U.S. high yield. An explanation would be that the size factor as documented in literature on the bond market effectively carries a premium for illiquidity of smaller issuers, but that this does not hold for the CDS market.

Interestingly, except for Europe investment grade, the call factor is not significant in the CDS-specific step. Because a call option is a fundamental difference between contract specifities for CDS and bond contracts, I would expect that this decomposing step would load on the call factor. There are two explanations for the insignificant results. Firstly, it might be the case that there is no risk premium for callable bonds. However Table 7 shows that the CAPM-alpha is significant for all indices except U.S. high yield. A second explanation would be that the factor definition is too restrictive. Constructing the call factor within-issuer has led to a time series based on only 10 to 20 issuers in some months, especially in the investment grade universe. This might inevitably have led to a bias in the return series. However, the within-issuer approach is necessary to isolate the effect of the call option on returns. Even though insignificant, there is a positive total CDS-bond index exposure on the call factor. Because CDS indices contain no call option, and the call factor is constructed as a long position in non-callable bonds and a short position in callable bonds, this is in line with the expectations. To understand the returns of the call factor, I investigate the relationship of the factor portfolio return with the risk free rate in Section 6.

I consider the proportion of variance explained by the risk factors, which is denoted by R^2, for the total CDS-bond return difference in Panel (4). The respective R^2s show that the risk factors are able to explain 90% of the variance for U.S. investment grade and 72% for Europe investment grade. For high yield, they explain 62% and 61% of the variance respectively. This implies that the goodness-of-fit is higher for the investment grade universe than for the high yield universe. This suggests that there are differences in CDS and bond dynamics between the two universes.

For none of the indices, the combination of the risk factors and roll-down can fully explain the arithmetic return differences. It would therefore be interesting to investigate which of the decomposed portfolio returns attributes most to the variance of the total CDS-bond index return series. Therefore, I conduct a variance decomposition in Section 6.

Table 7: Annualized CAPM-alpha and market-beta (%) of the factor portfolios for the high yield indices from 2005-2017

	High yield			
	U.S.		Europe	
	CAPM-alpha	Market-beta	CAPM-alpha	Market-beta
Seniority	0.59	0.18$^{(***)}$	1.14	0.55$^{(***)}$
	(1.22)	(0.03)	(3.23)	(0.08)
Financials	5.57	-0.20		
	(5.72)	(0.15)		
Maturity	0.17	-0.07$^{(***)}$	-2.20	0.09$^{(***)}$
	(0.44)	(0.01)	(1.30)	(0.03)
Rating	0.09	0.76$^{(***)}$	3.16	0.66$^{(***)}$
	(2.24)	(0.06)	(2.91)	(0.07)
Size	4.47	0.37$^{(***)}$	1.15	0.20
	(3.31)	(0.09)	(5.47)	(0.13)
Call	0.07	0.01$^{(***)}$	-0.51$^{(***)}$	-0.01$^{(**)}$
	(0.10)	(0.00)	(0.10)	(0.00)
Age	0.03	0.03	4.02	-0.48$^{(***)}$
	(1.74)	(0.05)	(3.54)	(0.08)
Value	1.47	0.66$^{(***)}$	6.08$^{(**)}$	0.90$^{(***)}$
	(2.03)	(0.05)	(2.88)	(0.07)
Momentum	-0.21	-0.62	-1.19	-0.49$^{(***)}$
	(4.26)	(0.11)	(3.58)	(0.09)
Low-risk	2.58	-0.70$^{(***)}$	-1.05	-0.80$^{(***)}$
	(1.97)	(0.05)	(3.75)	(0.09)
Market	4.38		5.86	

Notes: The table shows the annualized performance of the factor portfolios for the high yield indices in the U.S and Europe. The annualized return of the market is presented below the factor portfolios.
Portfolios are constructed as decile portfolios (if applicable). Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer. The financials factor is not created for Europe high yield due to a lack of financial companies in the respective CDS index.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses.

5.3.3 Differences in factor betas

Table 12 and Table 13 show the results of the Wald test that tests differences between factor betas between two universes. All columns except '$Wald$' show the factor betas per index[11] and

[11]The factor betas may differ from the ones estimated using ordinary least squares (Table 8 until Table 11) because they are estimated using generalized least squares

Table 8: Attributing the annual return difference to compounding, roll-down, and risk factors for U.S. investment grade from 2005-2017

		U.S. investment grade							
								(4) Total difference	
Geometric	*Compounding (%)*								*0.10*
Arithmetic	*Roll-down (%)*								*-0.01*
	Risk factors	(1) Composition		(2) Weighting		(3) CDS-specific		*(4) Total difference*	
		Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	*Factor beta*	*Attrib. (%)*
	Constant	0.02	0.19	0.02	0.22	0.03	0.42	0.07	0.83
		(0.03)		(0.02)		(0.06)		(0.05)	
	Seniority	0.06	-0.02	-0.03	0.01	-0.14(**)	0.04	-0.12(**)	0.04
		(0.04)		(0.02)		(0.07)		(0.06)	
	Financials	0.15(***)	0.01	0.06(**)	0.00	-0.19(***)	-0.01	0.02	0.00
		(0.04)		(0.02)		(0.07)		(0.06)	
	Maturity	0.39(**)	0.23	0.38(***)	0.22	-1.10(***)	-0.64	-0.33	-0.19
		(0.16)		(0.10)		(0.28)		(0.24)	
	Rating	0.32(***)	0.27	0.00	0.00	-0.30(***)	-0.26	0.02	0.02
		(0.06)		(0.03)		(0.10)		(0.09)	
	Size	-0.01	-0.02	0.04(*)	0.06	-0.03	-0.05	0.00	-0.01
		(0.04)		(0.02)		(0.06)		(0.05)	
	Call	0.01	-0.01	0.71(**)	-0.42	-1.13	0.67	-0.41	.24
		(0.45)		(0.30)		(0.87)		(0.74)	
	Age	-0.03	-0.04	0.08(*)	0.09	-0.23(*)	-0.26	-0.19(*)	-0.21
		(0.07)		(0.04)		(0.13)		(0.11)	
	Value	-0.18(***)	-0.05	0.11(***)	0.03	0.20(***)	0.06	0.14(**)	0.04
		(0.04)		(0.03)		(0.07)		(0.06)	
	Momentum	0.04(**)	-0.04	0.00	0.00	-0.01	0.01	0.03	-0.03
		(0.02)		(0.01)		(0.03)		(0.02)	
	Low-risk	-0.07	-0.10	-0.08(***)	-0.11	0.09	0.12	-0.06	-0.08
		(0.05)		(0.03)		(0.08)		(0.07)	
	Market	-0.07(***)	-0.07	0.00	0.00	-0.64(***)	-0.64	-0.70(***)	-0.71
		(0.01)		(0.01)		(0.02)		(0.02)	
	R^2	0.79		0.39		0.86		*0.90*	

Notes: The table shows the annual attribution of the CDS-bond return differences for each risk factor, roll-down and compounding for U.S. investment grade. Panel (4) represents the results on the total return difference time series. For the risk factor regression with the total CDS-bond index return difference as dependent variable (Panel (4)), the roll-down term has been subtracted from the dependent variable.

Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.

(***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.10$. Standard errors in parentheses.

Table 9: Attributing the return annual difference to compounding, roll-down, and risk factors for Europe investment grade from 2005-2017

Europe investment grade

Geometric	*Compounding (%)*							*(4) Total difference*	
								0.11	
Arithmetic	*Roll-down (%)*							*0.03*	

Risk factors	(1) Composition		(2) Weighting		(3) CDS-specific		*(4) Total difference*	
	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)
Constant	-0.01	-0.09	-0.02	-0.19	0.10$^{(**)}$	1.15	0.07$^{(**)}$	0.84
	(0.02)		(0.01)		(0.04)		(0.03)	
Seniority	0.01	0.00	-0.07$^{(***)}$	0.00	0.08	0.00	0.01	0.00
	(0.04)		(0.03)		(0.10)		(0.08)	
Financials	-0.08$^{(***)}$	-0.05	0.07$^{(***)}$	0.05	0.07	0.05	0.06	0.04
	(0.02)		(0.01)		(0.05)		(0.04)	
Maturity	0.00	0.00	0.02	0.00	0.19	0.04	0.21	0.05
	(0.07)		(0.05)		(0.18)		(0.15)	
Rating	0.23$^{(***)}$	0.29	0.07$^{(**)}$	0.09	0.09	0.12	0.40$^{(***)}$	0.49
	(0.05)		(0.03)		(0.12)		(0.10)	
Size	0.09$^{(***)}$	0.06	0.02	0.01	-0.17$^{(***)}$	-0.11	-0.05	-0.04
	(0.02)		(0.02)		(0.05)		(0.04)	
Call	0.78$^{(***)}$	0.24	0.09	0.03	-1.02$^{(**)}$	-0.32	-0.15	-0.05
	(0.23)		(0.16)		(0.57)		(0.47)	
Age	0.00	0.01	0.07$^{(***)}$	0.10	-0.21$^{(***)}$	-0.29	-0.13$^{(**)}$	-0.19
	(0.03)		(0.02)		(0.08)		(0.06)	
Value	-0.19$^{(***)}$	0.01	0.05$^{(**)}$	0.00	0.18$^{(**)}$	-0.01	0.03	0.00
	(0.03)		(0.02)		(0.08)		(0.06)	
Momentum	-0.01$^{(*)}$	-0.01	0.01$^{(**)}$	0.01	0.04$^{(**)}$	0.03	0.04$^{(**)}$	0.03
	(0.01)		(0.01)		(0.02)		(0.02)	
Low-risk	0.10$^{(***)}$	0.17	-0.07$^{(***)}$	-0.12	-0.26$^{(***)}$	-0.44	-0.23$^{(***)}$	-0.39
	(0.03)		(0.02)		(0.08)		(0.07)	
Market	-0.25$^{(***)}$	-0.18	0.07$^{(***)}$	0.05	-0.34$^{(***)}$	-0.25	-0.52$^{(***)}$	-0.37
	(0.01)		(0.01)		(0.03)		(0.03)	
R^2	0.85		0.57		0.58		*0.72*	

Notes: The table shows the annual attribution of the CDS-bond return differences for each risk factor, roll-down and compounding for Europe investment grade. Panel (4) represents the results on the total return difference time series. For the risk factor regression with the total CDS-bond index return difference as dependent variable (Panel (4)), the roll-down term has been subtracted from the dependent variable.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses.

Table 10: Attributing the annual return difference to compounding, roll-down, and risk factors for U.S. high yield from 2005-2017

U.S. high yield

		(4) Total difference
Geometric	*Compounding (%)*	*1.45*
Arithmetic	*Roll-down (%)*	*3.08*

Risk factors	(1) Composition		(2) Weighting		(3) CDS-specific		*(4) Total difference*	
	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)
Constant	-0.01	-0.15	0.05	0.55	0.27$^{(*)}$	3.18	0.30$^{(**)}$	0.50
	(0.03)		(0.05)		(0.15)		(0.13)	
Seniority	0.05	0.03	0.21$^{(***)}$	0.12	-0.45$^{(***)}$	-0.26	-0.19	-0.11
	(0.03)		(0.05)		(0.15)		(0.13)	
Financials	-0.01	-0.06	0.00	0.03	0.04	0.25	0.04	0.22
	(0.01)		(0.01)		(0.03)		(0.03)	
Maturity	0.55$^{(***)}$	0.09	-0.10	-0.02	0.19	0.03	0.63	0.11
	(0.11)		(0.15)		(0.49)		(0.42)	
Rating	0.01	0.00	0.23$^{(***)}$	0.02	-0.01	0.00	0.24$^{(*)}$	0.02
	(0.03)		(0.05)		(0.15)		(0.13)	
Size	0.00	-0.01	0.06$^{(**)}$	0.27	-0.09	-0.40	-0.03	-0.14
	(0.02)		(0.03)		(0.10)		(0.08)	
Call	0.39	0.03	-0.53	-0.04	1.52	0.11	1.37	0.10
	(0.37)		(0.51)		(1.64)		(1.42)	
Age	-0.05$^{(*)}$	0.00	0.04	0.00	-0.31$^{(***)}$	-0.01	-0.32$^{(***)}$	-0.01
	(0.03)		(0.04)		(0.12)		(0.10)	
Value	-0.12$^{(***)}$	-0.17	-0.11$^{(***)}$	-0.17	0.23$^{(*)}$	0.34	0.00	0.00
	(0.03)		(0.04)		(0.13)		(0.12)	
Momentum	-0.01	0.00	0.01	0.00	0.06	-0.01	0.05	-0.01
	(0.01)		(0.01)		(0.05)		(0.04)	
Low-risk	-0.08$^{(***)}$	-0.21	-0.01	-0.03	0.03	0.09	-0.06	-0.15
	(0.03)		(0.03)		(0.11)		(0.10)	
Market	-0.03$^{(***)}$	-0.14	0.15$^{(***)}$	0.67	-0.54$^{(***)}$	-2.34	-0.42$^{(***)}$	-1.82
	(0.01)		(0.01)		(0.05)		(0.04)	
R^2	0.30		0.74		0.69		*0.62*	

Notes: The table shows the annual attribution of the CDS-bond return differences for each risk factor, roll-down and compounding for U.S. high yield. Panel (4) represents the results on the total return difference time series. For the risk factor regression with the total CDS-bond index return difference as dependent variable (Panel (4)), the roll-down term has been subtracted from the dependent variable.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses.

Table 11: Attributing the annual return difference to compounding, roll-down, and risk factors for Europe high yield from 2005-2017

Europe high yield

								(4) Total difference	
Geometric	*Compounding (%)*								*0.03*
Arithmetic	*Roll-down (%)*								*1.24*
	Risk factors	(1) Composition		(2) Weighting		(3) CDS-specific		*(4) Total difference*	
		Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)	Factor beta	Attrib. (%)
	Constant	0.08	0.91	0.06	0.78	0.22	2.66	0.36 (**)	3.11
		(0.07)		(0.05)		(0.14)		(0.14)	
	Seniority	0.02	0.02	0.02	0.03	0.04	0.04	0.08 (*)	0.09
		(0.02)		(0.02)		(0.04)		(0.04)	
	Financials								
	Maturity	0.09 (*)	-0.20	-0.08 (**)	0.18	0.08	-0.18	0.09	-0.19
		(0.05)		(0.04)		(0.10)		(0.10)	
	Rating	-0.05	-0.15	-0.03	-0.11	0.05	0.16	-0.03	-0.10
		(0.03)		(0.02)		(0.06)		(0.06)	
	Size	0.03 (*)	0.04	0.06 (***)	0.07	-0.11 (***)	-0.13	-0.02	-0.02
		(0.02)		(0.01)		(0.03)		(0.03)	
	Call	0.74	-0.38	0.20	-0.10	-1.02	0.52	-0.09	0.04
		(0.68)		(0.47)		(1.30)		(1.34)	
	Age	0.03	0.12	0.01	0.05	-0.05	-0.21	-0.01	-0.04
		(0.02)		(0.02)		(0.04)		(0.04)	
	Value	-0.07 (**)	-0.42	-0.01	-0.09	0.05	0.31	-0.03	-0.20
		(0.03)		(0.02)		(0.05)		(0.06)	
	Momentum	0.04 (**)	-0.05	-0.04 (***)	0.04	0.03	-0.04	0.03	-0.04
		(0.02)		(0.01)		(0.04)		(0.04)	
	Low-risk	-0.16 (***)	0.16	0.03 (**)	-0.03	-0.01	0.02	-0.14 (***)	0.14
		(0.02)		(0.01)		(0.04)		(0.04)	
	Market	-0.23 (***)	-1.37	0.03 (***)	0.17	-0.27 (***)	-1.59	-0.48 (***)	-2.80
		(0.02)		(0.01)		(0.03)		(0.04)	
	R^2	0.58		0.31		0.43		*0.61*	

Notes: The table shows the annual attribution of the CDS-bond return differences for each risk factor, roll-down and compounding for Europe high yield. Panel (4) represents the results on the total return difference time series. For the risk factor regression with the total CDS-bond index return difference as dependent variable (Panel (4)), the roll-down term has been subtracted from the dependent variable.
Seniority: long in subordinate bonds, short in senior bonds. Financials: not created for Europe high yield due to a lack of financial companies in the CDS index. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.
(***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.10$. Standard errors in parentheses.

the standard errors below in parentheses. The '*Wald*' column provides the Wald statistic per factor and the corresponding p-value below.

Table 12: Seemingly unrelated regression (SUR) comparing the factor betas for investment grade and high yield (within one location) from 2005-2017

	U.S.			**Europe**		
	Inv. grade	High yield	*Wald, p*	Inv. grade	High yield	*Wald, p*
Seniority	-0.16	-0.05	*0.28*	0.01	0.03	*0.13*
	(0.03)	(0.00)	[*0.60*]	(0.01)	(0.00)	[*0.72*]
Financials	0.14	-0.04	*0.37*			
	(0.02)	(0.08)	[*0.54*]			
Maturity	-0.40	-0.06	*0.02*	0.11	0.16	*0.79*
	(0.04)	(0.02)	[*0.88*]	(0.04)	(0.03)	[*0.37*]
Rating	0.20	0.11	*0.52*	0.14	-0.04	*0.14*
	(0.00)	(0.27)	[*0.47*]	(0.05)	(0.07)	[*0.70*]
Size	-0.05	0.03	*0.13*	-0.03	-0.01	*0.01*
	(0.04)	(0.08)	*0.72*	(0.00)	(0.04)	*0.93*
Call	0.46	-0.86	*2.24*	0.90	0.44	*0.48*
	(0.00)	(0.05)	[*0.13*]	(0.10)	(0.02)	[*0.49*]
Age	-0.19	-0.06	*0.16*	0.05	0.07	*0.50*
	(0.16)	(1.05)	[*0.69*]	(0.00)	(0.88)	[*0.48*]
Value	0.09	-0.04	*0.14*	0.00	0.00	*0.00*
	(0.00)	(0.07)	[*0.71*]	(0.06)	(0.03)	[*0.96*]
Momentum	-0.02	-0.01	*0.08*	0.01	-0.05	*2.93*
	(0.06)	(0.07)	[*0.78*]	(0.00)	(0.04)	[*0.09*]
Low-risk	0.14	0.06	*0.29*	-0.11	-0.12	*1.66*
	(0.00)	(0.03)	[*0.59*]	(0.03)	(0.03)	[*0.20*]
Market	-0.73	-0.51	*15.02*$^{(***)}$	-0.57	-0.54	*19.88*$^{(***)}$
	(0.03)	(0.07)	[*0.00*]	(0.00)	(0.03)	[*0.00*]

Notes: The table shows the results for comparing factor betas between investment grade and high yield universes (keeping the location constant). I provide the factor betas for a SUR regression and the standard error below in parentheses. The '*Wald*' column provides the Wald statistic per factor and the corresponding p-value below in square brackets. A p-value below 0.05 for the Wald test shows that the factor betas between investment grade and high yield (within one location) are statistically significantly different.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer. The financials factor is not created for Europe high yield due to a lack of financial companies in the CDS index.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses, Wald test p-values in square brackets.

Table 12 shows the results of the Wald test between the different credit universes. For both the U.S. and Europe, I generally cannot reject that the factor betas are significantly different between investment grade and high yield ($\alpha = 0.05$). However, the factor betas are different for the market between the investment grade universe and high yield universe. Because the market factor beta is more negative for investment grade than for high yield (both for the U.S. and Europe), this implies that the CDS indices in the investment grade universe have significantly less exposure to the bond market than in the high yield universe.

Table 13 shows the results of the Wald test between the different locations. I conclude that factor betas are different for the market between the U.S. and Europe (both for investment grade and high yield). In the investment grade universe, the CDS index in the U.S. has less exposure to the market factor than in Europe. However, in the high yield universe the opposite result holds. For all other factors, I cannot reject that the factor betas are equal.

Table 13: Seemingly unrelated regression (SUR) comparing the factor betas for investment grade and high yield (within one credit rating) from 2005-2017

	Investment grade			**High yield**		
	U.S.	Europe	*Wald*	U.S.	Europe	*Wald*
Seniority	-0.05	0.02	*0.02*	0.11	0.05	*0.08*
	(0.02)	(0.00)	[*0.88*]	(0.02)	(0.00)	[*0.78*]
Financials	0.02	0.11	*1.24*			
	(0.01)	(0.04)	[*0.27*]			
Maturity	-0.16	0.34	*0.84*	0.63	-0.01	*0.00*
	(0.03)	(0.02)	[*0.36*]	(0.05)	(0.03)	[*0.99*]
Rating	0.05	0.21	*0.84*	0.28	-0.01	*0.00*
	(0.00)	(0.08)	[*0.36*]	(0.08)	(0.06)	[*0.97*]
Size	-0.01	0.01	*0.03*	-0.05	0.00	*0.00*
	(0.03)	(0.05)	[*0.87*]	(0.00)	(0.04)	[*0.96*]
Call	-0.11	0.30	*0.26*	1.53	-0.67	*0.21*
	(0.00)	(0.02)	[*0.61*]	(0.25)	(0.02)	[*0.65*]
Age	0.00	-0.12	*0.54*	-0.18	0.03	*0.06*
	(0.13)	(0.26)	[*0.46*]	(0.00)	(0.94)	[*0.80*]
Value	0.06	0.02	*0.01*	-0.08	-0.10	*0.33*
	(0.00)	(0.03)	[*0.91*]	(0.07)	(0.03)	[*0.56*]
Momentum	-0.02	0.01	*0.02*	0.06	0.00	*0.00*
	(0.05)	(0.03)	[*0.89*]	(0.00)	(0.03)	[*0.99*]
Low-risk	0.07	-0.13	*0.62*	0.09	-0.09	*0.30*
	(0.00)	(0.01)	[*0.43*]	(0.05)	(0.02)	[*0.58*]
Market	-0.72	-0.54	*11.54*$^{(***)}$	-0.44	-0.49	*5.05*$^{(**)}$
	(0.03)	(0.04)	[*0.00*]	(0.00)	(0.02)	[*0.02*]

Notes: The table shows the results for comparing factor betas between the U.S. and Europe (keeping the credit rating constant). I provide the factor betas for a SUR regression and the standard error below in parentheses. The '*Wald*' column provides the Wald statistic per factor and the corresponding p-value below in square brackets. A p-value below 0.05 for the Wald test shows that the factor betas between U.S. and Europe (within one credit universe) are statistically significantly different.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer. The financials factor is not created for Europe high yield due to a lack of financial companies in the CDS index.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses, Wald test p-values in square brackets.

5.3.4 Factor beta vs. characteristics

Table 14 shows the Pearson correlation coefficients between the factor betas and the underlying firm's characteristics. Beta exposures and characteristic values are ranked in the same direction. On average, the correlation coefficient is only 12% which is similar to the results of Chen et al. (2018). The correlation is relatively high for the financials (33%) and rating factor (27%). On the other hand, the correlation is negative for the maturity (-3%) and size factor (-26%). Take the size factor as an example. The negative correlation implies that bonds with a high loading to the size factor (that goes long in small issuers and short in large issuers) are generally not bonds from small issuers. This result is consistent across all four universes and indicates that the size factor is not able to capture the true variation in returns driven by differences in size.

Overall, the low correlations between the factors and underlying characteristics indicate that the regressions in Tables 8 until 11 may not be sufficient to capture the return attributed to characteristics. Chen et al. (2018) propose a measure to calculate characteristic-adjusted returns which can be used in future research to attribute return differences based on characteristics.

Table 14: Cross-sectional correlations between factor betas and underlying characteristics from 2005-2017

	Inv. grade		**High yield**		
	U.S.	EU	U.S.	EU	*Mean*
Seniority	0.06	0.16	0.31	0.27	*0.20*
Financials	0.37	0.32	0.29		*0.33*
Maturity	0.08	0.06	-0.22	-0.03	*-0.03*
Rating	0.43	0.22	0.28	0.14	*0.27*
Size	-0.32	-0.21	-0.16	-0.33	*-0.26*
Call	0.32	0.06	0.25	-0.02	*0.15*
Age	0.17	0.19	0.32	0.08	*0.19*

Notes: The table shows the cross-sectional Pearson correlations between factor betas and the underlying characteristics. Correlations are first calculated cross-sectionally and then averaged over time.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. The financials factor is not created for Europe high yield due to a lack of financial companies in the CDS index.

5.4 Sensitivity analysis

I test my results for robustness in two ways. Firstly, I check the robustness of my findings by changing the construction of the factor portfolios. Secondly, I check the robustness of my findings by changing the sample period.

5.4.1 Factor definitions

Originally, I defined the size, age, value, momentum, and low-risk factors as decile portfolios. I check whether the results are robust to the specification of these factors by creating quintile portfolios. I expect that, since quintile portfolios are less tilted to risk factors than decile portfolios, the results to be weaker in size but similar in sign.

Table 22 and Table 23 in Section A.4 in the Appendix show the annualized CAPM-alphas and market-betas for the quintile portfolios. Contrary to the expectations, the size CAPM-alphas

Table 15: Annualized CAPM-alphas and Market-betas (%) for the sub sample for the investment grade indices from 2010-2017

	Investment grade			
	U.S.		Europe	
	CAPM-alpha	Market-beta	CAPM-alpha	Market-beta
Seniority	0.74	0.49$^{(***)}$	-0.45	1.55$^{(***)}$
	(0.57)	(0.05)	(0.75)	(0.07)
Financials	0.64	-0.03	0.94	0.23$^{(***)}$
	(0.42)	(0.03)	(0.6)	(0.06)
Maturity	0.73$^{(***)}$	-0.33$^{(***)}$	0.00	0.15$^{(***)}$
	(0.22)	(0.02)	(0.22)	(0.02)
Rating	0.43	0.46$^{(***)}$	0.34	0.78$^{(***)}$
	(0.38)	(0.03)	(0.38)	(0.04)
Size	1.92$^{(***)}$	-0.47$^{(***)}$	1.01	-0.14$^{(***)}$
	(0.49)	(0.04)	(0.57)	(0.05)
Call	-0.89$^{(***)}$	-0.01$^{(***)}$	0.14$^{(**)}$	-0.02$^{(***)}$
	(0.03)	(0.00)	(0.05)	(.00)
Age	1.36$^{(***)}$	0.03	2.11$^{(***)}$	-0.63$^{(***)}$
	(0.37)	(0.03)	(0.61)	(0.06)
Value	0.94	1.00$^{(***)}$	0.02	2.04$^{(***)}$
	(0.55)	(0.05)	(1.03)	(0.09)
Momentum	-0.78	-0.29$^{(**)}$	0.50	-0.28$^{(**)}$
	(1.41)	(0.12)	(1.48)	(0.14)
Low-risk	2.87$^{(***)}$	-1.79$^{(***)}$	2.54$^{(***)}$	-1.58$^{(***)}$
	(0.54)	(0.04)	(0.48)	(0.04)
Market	1.79		1.74	

Notes: The table shows the annualized CAPM-alphas and Market-betas for a post-2010 sub sample for the investment grade indices.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses.

are higher than for the decile portfolios. In the investment grade universe, they almost doubled to 2.67 for the U.S. and 1.17 for Europe. In the high yield universe, the size CAPM-alpha increased from 4.47 to 6.77 in the U.S. and from 1.15 to 2.04 in Europe.

On the other hand, the results for age, momentum, and low-risk are generally comparable with the decile portfolios but less strong in magnitude. The CAPM-alphas for value are generally lower using quintile portfolios. Table 24 in Section A.4 in the Appendix shows the change in annual attribution to the total CDS-bond index return difference going from decile to quintile portfolios. The changes for size, value, and momentum are relatively small in all universes. The change in annualized attribution is negative for age in the U.S. (-0.17% and -1.16% for investment grade and high yield respectively), and positive in Europe (0.15% and 0.16% respectively). Using quintile portfolios for low-risk instead of decile portfolios lowers the attribution in all universes except U.S. investment grade where it remains relatively comparable with a change of 0.01 in annualized attribution.

Altogether, I conclude that the results are generally robust to changes in factor definitions, but that using quintile portfolios instead of decile portfolios makes the results less pronounced.

5.4.2 Sample period: financial crisis

To check the robustness of my findings to the chosen sample period, I repeat the analysis for a post-2010 subsample.

The post-2010 results for compounding are consistent with the previous findings for the entire sample period. The geometric compounding term is positive for all four universes. It is relatively small for the investment grade universes with an annual term of 0.03% for the U.S. and 0.01% for Europe. This effect is smaller than the compounding effect for the total period which may be driven by the fact that the bond index returns were especially more volatile during the financial crisis in 2008. For high yield it is an important contributor to the CDS-bond outperformance. The compounding term is 1.54% for the U.S. and 1.09% for Europe.

The results for roll-down are robust to the chosen sample period. Again, the roll-down is negligible for the investment grade universe whereas it is a main driver of the CDS-bond outperformance for the high yield universe. U.S. investment grade has an annualized roll-down of 0.082% which is close to the roll-down of 0.069% for Europe. The annualized roll-down is 2.71% and 2.53% for the high yield universes respectively. The consistency of the magnitude of roll-down across the entire sample and sub sample also indicates that roll-down is relatively stable over time. This confirms my approach of calculating the contribution of roll-down to the CDS-bond index return differences as a constant term.

Next, I consider the change in factor portfolio CAPM-alphas. The financial crisis of 2008 is not included in the sample anymore and therefore I expect that the bonds of banks will perform similar to the bonds of other financial companies. Moreover, the momentum factor generally performs well during phases of recovery and expansion (Jegadeesh and Titman, 1993). Since 2010-2017 is a phase of recovery and expansion, I expect that the momentum factor portfolio generates high CAPM-alphas during the post-2010 sub sample compared to the entire sample period. Table 15 and 16 show the annualized CAPM-alphas for a post-2010 sub sample.

For U.S. high yield, the CAPM-alpha for the financial factors decreased from 5.57 in the entire sample period to 1.18 in the sub sample period. This can be explained by the fact that this sub sample does not include the financial crisis in 2008, which affected banks more heavily than other financials. Except for U.S. investment grade, the momentum factor shows a high annualized CAPM-alpha compared to the entire sample period. This is in line with the insight that momentum generally performs best during expansion of the economy which is strongly present from 2010 until 2017.

Table 16: Annualized CAPM-alphas and Market-betas (%) for the sub sample for the high yield indices from 2010-2017

	High yield			
	U.S.		Europe	
	CAPM-alpha	Market-beta	CAPM-alpha	Market-beta
Seniority	0.89	0.05	-2.46	0.81$^{(***)}$
	(1.39)	(0.05)	(3.83)	(0.13)
Financials	1.18	-0.04		
	(2.01)	(0.08)		
Maturity	1.19$^{(***)}$	-0.15$^{(***)}$	-0.90	0.08
	(0.33)	(0.01)	(1.27)	(0.04)
Rating	-0.94	0.79$^{(***)}$	3.34	0.82$^{(***)}$
	(2.26)	(0.09)	(3.04)	(0.1)
Size	5.64	0.22	8.31	0.05
	(3.59)	(0.14)	(5.85)	(0.19)
Call	0.75$^{(***)}$	0.00	-1.17$^{(***)}$	0.00
	(0.07)	(0.00)	(0.09)	(0.00)
Age	1.57	-0.18$^{(***)}$	2.81	-0.24$^{(***)}$
	(1.33)	(0.05)	(1.44)	(0.05)
Value	0.65	0.91	5.79	1.20$^{(***)}$
	(2.46)	(0.1)	(3.25)	(0.11)
Momentum	-1.19	-0.54$^{(***)}$	-0.81	-0.27$^{(**)}$
	(4.76)	(0.19)	(3.85)	(0.13)
Low-risk	4.44$^{(***)}$	-0.94$^{(***)}$	-4.26	-0.91$^{(***)}$
	(0.89)	(0.04)	(3.25)	(0.11)
Market	5.53		6.33	

Notes: The table shows the annualized CAPM-alphas and Market-betas for a post-2010 sub sample for the high yield indices.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Maturity: long in 4-6 years to maturity, short in others. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer. The financials factor is not created for Europe high yield due to a lack of financial companies in the CDS index.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. Standard errors in parentheses.

The CAPM-alpha of the seniority factor for Europe is now negative (-0.45 for investment grade and -2.46 for high yield) but not statistically significant. The mean portfolio returns for the rating factor are generally much lower for the sub sample (0.43, 0.34 for investment grade, -0.94, 3.34 for high yield) than for the original sample (0.86, 1.25 for investment grade, 0.09, 3.16 for high yield) for the U.S. and Europe respectively. Due to the aftermath of the crisis, a relatively high number of companies with bonds in lower rating categories may have had a default.

6 Extension

In this section, I extend my research by investigating several results of the previous section in greater detail.

6.1 Variance decomposition

In Section 5, I quantified the contribution for each of the decomposing portfolios to the total CDS-bond index returns difference based on the returns of the decomposing portfolios. Next, I consider the contribution of each of the decomposing portfolios to the variance of the total CDS-bond index returns. As explained in Section 4.4, I use the sum of squared residuals (SSR) that results from a regression whereby I omit one portfolio return series as explanatory variable, as a measure of variance attribution. I present the results of the variance decomposition in Table 17.

For all four universes, the contribution of the return series that capture CDS-specific effects is the largest. However, this return series is defined as a remainder and may therefore also capture error terms resulting from a mismatch between the constituents of the CDS index and its reference bonds. Moreover, the CDS index is actually a traded instrument and due to for example differences in liquidity, the CDS index may trade differently than the average of its constituents. Due to a lack of individual CDS data, the CDS-specific effects also contain the difference in returns between the average of CDS index constituents and the CDS index itself. Therefore, even though this return series contributes to the variability of the CDS-bond index return differences, the source of the variability is not entirely clear. I propose a solution in Section A.3 in the Appendix that requires availability of individual CDS data.

Table 17: Absolute and relative sum of squared residuals (SSR) per decomposing portfolio from 2005-2017

	Investment grade		**High yield**	
	U.S.	Europe	U.S.	Europe
Relative SSR (%)				
Composition	15.01	35.84	5.26	38.61
Weighting	2.13	4.21	11.21	7.55
CDS specific	82.87	59.96	83.54	53.84

Notes: The table shows the absolute and relative SSR per decomposing portfolio for each of the four universes. The larger the number, the higher contribution of the portfolio to explaining the variability of CDS-bond return differences.

6.2 Callability and interest rates

A call option embedded with a bond allows the bond issuer to call the bond prematurely for a fixed price. The prevalence of callable bonds is relatively high in the high yield market, where currently the majority of the bonds are embedded with a call option. When interest rates decrease, bond prices increase which in turn increases the likelihood of call execution. In that case, non-callable bonds are expected to outperform callable bonds, ceteris paribus.

To formally test this hypothesis, I regress the callability factor portfolio returns on the change in risk-free interest rate. The factor portfolio takes a long position in callable bonds and short position in non-callable bonds[12]. The portfolio is constructed within issuer as described in Section 4 to exclude the effect of for example rating and sector. For the risk-free rate, I take the 10-year Treasury rate for the U.S. and the 10-year German Bund rate for Europe. I test two different horizons: a 1-month change in interest rate and a 3-month change in interest rate. For the latter case, I calculate quarterly returns for the factor portfolio to prevent from autocorrelation resulting in $\frac{150}{3} = 50$ observations. The regressions can be formalized for universe h with $h \in \{1, 2, 3, 4\}$ as

$$R^q_{h,call-noncall,t} = c_h + \beta_h \Delta^q(RF_{h,t}) + \epsilon_{h,t} \tag{45}$$

where $q \in \{1, 3\}$ and $t = 1, ..., T$ with $T = 150$ for $q = 1$ and $T = 50$ for $q = 3$. Furthermore, $\Delta^1(RF_{h,t})$ denotes the 1-month change in risk-free rate at time t and $\Delta^3(RF_{h,t})$ denotes the 3-month change in risk-free rate at time t. Because a decrease in risk-free rate is expected to increase the probability of call execution, hence lowering the price of callable bonds compared to non-callable bonds, I would expect that if $\Delta^q(RF_{h,t}) < 0$, then $R^q_{h,call-noncall,t} < 0$ and hence $\beta_h > 0$.

Moreover, considering the difference between the option-adjusted spread[13] and the traded spread for callable bonds, the spread premium attributed to the call option is on average larger for high yield than for investment grade. This holds for both the U.S. and Europe. Therefore, I would expect $\beta_{HY} > \beta_{IG}$ where HY and IG refer to the investment grade and high yield universe respectively.

Table 18 reports the results of the regression for the four universes. Even though the results are generally not statistically significant at the 5% level, the difference in signs between the credit segments suggest differences between the investment grade and high yield universes. The coefficients are positive for the investment grade universes and negative for the high yield universes. These results are consistent across the 1-month and 3-month horizons. These results contradict my expectations about the sign and size of β. This may be explained by the fact

[12]Note: this is opposite to the construction of the risk factor. I switch signs to allow for an intuitive interpretation of the results.

[13]The option-adjusted spread is an adjusted spread that removes the spread attributed to the (call) option. For more details I refer to Miller (2010).

Table 18: Regression of change in risk-free rate on the (opposite) callability factor from 2005-2017

		Investment grade		**High yield**	
		U.S.	EU	U.S.	EU
Horizon					
One-month	Constant	0.05	-0.01	-0.03	0.04
		(0.00)	(0.00)	(0.00)	(0.00)
	Callability factor	0.02	-0.04	0.05	-0.01
		(0.02)	(0.03)	(0.04)	(0.04)
Three-month	Constant	0.15	-0.02	-0.08	0.13
		(0.00)	(0.00)	(0.00)	(0.00)
	Callability factor	0.04	-0.08	0.26$^{(***)}$	-0.07
		(0.04)	(0.08)	(0.09)	(0.11)

Notes: The table shows the regression coefficient from regressing the change in risk-free rate on the (opposite) callability factor portfolio.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses.

that callable bonds are often noncallable for a period of time. During this period, callable bonds may be relatively insensitive to changes in the risk-free interest rate. If this holds for the majority of callable bonds, this may explain why no coefficient (except for the 3-month Europe investment grade regression) is statistically significant.

6.3 Roll-down

Roll-down turned out to be one of the most important drivers of the outperformance of the high yield CDS indices (assuming that bond index roll-down is 24% of the CDS index roll-down). Therefore, it is important to understand the mechanism behind this. Desclée and Polbennikov (2016) suggest that this may be driven by pricing pressure around the issuance date of a new CDS index. They claim that hedgers (short credit risk) systematically roll into the new index as soon as it is available whereas speculators (long credit risk) may be relatively indifferent between the new index and the off-the-run index. Another study by Oehmke and Zawadowski (2016) also suggests that the CDS market is mainly used by hedgers due to difficulties with shorting risk in the bond market.

I therefore hypothesize that the large roll-down effect is driven by hedging demand following the issuance of a new CDS index. As a consequence, supply/demand dynamics would drive up the spread of the new index compared to the off-the-run index. In order to investigate this hypothesis, I consider the spread difference between the on-the-run index and the most recent off-the-run index denoted by $S_{h,On-Off}$ for universe h, with $h \in \{1, 2, 3, 4\}$. Let T_0 denote the issuance date of the newly issued CDS index. If the hypothesis were true, one would expect to see the spread difference $S_{h,On-Off}$ to be relatively large for $T_0, T_1, T_2, ...$ after which it would decrease and stabilize once the hedging demand has been met. The actual spread differences show no evidence of such a pattern. One possible explanation is that the constituents of the on-the-run and off-the-run index differ, and therefore the spread measure may be contaminated with spread differences driven by differences in constituents. Even though research by Desclée and Polbennikov (2016) has shown that differences in composition have a small impact on the total CDS index roll-down, one could develop a better measure using individual CDS data.

A thorough understanding of the difference in roll-down between CDS and bond indices is very challenging. Alternative explanations for the relatively flat spread curve of bonds are (1) the prevalence of call options and (2) the lower liquidity of bonds (Desclée and Polbennikov, 2016). To test these explanations, one should compare the CDS spread curve with the bond spread curve of the same issuer. However, this requires individual CDS data which is not readily available. Estimating the bond spread curve certainly is not an easy task either which is reflected by the vast amount of literature on improving estimation techniques (Nelson, 1987; Duffie and Singleton, 1999; Diebold et al., 2005). Moreover, one would require observations for multiple bonds of all companies with relevant time to maturities whereas some companies only have one bond outstanding.

7 Conclusion

This study investigates the drivers behind CDS and bond index return differences. The CDS indices have substantially lower volatility than the bond indices and therefore the higher returns cannot be explained by higher risk. Moreover, I show that even when controlling for differences in composition, high yield CDS indices strongly outperform bond indices. However, the return difference between investment grade CDS and bond indices is much smaller and may even be negative depending on the chosen sample period. This suggests that differences in returns between CDSs and bonds are mainly present in the lower credit segments. The results are based on monthly data from 2005-2017 for four different universes based on geographic location and credit segment: U.S. investment grade, U.S. high yield, Europe investment grade, and Europe high yield.

There are several driving elements consistent across the universes. Firstly, the CDS market has a beta lower than one to the bond market. This has a negative effect on the average arithmetic CDS-bond return difference since the bond market has shown a positive average return over the sample period. Secondly, for all four universes, the CDS index is less volatile than the bond index which is beneficial when using geometric compounding. Thirdly, I cannot reject that the loading to a risk factor is different across the four universes, except for the market factor.

Using decomposing portfolios, I attribute return differences to driving elements (risk factors, roll-down and compounding) based on difference in composition, weighting scheme and CDS-bond specific dynamics. In line with previous studies, I show that the composition of CDS indices compared to bond indices attribute positively to the CDS-bond index returns in the investment grade universe and negatively in the high yield universe. Moreover, CDS-bond specific dynamics attribute positively to the CDS-bond index returns in the high yield universe whereas their effect is strongly negative in the investment grade universe. Based on sensitivity analysis, I conclude that the results are generally robust to changes in construction of the risk factors and changes in the sample period.

Based on the lower volatility and substantially higher roll-down, high yield CDS indices provide an attractive alternative to bond indices. Roll-down is an important contributor of outperformance in the high yield universe and has generated fairly consistent returns over the sample period. This finding relies heavily on the assumption that bond index roll-down is approximated as 24% of the CDS index roll-down. In contrast with a previous study by Desclée and Polbennikov (2015), I do not find a consistent outperformance of CDS indices in the investment grade universe. I do agree, however, with their finding that the composition differences between investment grade CDS and bond indices are in favor of CDS indices.

This study extends previous literature by creating a factor portfolio based on the callability of bonds. Controlling for issuer, sector, and rating effects I find that non-callable bonds generate higher returns than callable bonds in the high yield universes, even though this effect is only significant in Europe. Moreover, a different exposure to callability does not explain total the return difference between CDS and bond indices.

7.1 Future research

This study raises several questions that may be addressed in follow-up research. First of all, the variance decomposition of the different portfolios indicates that a large part of the variability in the CDS-bond return differences can be explained by CDS-specific effects. However, the CDS-specific return series are constructed as a residual and therefore the explicit source of variability cannot be determined. To understand this in greater detail, one could create an additional decomposing portfolio based on individual CDS contracts. This would allow one to study the return differences between a CDS and a bond on the individual level, as well as study the return difference between the CDS index and its constituents.

Secondly, I have shown that the cross-sectional correlation between factor betas and underlying firm characteristics is generally low. This suggests that risk factor analysis may not be sufficient to capture the returns attributed to differences in characteristics. Therefore, one could repeat the return analysis using characteristics-based attribution as discussed in (Chen et al., 2018).

Furthermore, the research shows that roll-down is a large contributor to the outperformance of CDS indices. A limitation of this study is that it assumes that the bond index roll-down is a fixed percentage of the CDS index roll-down. To get a more accurate estimate of the roll-down difference between CDS and bond indices, one should also explicitly measure the bond index roll-down. Moreover, the method of measuring CDS index roll-down could be more sophisticated using individual CDS data which would remove the part of the roll-down generated by differences in constituents between the on-the-run and off-the-run CDS index.

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Appendix

A.1 Credit default swaps and bonds

Credit default swaps

A CDS can be used by an investor to hedge against the risk of default of a bond to express his views on the creditworthiness of the corporate in general[14]. It is a bilateral contract in which the hedger pays a coupon S_{CDS} at coupon dates $\{T_j : j = 1, ...h\}$ and in exchange he will be paid (1-R)·N by the seller of the CDS upon default at time τ, where R denotes the recovery (as a fraction) of the bond's face value and N denotes the notional amount of the CDS contract. Following the approach of Kang (2012), the value of the CDS contract to the protection seller equals the value of the coupon leg and the protection leg, that is, $V(t, S_{CDS})$ $= V_{Premium}(t, S_{CDS}) + V_{Default}(t)$.

Valuing a CDS index

CDS indices are comparable with individual CDS contracts in terms of cash flows. Consider a CDS index with M equally weighted constituents. The outstanding notional on the index at time t is defined by $N_{index,t} = \sum_{i=1}^{M} N_i(1 - \mathbb{I}_{\tau_i \le t})$ where N_i corresponds to the notional amount of constituent i, i = 1, 2, ... , M, $\mathbb{I}$ is an indicator variable and τ_i denotes the time of default if applicable. Note that $\mathbb{I}_{\tau_i \le T} = 1$ indicates that CDS contract i defaulted before the maturity date T. Moreover define the total payments of the portfolio at time t to be $L(t) = \sum_{i=1}^{M} N_i(1-R_i)\mathbb{I}_{\tau_i \le t}$ where R_i denotes the recovery rate of the bond for constituent i.

The value of the coupon leg of the CDS index contract, $W_{Premium}(CDS_{index}, t)$, is given by

$$W_{Premium}(CDS_{index}, t) = \frac{1}{M} \sum_{i=1}^{M} V^i_{Premium}(t, C_{fixed})$$

and the value of the default leg of the CDS index contract, $W_{Default}(CDS_{index}, t)$, is given by

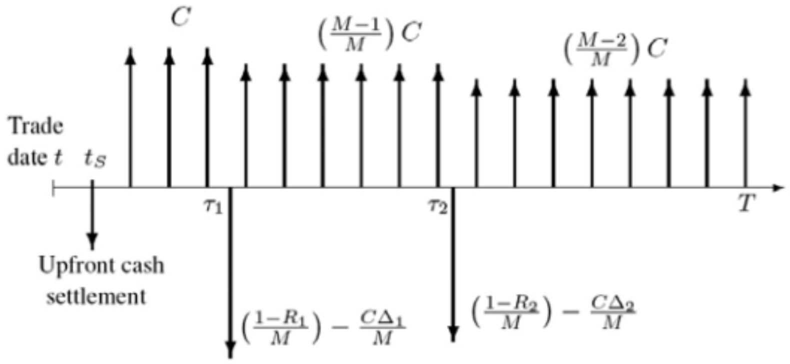
$$W_{Default}(CDS_{index}, t) = \frac{1}{M} \sum_{i=1}^{M} V^i_{Default}(t)$$

because the CDS index is equally weighted. Similarly, the upfront and accrued interest payment required by the protection seller to enter the contract is given by the average upfront and accrued payment interest of the individual constituents. In Figure 4, an overview of all possible cash

[14] In this study, we consider CDS contracts on corporate bonds but there is also a market for sovereign CDSs.

flows in a CDS index contract is displayed.

Figure 4: Payments of a CDS index contract



Notes: The graph represents the cash flows of a m-constituent CDS index paying fixed coupon C and originally issued at time t. The parties enter the contract at time t_s with an upfront cash settlement consisting of the upfront and accrued interest. Upward arrows are positive cash flows to the protection seller, downward arrows are positive cash flows to the protection buyer. At times τ_1 and τ_2 a default occurs after which the protection buyer receives the compensation based on the recovered value of the bond. The protection seller receives the fraction of coupon which has accrued from the previous coupon date on the defaulted credit until time τ of default (O'Kane, 2011).

Bonds

A corporate bond is a security that is purchased by making an upfront payment P_0 to the issuing company. In return, the investor receives coupon payments C_{bond} plus a return on P_0 at the maturity date T unless the bond defaulted at time $\tau < T$. Similar to the pricing of a CDS, no-arbitrage conditions imply that at time t, the price of the bond must equal the expected value of the compensation, that is:

$$V_{payment}(t) = V_{compensation}(t) \tag{46}$$

$$\iff P_t = \mathbb{E}_t\Big[\sum_{r=t}^{T} \frac{C_{bond}}{(1+YTM)^{r-t+1}} + \frac{F}{(1+YTM)^{T-t+1}}\Big] \tag{47}$$

where V denotes expected value, F denotes the face value of the bond and r denotes the discount rate. The yield to maturity at time t, y_t, can be found by solving the relation in (47) for YTM. Note that because the investor is not only compensated for the credit risk he takes on, but he also receives a premium for the funding and the interest rate risk he takes on. Therefore, we must have that

$$y(t) = S_{credit} + S_{funding} + S_{interest}$$

To study the relationship between CDS and bonds, it is therefore important to isolate the part of the yield that concerns the credit risk premium: the credit spread S_{credit}. This is further discussed in the next section.

No-arbitrage relationship

The parity relationship between CDSs and bonds can be proven based on no-arbitrage conditions using a replicating portfolio (Zhu, 2006). The pay-off of a short position in a CDS contract (that is, a protection buyer) as visualized in Figure 5 can be replicated in the following way: enter a maturity-matched asset swap position where the investor funds himself at LIBOR to buy a bond that is traded at its face value P. This bond pays a fixed coupon C_{bond} and is issued by the same company i with the same time to maturity T and seniority as the CDS[15]. The received coupons C_{bond} are swapped against floating payments from the interest rate swap: LIBOR and the maturity-matched par asset swap spread ASW. Note that in both case (a) No default and case (b) Default, the investor is fully hedged and therefore the position is risk-free. Using risk-neutral pricing, it follows that we must have the following relation:

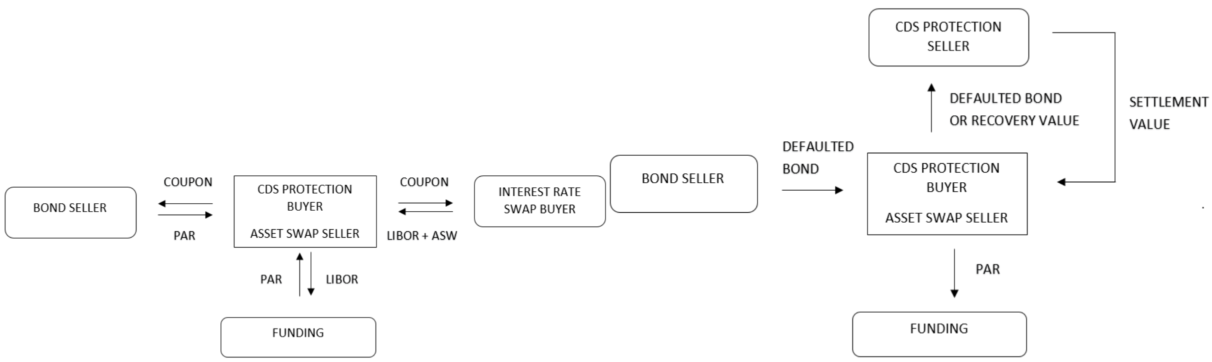
$$S_{CDS} = C_{bond} - S_{funding} - S_{interest}$$
$$S_{CDS} = S_{credit}$$

and if we define the CDS-bond basis as $Basis_t = S_{CDS,t} - S_{credit,t}$ we must have

$$\begin{aligned} Basis_t &= S_{CDS,t} - S_{credit,t} \\ &= 0 \end{aligned}$$

where t denotes the time.

Figure 5: Credit risk replicating portfolio



(a) No default/credit event

(b) Default/credit event

[15] I also assume that there are no fundamental contractual differences, such as call options and restructuring clauses.

CDS-bond indices basis

The no-arbitrage relationship between individual CDSs and bonds can easily be extended to the aggregate level: CDS and bond indices. The pay-off of a long position in a CDS index can be replicated by taking an equally weighted long position in all constituents. Therefore, using no-arbitrage argumentation, an index should trade as the (weighted) average of its constituents:

$$S_{t,\tau_{index}}^{CDS_{index}} = \frac{1}{M}\sum_{i=1}^{M} S_{t,\tau_i}^{CDS_i}$$

where t denotes the time, τ denotes the time to maturity, M denotes the number of constituent in the index and i denotes the i^{th} CDS in the index. Now consider an equally weighted composite bond index that matches the issuers of the CDS index constituents. Moreover, the respective bonds must have the same seniority, rating, maturity and coupon payment dates as the corresponding CDS in the CDS index. Then it follows that

$$\begin{aligned} Basis_{index,t} &= S_{CDS_{index},t} - S_{credit_{index},t} \\ &= \frac{1}{M}\sum_{i=1}^{M} S_{CDS_i,t} - \frac{1}{M}\sum_{i=1}^{M} S_{credit_i,t} \\ &= 0 \end{aligned}$$

with M the number of constituents in the indices and where $i \in \{1, 2, \ldots, M\}$ refers to issuer i in the indices.

A.2: Selecting a CDS-matched bond

I use the following steps to select a bond that matches the CDS constituent l for index i that is issued in month k. Only bonds from the same issuer as the CDSs are put in the potential bond list.

1. If constituent l has a contract-specified reference bond that is traded in month k, select that bond.
2. Else if there is a bond with the same seniority and traded in month k, put that bond in basket 2.
3. Else if there is a bond traded in month $k \pm 2$ months, put that bond in basket 4.
4. Else if there is a bond with the same seniority and traded in month $k \pm 2$ months, put that bond in basket 5.

5. Else place the remaining bonds from the potential bond list in basket 6.

If there is no reference bond selected, I select a bond from baskets 2 - 6. In any case I prioritise basket 2 over 3 over ... 6. If a prioritised basket contains multiple bonds, I select the bond for which $|5.25 - TTM|$ is the smallest (where TTM denotes the remaining time to maturity in years), as the CDS has 5.25 years to maturity at the issuance date of the series.

A.3: Use of individual CDS data

As explained in Section 6, the CDS-specific effects contain two terms: (a) the difference between the returns of individual CDSs and individual bonds, and (b) the difference between the returns of the individual CDSs and the index. Therefore, I would ideally split step (3) CDS-bond specific effects into two steps by creating an additional portfolio consisting of the individual CDS contracts of the issuers in a CDS index. The updated decomposing steps then become:
(3): The difference in returns between the equally weighted matched bond portfolio and the equally weighted individual CDSs. I denote this return difference as 'individual effects'.
(4): The difference in returns between the equally weighted individual CDSs and the CDS index, which I denote by 'index effects'.

In this case, step (3) would truly capture the difference between CDS and bond returns if one is able to fully match the CDS constituents with bonds. Step (4) would capture the specifics of trading CDS contracts in one product rather than trading them separately.

In Table 19 in Section A.4 of the Appendix, I list driving factors related to the new step (3) below 'Individual effects'. Moreover, I list driving factors related to the new step (4) below 'Index effects'. Future studies could incorporate these elements in their research.

A.4: Tables

Table 19: Overview of driving elements and their effects on CDS-bond performance

	Effect	Comment	Paper
		Composition effects	
Seniority, sector, quality, maturity, market-cap	x, persistent	Composition differences cannot fully explain return differences	Desclée and Polbennikov (2015), Desclée and Polbennikov (2016)
Rebalancing following upgrades and downgrades	+, persistent	CDS roll less frequently	Desclée and Polbennikov (2016), Dor (2011)

Table 19: Overview of driving elements and their effects on CDS-bond performance

	Effect	Comment	Paper
Size effect	+, persistent	SC outperforms LC, more SC in CDS	Desclée and Polbennikov (2016)
		Individual effects	
Restructuring clauses	+, temporary	CDS may offer broader protection	O'Kane and McAdie (2001), Zhu (2006), Blanco et al. (2005), De Wit (2006)
Roll-down (I)	+, persistent	CDS curve steeper than bond curve	Desclée and Polbennikov (2016)
Cheapest-to-deliver option CDS	+, temporary	Credit event auction standard since 2005	De Wit (2006), O'Kane (2011)
Profit realization	+, persistent	CDS: requires offsetting transaction	O'Kane and McAdie (2001), De Wit (2006)
CDS premia floored at zero, bond credit spread may be negative	+, persistent	Small effect and especially for IG	O'Kane and McAdie (2001), De Wit (2006)
Bond issuance	+, persistent	Increases demand for protection	O'Kane and McAdie (2001), Calamaro and Thakkar (2004), De Wit (2006)
Call option bond	x, persistent	Especially HY, decreases basis	Desclée and Polbennikov (2016), Brennan and Schwartz (1977), Booth et al. (2014)
Synthetic CDO issuance	+, temporary	Especially 2004-2009	O'Kane and McAdie (2001), Calamaro and Thakkar (2004), De Wit (2006)
Funding issues	-, persistent	Cash investors cannot always fund themselves at Libor	O'Kane and McAdie (2001), Calamaro and Thakkar (2004), De Wit (2006)
Counterparty risk	-, persistent	No strong support in literature	O'Kane and McAdie (2001), Zhu (2006), De Wit (2006)
Accrued interest differences	-, persistent	CDS protection buyers must pay accrued premium up to credit event	O'Kane and McAdie (2001), Zhu (2006), De Wit (2006)
Intermediary rating	-, persistent	Unobserved underlying factor, not driving in itself	De Wit (2006), Kim (2017)

Table 19: Overview of driving elements and their effects on CDS-bond performance

	Effect	Comment	Paper
Liquidity premiums	x, persistent	Relative liquidity, flight-to-liquidity, on-the-run premium, index inclusion	O'Kane and McAdie (2001), Blanco et al. (2005), Goldreich et al. (2005), Zhu (2006), Kitwiwattanachai and Pearson (2014)
Bond not trading at par	x, persistent	CDS guarantees par amount	O'Kane and McAdie (2001), Zhu (2006), Blanco et al. (2005), De Wit (2006)
Coupon specificities	x, persistent	Depends on up/downgrade clause	O'Kane and McAdie (2001), De Wit (2006)
		Index effects	
Restructuring clauses	x, temporary	Index and single-issue convention may differ	O'Kane (2011)
Roll-down (II)	+, persistent	CDS index curve steeper than bond index curve	O'Kane (2011); Desclée and Polbennikov (2016)
Liquidity premiums	x, persistent	Relative liquidity, flight-to-liquidity	O'Kane (2011)

Notes: This tabel presents an exhaustive list of the potential elements that drive differences between CDS and bond returns as well as their impact on the CDS-bond performance. The elements are distinguished into composition effects, individual effects and index effects. Bold-faced entries are discussed in the main text. A positive mark (+) means that it explains the outperformance of a CDS (index) compared to a bond (index), and a negative mark (-) vice versa. If the effect on the performance is undecided (x), it means that the total effect depends on other elements as well.

Table 20: The correlation between the factor portfolio returns from 2005-2017 for investment grade

U.S. investment grade

	Sen.	Fin.	Mat.	Rat.	Size	Call	Age	Val.	Mom.	Low-R.
Seniority	1.00									
Financials	0.30	1.00								
Maturity	0.66	0.02	1.00							
Rating	0.55	-0.10	0.63	1.00						
Size	-0.01	0.12	-0.05	-0.15	1.00					
Call	0.16	-0.23	0.13	0.21	-0.20	1.00				
Age	-0.13	-0.08	0.05	0.26	-0.30	0.19	1.00			
Value	-0.29	0.07	-0.34	-0.24	0.08	-0.52	-0.06	1.00		
Momentum	-0.17	0.54	-0.60	-0.30	0.06	-0.14	0.21	0.28	1.00	
Low-risk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Europe investment grade

	Sen.	Fin.	Mat.	Rat.	Size	Call	Age	Val.	Mom.	Low-R.
Seniority	1.00									
Financials	-0.33	1.00								
Maturity	-0.39	-0.09	1.00							
Rating	-0.09	-0.49	0.72	1.00						
Size	-0.22	0.29	-0.14	-0.32	1.00					
Call	-0.07	-0.40	0.65	0.79	-0.53	1.00				
Age	-0.05	-0.43	0.40	0.45	-0.49	0.67	1.00			
Value	-0.28	0.32	-0.36	-0.47	0.57	-0.52	-0.28	1.00		
Momentum	0.14	0.17	-0.25	-0.23	0.02	-0.17	-0.08	0.06	1.00	
Low-risk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Notes: This table shows the correlation between the factor portfolio return series for the investment grade universes. A value of 1.00 means total positive linear correlation, a value of 0.00 no correlation, and a value of -1.00 total negative linear correlation.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.

Table 21: The correlation between the factor portfolio returns from 2005-2017 for high yield

U.S. high yield

	Sen.	Fin.	Mat.	Rat.	Size	Call	Age	Val.	Mom.	Low-R.
Seniority	1.00									
Financials	0.04	1.00								
Maturity	-0.24	0.01	1.00							
Rating	-0.01	0.20	0.76	1.00						
Size	-0.14	0.08	0.16	0.20	1.00					
Call	-0.02	0.18	0.31	0.55	0.13	1.00				
Age	-0.09	-0.07	0.79	0.69	0.15	0.24	1.00			
Value	-0.02	-0.29	-0.34	-0.54	-0.15	-0.52	-0.29	1.00		
Momentum	0.29	0.55	-0.32	-0.13	-0.11	-0.18	-0.15	0.01	1.00	
Low-risk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Europe high yield

	Sen.	Mat.	Rat.	Size	Call	Age	Val.	Mom.	Low-R.
Seniority									
Maturity	0.15	1.00							
Rating	-0.02	0.59	1.00						
Size	-0.17	-0.06	-0.07	1.00					
Call	-0.14	-0.29	-0.04	-0.10	1.00				
Age	-0.10	0.35	0.44	-0.11	0.22	1.00			
Value	0.02	-0.02	-0.15	-0.17	0.15	-0.13	1.00		
Momentum	0.12	-0.28	-0.42	0.14	-0.23	-0.44	-0.04	1.00	
Low-risk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Notes: This table shows the correlation between the factor portfolio return series for the high yield universes. A value of 1.00 means total positive linear correlation, a value of 0.00 no correlation, and a value of -1.00 total negative linear correlation.
Seniority: long in subordinate bonds, short in senior bonds. Financials: long in other financials, short in banking. Rating: long in low rating, short in high rating. Size: long in small issuers, short in large issuers. Call: long in non-callable bonds, short in callable bonds. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating. Market: market value weighted bond returns. Seniority, maturity, call, and age are constructed within issuer.
The financial factor is not created for Europe high yield due to a lack of financial companies in the CDS index.

Table 22: Annualized CAPM-alpha (%) of the residualized quintile factor portfolios for the investment grade indices from 2005-2017

	Investment grade			
	U.S.		Europe	
	CAPM-Alpha	Market-Beta	CAPM-Alpha	Market-Beta
Size	2.67	-0.43$^{(***)}$	1.17	0.82$^{(***)}$
	(1.55)	(0.08)	(2.13)	(0.17)
Age	1.16$^{(***)}$	-0.20$^{(***)}$	0.90	-0.17$^{(***)}$
	(0.23)	(0.01)	(0.65)	(0.05)
Value	-0.28	-0.81$^{(***)}$	0.22	-1.96$^{(***)}$
	(0.75)	(0.04)	(1.33)	(0.1)
Momentum	-0.60	-0.36$^{(***)}$	0.69	-1.09$^{(***)}$
	(1.39)	(0.08)	(2.17)	(0.17)
Low-risk	1.10$^{(***)}$	-1.10	1.58$^{(***)}$	-1.44$^{(***)}$
	(0.92)	(0.05)	(0.42)	(0.03)

Notes: The table shows the annualized CAPM-alphas for quintile portfolios for the investment grade indices.
Size: long in small issuers, short in large issuers. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. *Standard errors in parentheses.*

Table 23: Annualized CAPM-alpha (%) of the residualized quintile factor portfolios for the high yield indices from 2005-2017

	High yield			
	U.S.		Europe	
	CAPM-Alpha	Market-Beta	CAPM-Alpha	Market-Beta
Size	6.77	0.22	2.04	0.39$^{(**)}$
	(4.35)	(0.11)	(7.18)	(0.17)
Age	1.54	-0.10$^{(***)}$	4.07	-0.48$^{(***)}$
	(1.27)	(0.03)	(3.54)	(0.08)
Value	-0.93	-0.59$^{(***)}$	-4.66	-0.84$^{(***)}$
	(1.84)	(0.05)	(2.44)	(0.06)
Momentum	-0.74	-0.51$^{(***)}$	-0.88	-0.43$^{(***)}$
	(3.4)	(0.09)	(3.03)	(0.07)
Low-risk	2.39	-0.62$^{(***)}$	-0.08	-0.64$^{(***)}$
	(1.44)	(0.04)	(2.61)	(0.06)

Notes: The table shows the annualized CAPM-alphas for quintile portfolios for the high yield indices. Standard errors are provided in parentheses.
Size: long in small issuers, short in large issuers. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating.
$^{(***)}$ $p < 0.01$, $^{(**)}$ $p < 0.05$, $^{(*)}$ $p < 0.10$. *Standard errors in parentheses.*

Table 24: Change in annualized attribution (%): quintile portfolio attribution - decentile portfolio attribution from 2005-2017

	Inv. grade		**High yield**	
	U.S.	Europe	U.S.	Europe
Change in attrib. (%, ann.)				
Size	0.07	0.01	0.13	-0.02
Age	-0.17	0.15	-1.16	0.16
Value	-0.01	0.08	-0.01	-0.04
Momentum	0.01	0.02	-0.04	0.02
Low-risk	0.01	-0.15	-0.54	-0.12

Notes: The table shows the change in annual attribution to the total CDS-bond index return difference going from decile to quintile portfolios.
Size: long in small issuers, short in large issuers. Age: long in old bonds, short in young bonds. Value: long in high value bonds, short in low value bonds. Momentum: long in recent winners, short in recent losers. Low-risk: long in short maturity x high rating, short in long maturity x low rating.