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Assessing Diversification of S&P500 and CDX indexes

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Jeffrey A. Palma

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Dissertation Supervisor: Dr. Lorán Chollete Signature: ____________

Committee Member: Dr. Lawrence Hatheway Signature: ____________

Committee Member: Dr. Lucjan Orlowski Signature: ____________

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Doctoral Dissertation Paper

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Abstract

In this paper, I conduct a study of comovement between equity and corporate bonds using S&P500 and Investment Grade and High Yield CDX Indexes to evaluate the diversification benefits of holding these assets in portfolios. I assess comovement and diversification potential using DCC-GARCH and copulas. This approach allows for a review of equity and credit linkages through multiple lenses and evaluation of how these relationships have evolved over time. In general, I find only modest potential for diversification between equity and CDX markets and strong evidence of increased comovement over time.

Keywords: CDS index, CDX, Comovement, Copula, DCC-GARCH, Diversification, SPX

JEL Classification: G11, G12, G13

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1. Introduction

I conduct a study of the comovement of equity and corporate bonds using S&P500 and Investment Grade and High Yield credit default swap index (CDX) markets to evaluate the diversification benefits of holding these assets together in a portfolio. I assess this relationship using multiple tools, including DCC-GARCH and copulas, allowing for a review of equity and credit linkages through multiple lenses and over time. Employing a range of methodologies allows for a robust discussion on the consistency of the output, as different measures of dependence may not always relate at all times. The result is a better understanding about whether these asset classes offer diversification potential.

There are multiple implications of this analysis and it is relevant to several types of institutions and investors. For investment managers and risk managers, portfolio construction seeks to improve the risk and return trade-off of a portfolio by combining asset classes with different return, volatility, and correlation characteristics. Assessing correlation of returns is foundational to understanding how a portfolio might behave, particularly during periods of market stress when diversification may be most desired to reduce overall portfolio downside.

For asset allocators who seek to boost returns through tactical positioning between asset classes in a portfolio, combining assets with lower correlations allows for the potential of higher alpha generation. Higher correlations between assets makes this endeavor more challenging as there are fewer opportunities to capitalize on directional differences in asset price movements. To that end, creating a simple portfolio that consists of S&P500 and credit default swaps, each at 50% weights and rebalanced quarterly, provides a useful example. At first glance, diversification potential appears limited. Indeed, the correlation of a portfolio consisting of S&P500 and investment grade CDX to a portfolio of S&P500 alone is 0.995, suggesting very little diversification from the addition of CDX to the equity-only portfolio. In a portfolio that is composed of S&P500 and high yield CDX, the correlation to the S&P500 is 0.973 – also very high. In these portfolios, tactical asset allocation alpha is likely be driven by almost entirely by directional trades – owning the higher volatility asset when returns are positive and preferring the lower volatility asset when returns are negative. Thus, attaining a deeper understanding of the stability of correlations and other portfolio attributes will be beneficial.

For central banks and policymakers, analysis of the connection between equity and corporate bond markets, particularly during extreme events, can improve anticipation of increasing risk of financial system instability. For banks, high correlations across markets during drawdowns can increase difficulties hedging balance sheets. For investors, these linkages are important to portfolio construction for strategic asset allocation when designing robust portfolios that offer diversification when it is most desired.

1.1. Equity and credit market linkages

Merton (1974) noted that a corporate bond can be regarded as a zero-coupon bond combined with a short put option, highlighting the fundamental linkage between equity and corporate debt, as each asset owns a claim on the value of a company. Equity shareholders benefit from growth in the value of the firm and have the sole claim to upside in firm value. Debtholders expect repayment of borrowed funds plus interest, but still share in downside and have the first call on recovery value in the event of bankruptcy. Thus, higher stock prices do not necessarily benefit bondholders, except to the extent that the risk of default may be falling when equity values are increasing. This may not be the case if higher equity prices are the result of shareholder-friendly actions (e.g., stock buybacks, acquisition, investment) financed by debt or that threaten credit quality and default risk. Rising equity prices and falling credit spreads would be expected to be coincident following economic downturns or recessions when both markets benefit from improving macroeconomic conditions, growth prospects, and lower default risk. Under normal cyclical conditions, rising credit risk (wider spreads) would be anticipated to result in a simultaneous decline in equity prices since an increased chance of default will also impact the value of equity.

A quick glance at Figure 1, which shows the S&P500 index compared to investment grade (IG) and high yield (HY) CDX spreads between 2005 and 2022 does not show a tight fit. To be sure, there are episodes where it appears that spreads moving wider coincide with equity prices moving lower. But a close linkage is difficult to observe. Over long periods of time, this is consistent with the discussion above. Namely, growth accrues to shareholders; only during periods of stress, when default risk is rising substantially, are linkages more apparent.

Insert Figure 1 here

Upon closer inspection, however, we can observe periods when the comovement between equity and credit markets is clearer. In Figure 2, which shows a series of charts of S&P500 compared to HY CDX during shorter time periods, a closer connection is visible, particularly during periods of stress such as the Global Financial Crisis, the Covid-19 pandemic, and during periods of aggressive monetary policy tightening in 2018 and 2022. During other episodes, such as 2017 and 2021, equity prices moved steadily higher while credit spreads did not move substantially. In other words, despite higher equity prices, the market-demanded compensation for credit risk did not continue to fall while upside accrued to shareholders.

Insert Figure 2 here

Existing literature has largely focused on evaluating the appropriate credit spread for given equity conditions, leading to discussion of the widely cited credit spread puzzle, or analyzing comovement at the company-level or using matched-index analysis to assess efficiency of processing new information in each market. Because traded credit default swap indexes have only existed since the early-2000s, the ability to analyze these markets through multiple economic and market cycles has been limited. With roughly 18 years of CDX data now available and greater trading volume and liquidity in these vehicles, I believe it is useful to look at index-level data, accepting company and sector compositional differences between equity and CDX indexes, since they are widely traded markets for taking directional positions and for hedging purposes. As of the first half of 2022, the size of the credit default swap index market exceeded $5 trillion of notional exposure and accounts for more than 50% of the overall credit default swap market according to the Bank of International Settlements.

This paper is organized as follows. Section 2 provides a literature review of previous research across multiple relevant topics. Section 3 discusses the data used in this paper, including details about the credit default swap index markets. Section 4 describes the methodology employed in each section of the analysis. Section 5 covers results of the analysis, and the paper concludes in Section 6.

2. Literature review

A large body of research including Chen, Collin-Dufresne, Goldstein (2009) and Huang and Huang (2012) has addressed the ‘credit risk puzzle’ – the finding that most models linking equity and corporate bonds produce results of credit spreads that are tighter than market-observed levels. Related, research on the “excess bond premium (EBP),” for example by Gilchrist and Zakrajšek (2012), decomposes credit spreads into components to identify the portion of spreads that is related to default risk and the portion that appears reflective of investor sentiment and risk appetite. More recently, research has employed novel approaches to find a better fit. Culp, Nozawa, and Veronesi (2018) created “pseudo firms”, which are equivalent to Treasuries minus put options, and find that spreads behave as a risk premium for tail and idiosyncratic asset risks. Du, Elkamhi, and Ericsson (2019) develop a model to fit medium- and long-term spreads using priced stochastic volatility using firm-level data. Including jumps, the model also helps explain short-term spread movements.

There is also a deep pool of literature studying comovement of equity and credit markets. Most research in this area analyzes firm-level data in equity and corporate bond markets or using matched indexes, where constituents of an equity (bond) index are matched with bonds (equities) from the same company to compare movements. For corporate bond data, a mix of cash bonds and, more recently, credit default swaps (CDS) are used in this research. Substantial work has shown that default risk alone does not explain changes in values of corporate bonds. Collin-Dufresne, Goldstein, and Martin (2001) show that default risk accounted for only 25% of the movement in corporate bond yields with principal component analysis finding a specific factor driving the rest. Huang and Huang (2012) find similar results in investment grade bonds, while credit risk accounted for a bigger share of valuation changes in high yield markets. These results led to a belief that bond market liquidity was a key driver in this disconnect, which was specifically identified by Chen, Lesmond, and Wei (2007). They find a significant link between bond market liquidity and changes in credit spreads with robust results looking at cross-sectional variation of the data and compared to default risk alone, as measured by credit ratings.

Other research has found significant linkages between equity and credit markets. When looking at firm-level panel data, Campbell and Taksler (2003) show that volatility explains as much movement in corporate yields as default risk. Additionally, Ericsson, Jacobs, and Oviedo (2009) find that leverage and volatility had significant explanatory power. Moreover, this analysis showed "limited evidence for a residual common factor" in contrast to the studies noted earlier. Hibbert et al. (2011) identify systematic equity and bond factors that drive changes in credit spreads, with specific emphasis on the explanatory power of increases in equity market volatility. Similarly, Rugås and Winberg (2015) find high correlation between VIX, CDX, and S&P500.

In addition to evaluating the level of credit spreads when compared to equities, various studies have assessed the timeliness of incorporating information into each market, drawing inference into the efficiency of each market. Two recent papers use CDX data to address different issues. Differing results have been found regarding this lead-lag relationship. Citing the benefits of CDS market size and liquidity, Greatrex and Rengifo (2012) use CDS data for a large sample of financial and non-financial companies to assess the market response to policy announcements during the Global Financial Crisis (GFC) and conclude that CDS spreads responded favorably to government intervention.

Procasky (2021) looks at the speed of information pricing in equity and credit using CDX Indexes for investment grade and high yield markets against matched equity samples, finding that HY CDX leads equities pricing negative information, while equity markets more efficiently price positive news. Neither stocks nor investment grade CDX appear to have an informational advantage. Shi, et. al (2022) analyze comovement of CDS and S&P500 index volatility, finding evidence that correlations of these markets have increased since the GFC in the late-2000s. Boyarchenko et al. (2019) provide insight into a possible driver of this trend in a study of the evolution of CDS trading in the post-GFC period, finding that dealers became buyers of protection in CDX index markets beginning in 2014.

Finally, other research has assessed linkages between CDX and equity markets through the lens of volatility. For example, Fung et al. (2008) study the relationship between CDX markets and the stock market, finding that there is significant mutual feedback between the S&P500 and HY CDX in both prices and volatility, while the stock market only leads the IG CDX market in pricing. Collin-Dufresne, Junge, and Trolle (2022) analyze the consistency of equity and credit pricing using Investment Grade CDX and S&P500 Index options, finding that CDX index options appear too expensive relative to S&P 500 option pricing.

Given its importance to portfolio theory, correlation, diversification, and extreme events have been widely researched and generally find limits to diversification potential. For example, Ang, Chen, and Xing (2002) study individual stocks while Longin and Solnik (2001) analyze country equity markets and Hartmann, Straetmans, and de Vries (2010) assess currency markets. Cappiello, Engle, and Sheppard (2006) perform cross-asset analysis on international equity and bond markets.

Studies on tail dependence produce generally consistent results, showing less benefit from portfolio diversification during periods of stress. García-Feijoo, Jensen, and Johnson (2012) showed that when US equity returns are in their bottom 5%, several other asset classes experience negative returns in excess of what would be expected from correlations over the full data set. Hartmann, Straetmans, and de Vries (2010) showed that currencies co-crash more often than would be predicted by a bivariate normal distribution. Chollete, de la Peña, and Lu (2011 and 2012) evaluate portfolio diversification of equity markets across 14 countries using correlations, copulas, and extreme dependence analysis. Across these approaches, they find limits to international diversification. More recently, Page and Panariello (2018) present analysis with data that includes the Global Financial Crisis to show that correlations between many asset classes, including stocks and corporate bonds, are higher in the 'left-tail' than in the 'right-tail'.

Dynamic conditional correlation multivariate GARCH (DCC-GARCH), developed by Engle (2002), efficiently models time varying multivariate correlation of large data sets. Engle and Sheppard (2001) use the model to estimate dynamic conditional correlation of up to 100 assets using equity sector data. This framework has been used extensively across and within many assets. For example, in a cross-asset analysis that includes equity and bonds, Choudhury, Kinateder, and Neupane (2022) employ DCC-GARCH study whether gold and sovereign bonds act as safe haven assets compared to S&P500 and MSCI Emerging Markets Indexes.

Copula analysis has been widely employed to study diversification between assets given the ability to analyze dependence through the entire joint distribution of returns, which is particularly useful during extreme events as financial market data tend not to be normally distributed. Rodriguez (2007) finds that dependence structures of East Asian stock indexes change during times of financial distress, using data during the Asia Financial Crisis, with increased dependence and asymmetry in periods of higher volatility. Heinen and Rengifo (2007 and 2008) use copulas to study stock-specific behavior and equity market microstructure alongside time series count data and multivariate reduced rank regression, respectively.

The contribution of this paper to the body of existing research is twofold. First, to the best of my knowledge, this is the first paper to study comovement and diversification properties of S&P500 index and IG and HY CDX data. Second, my research evaluates diversification through several analytical approaches – correlation and conditional correlation, DCC-GARCH, and with copulas – to assess the consistency of the results using multiple methodologies.

3. Data

3.1. CDS and CDX index overview

Credit default swaps are derivative securities that allow investors to manage risk or take a view on whether credit risk of a company will rise or fall (IHS Markit, 2021). CDS contracts were created in the mid-1990s by banks to better manage risk and were subsequently standardized, which led to a wider range of participants using the products. In a CDS contract, there are two sides to the transaction. On one side, there is a ‘protection buyer’ who is looking to safeguard against credit losses or who anticipates credit risk to rise (spreads to move wider). On the other, there is a ‘protection seller’, who is taking the opposing view. For compensation, the buyer pays a fixed premium to the seller, who must make the buyer whole for losses in the event of a defined ‘credit event’ (e.g., bankruptcy, failure to pay, restructuring). Unlike a corporate bond, investors in CDS markets only trade the credit risk (i.e., spread) component of a company; there is no other yield component to the return. Moreover, since these are derivative instruments, the securities are not issued by companies and investors have no residual claim on a firm's assets. However, standardization of terms of a CDS contract, such as maturity, pricing convention, assumed recovery rate, and the size of the derivatives market means that liquidity in CDS can be high.

A CDS index is a basket of single-name CDS securities that are combined based on a set of characteristics (e.g., sector, geography, credit quality). CDX allows investors to express views or manage risk on larger segments of the credit market than a CDS contract, which is company-specific.

CDX Indexes originated in 2002. In 2004, two index providers, TRAC-X and iBoxx CDS indices merged and in November 2007, IHS Markit (then 'Markit') acquired these indexes. For the purposes of this paper, I focus on two specific CDX Indexes – CDX.NA.IG (North America Investment Grade) and CDX.NA.HY (North America High Yield), each using the 5-year tenor, which is the most liquid. The investment grade index is made up of 125 equal-weighted companies, while the high yield index consists of 100 equal-weighted companies. Collin-Dufresne, Junge, and Trolle (2020) and IHS Markit (2021) provide a detailed overview of CDX Indexes. A new index series is created every six months, on the 20th of March and September, which becomes the on-the-run reference index. Trading liquidity also tends to be greatest in the on-the-run series. This analysis uses data beginning with Series 3 and runs through Series 39 as the most current series.

3.2. Data for analysis

This analysis covers 18 years, from December 1, 2004 to November 30, 2022. The starting point was chosen as the earliest date when daily composite price data are available for both IG and HY CDX. This period encompasses multiple economic cycles and episodes of market dislocation, including the Global Financial Crisis and the Covid-19 pandemic. It includes periods of monetary and fiscal policy accommodation as well as sharply rising interest rates in 2018 and 2022. Periods of positive, sustained, equity and credit returns can be observed during this analysis window as can episodes of substantial declines in asset prices.

For equity markets, the S&P 500 Index is used with weekly data on Wednesdays to reduce the instances of holidays and market closures. For any holidays or non-trading days that fall on a Wednesday, I use the closing value on Tuesday. Returns are calculated using log differences of the weekly index levels.

For credit markets, data for CDX Indexes come from IHS Markit, a division of S&P Global. The license to use these data was acquired directly from S&P Global in an academic agreement with Sacred Heart University. This analysis focuses on the Investment Grade and High Yield corporate CDX indexes using the 5-year maturity, which is the most liquid index tenor. As is the case with equity prices, weekly prices on Wednesday are used and closing price values on Tuesday are taken in the event of no trading on Wednesday.

As each new CDX index series changes it is not appropriate to compare the price of one series to another. Therefore, it is necessary to create a time series of returns for the Investment Grade and High Yield series by splicing together the composite price indexes. To do so, weekly Wednesday prices are obtained for the on-the-run series and the log difference return is calculated. Following the commencement of a new on-the-run series, the reference index is rolled forward once there is a complete one-week return available for the new series. The time series of resulting weekly log differences is used for this analysis.

3.3. Descriptive statistics

Descriptive statistics can be seen in Table 1, with details of the full data sample as well as a breakdown of the data into equal halves. For the full sample, the average weekly log change is 0.131 for the S&P500, -0.001 for IG CDX and 0.037 for HY CDX. The standard deviation of returns is 2.352 for the S&P500, 0.309 for IG and 1.227 for HY. As would be expected, equity returns are more volatile than CDX, while HY returns have a higher standard deviation than IG. All three data series, particularly S&P500, show negative skew and all are leptokurtotic.

Insert Table 1 here

When looking at the data divided into equal halves, the mean weekly log change is lower for S&P500 and IG CDX in the first half than the second half, but is higher in the first half for HY CDX. The median return is also lower in the first half for the S&P500 than in the second half, but is higher for both IG and HY CDX markets. Standard deviation differences are more consistent. In the second half, S&P500 standard deviation declined from 2.450 to 2.251 – a modest decline. However, there was a sharp, statistically significant decline in the standard deviation for both IG and HY CDX. For IG, the standard deviation fell from 0.364 to 0.242 and dropped from 1.434 to 0.978 for HY. At the same time, skew became more negative and kurtosis moved sharply higher for IG and HY CDX but was more stable for S&P500. The presence of the GFC in the first half of the data sample likely plays a role explaining differences in standard deviation across time periods. However, it is more difficult to explain the increased negative skew and higher kurtosis.

A graphic representation of returns can be seen in the scatter plots in Figure 3. For the S&P compared to both IG and HY CDX, there is a visible difference between the first and second half. The decline in standard deviation of CDX returns in the second half of the data compared to the first half is apparent with less dispersion of returns on the y-axis for both markets.

Insert Figure 3 around here

4. Methodology

I use DCC GARCH and copulas to assess comovement and diversification potential between equity and CDX Index markets in this paper, both of which have been used widely in previous research to assess linkages between and within other asset markets. By employing these tools, I present a multi-pronged assessment of the consistency of results. For all analysis, I evaluate the full data sample and subsets, dividing the sample into halves, to assess changes that may have occurred in market linkages or diversification benefits over time.

My hypothesis is that S&P500 and CDX markets will offer somewhat limited diversification potential, particularly during periods of market stress, consistent with previous literature and theory that links equity and corporate bond returns. Compared to the S&P500, I expect correlation to be higher and diversification potential to be lower for High Yield CDX than for Investment Grade CDX. The higher risk (lower credit quality) of HY is expected to generate more equity-like outcomes than IG CDX, where lower default rates are likely to dampen volatility and linkage to equity markets.

4.1. DCC-GARCH

The Dynamic Conditional Correlation – GARCH (DCC-GARCH) model proposed by Engle (2002) built on Bollerslev's (1990) constant conditional correlation multivariate model, is employed to evaluate changes in correlation between S&P500 and CDX Indexes over the sample period. The benefit of this model is that it allows for analysis of time-varying correlation for large data sets. The process first estimates univariate GARCH models for each asset and then, in the second step, estimates conditional correlation using the residuals from the first stage calculation. The DCC-GARCH(p,q) model is written as follows:

$$H_t = D_t \, R_t \, D_t \tag{1}$$

where H_t is a k x k conditional variance matrix, D_t is a diagonal matrix of conditional standard deviation, and R_t is a time-varying conditional correlation matrix. In this construct, H_t and R_t must each be positive definite and all elements in the R_t correlation matrix must be equal to or less than one.

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{2}$$

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} - \beta Q_{t-1} \tag{3}$$

$$Q_t^* = diag(\sqrt{q_{11,t}}, \sqrt{q_{22,t}}, \ldots, \sqrt{q_{nm,t}}) \tag{4}$$

Where $\bar{Q}$ is the unconditional covariance matrix of the standardized errors, ε_t. The correlation can be extended to the general DCC(p,q) model in the following:

$$Q_t = \left(1 - \sum_{p=1}^{P} a_p - \sum_{q=1}^{Q} b_q\right)\bar{Q}_t + \sum_{p=1}^{P} a_p a_{t-1} a_{t-1}^T + \sum_{q=1}^{Q} b_q Q_{t-1} \tag{5}$$

4.2. Copulas

Copula models allow modeling of multivariate dependence throughout the distribution of returns. Introduced by Sklar (1959), his theorem shows that unique copulas can represent any two continuous distributions, even those that are non-normally distributed. Assuming continuous data with marginal distributions of:

$$F_i(x_i y_i) = \Pr(X_i \leq x_i, Y_i \leq y_i) \tag{6}$$

With marginals that are uniformly distributed on [0,1], the copula, C, can be defined as:

$$\mathrm{C}(u, v) = \Pr\,[\mathrm{U} \leq u, \mathrm{V} \leq v)] \tag{7}$$

Sklar's Theorem states that there exists a copula function, C, where the joint distribution can be shown as:

$$C(x, y) = \mathrm{C}(F_x(\mathrm{x}), F_y(\mathrm{y})) \tag{8}$$

Copulas are often distinguished by their dependence parameters, which don't always correspond to standard correlation metrics. They do, however, often correspond to some form of rank correlation or related measure such as Kendall τ, a rank correlation metric that measures the similarity of the data when they are ranked by quantiles. As can be seen in equation 9 below, Kendall τ expresses the agreement of the variables *x* and *y*. In particular, it measures the probability of concordance minus the probability of discordance. Therefore, if *x* and *y* move in the same direction, τ will be positive and equal to one if the agreement is perfect. If *x* and *y* are moving in opposite directions, τ will be negative and equal to -1 if there is perfect disagreement. If *x* and *y* are independent, τ will equal zero.

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} sgn(x_i - x_j) sgn(y_i - y_j) \tag{9}$$

In this analysis, I analyze three copula distributions – normal (Gaussian), student-t, and Gumbel, which is part of the Archimedean family. For normal and student-t copulas, their dependence parameter has a close interpretation to that of standard Pearson correlations (see appendix for details). The Gumbel copula allows one to capture a different comovement attribute – tail dependence. The student-t distribution also has tail dependence characteristics, but has tails that are equal on each side, where Gumbel copula tails are asymmetric. The definitions of the distribution, parameter, and details that define ranges of dependence and independence of each copula can be found in the appendix.

5. Results

5.1. Dynamic conditional correlation

The equity – credit relationship through the lens of the DCC-GARCH model shows results that appear generally consistent with aggregate correlation metrics, but also offer additional insight. When looking at the entirety of the sample, shown in Figure 4, the dynamic conditional correlation between S&P500 and IG as well as HY follow a similar path, albeit with some differences. Both exhibit modest levels of correlation in the early years of the data, even during the GFC, but show a steady rise between 2009 and 2010. Other periods during 2015, 2017, and 2020 show declines in the conditional correlation, but otherwise stability around 0.80. In general, dynamic conditional correlation of HY CDX to S&P500 appears more volatile than IG CDX.

Insert Figure 4 around here

Similar trends can be observed when running the dynamic conditional correlation analysis on the first and second halves of the data series, shown in Figure 5, with some notable differences. In the first half, as was observed in the full history, the correlation was low in early years and rose steadily through 2010-2011 to a level of around 0.80. In this period, IG CDX registered lower correlation to S&P500 than HY, which was not the case in the full sample, with lows of 0.30. The low for HY CDX against S&P500 was around 0.50.

Dynamic conditional correlation for IG and HY CDX to S&P500 generally moved consistently in the full sample and the first half. For the second half of the data, notable differences are observed. While dynamic conditional correlation is broadly stable around 0.80, there are periods when IG and HY conditional correlations diverge sharply. One episode occurred in 2014-2016, which contained two significant market events – the equity 'flash crash' on August 24, 2015 as well as a sharp drop in oil prices from over $100/bbl in 2014 to $37/bbl at the end of 2015 and a low in April 2016 when spot prices briefly traded negative. HY credit markets were more impacted by the decline in oil prices than IG because of the higher index exposure to energy companies. The other large divergence occurred during early-2020 at the onset of the Covid-19 pandemic. The sharp decline in dynamic conditional correlation of IG spreads is surprising, but potentially can be explained by policy response, where the Federal Reserve created corporate credit facilities to buy investment grade bonds to stabilize market conditions.

Insert Figure 5 around here

5.2. Copula

In the final portion of analysis, S&P500 and CDX Index returns were fit to three copula shapes – normal (Gaussian), student-t, and Gumbel. The results of the analysis can be seen in Table 2 for returns of S&P500 and HY CDX and Table 3 for returns of S&P500 and IG CDX. The output shows the results for the full data sample and, as in prior steps, sub-sample periods that divide the data into halves.

In the normal copula, the correlation parameter, ρ, shows a high level of comovement between S&P500 with both IG and HY. The second half time period shows a somewhat higher ρ than the first half. While the correlation parameter is slightly higher for HY CDX than for IG when compared to S&P500, the difference is modest. This suggests elevated levels of dependence between these markets.

Turning to the student-t copula, a similar pattern is observed with regard to the Pearson correlation coefficient, ρ, and Kendall's τ for the relationship between IG and HY CDX and S&P500 returns. That is, there appears to be high dependence, with ρ values of around 0.80 for all time periods studied and τ ranging from 0.57 to 0.61.

For the parameter v, degrees of freedom, somewhat different results were observed, though the t-statistic was significant for all observations. For the full data sample, v measured 6.314 between HY and S&P500 returns and 6.108 when looking at IG and S&P500 returns, overall similar results. However, bigger differences exist when looking at shorter time periods. Beginning with the relationship between high yield CDX and S&P500 returns (Table 3), there is a large increase in v from the first half of the sample (4.650) to the second half (7.502), suggesting fatter tails in more recent years. This finding is consistent with the descriptive statistics previously discussed. When looking at investment grade CDX and S&P500 returns (Table 4), a modest decline in degrees of freedom, from 5.954 to 4.597 is observed, in contrast to the large increase in the high yield – S&P 500 relationship. In aggregate, despite the correlation, the relatively high value of v suggests that the degree of tail dependence is limited in the student-t copula.

Finally, for the Gumbel copula, Θ is similar for both IG and HY across all time periods. As a result, the computed values of Kendall's τ and λ_u are also similar. For the SP500 – IG CDX relationship, τ registers 0.541 for the first half and 0.563 for the second. For SP500 – HY CDX, τ is 0.560 and 0.569 for the first and second half, respectively. Compared to the other two copulas, this is a slightly lower value of τ. However, the t-statistic is the highest using the Gumbel copula and there is a small standard error. The measures of tail dependence, λ_u, are higher than in the student-t copula. For SP500 – HY CDX, λ_u is 0.638 for the full sample, and rises slightly from 0.643 in the first half to 0.652 in the second half of the sample. For SP500 – IG CDX, λ_u is slightly lower at 0.627 for the full sample. As was the case in the SP500 – HY CDX relationship, tail dependence rose slightly in the second half sample.

Insert Table 2 and Table 3 around here

5.3. Robustness check

The data set in this analysis included two periods of severe market dislocation – the first during the GFC in 2008-2009 and the second during the COVID-19 pandemic in 2020. Equally, each of the sub-sample periods examined contains one major dislocation. To test whether the observed high correlations are being dominated by these extreme events, I created an additional sample period that excluded these events, running between 2010 and 2019. The notable differences in the data (see Table 4 for descriptive statistics) are a sharply lower standard deviation of returns, which is to be expected given the removal of the most volatile periods in the sample, as well as less skew and lower kurtosis.

Results consistent with the original analysis were achieved using DCC-GARCH (see Figure 6), with readings of both IG and HY CDX compared to S&P500 of around 0.80 to 0.90. Only during 2015-2016 did HY CDX correlation to SP500 briefly move lower, as was observed in the original analysis. Using this sample period there was no trend of rising DCC-GARCH correlations observed.

Finally, looking at copulas (Table 4), the results of the normal copula were in line with the original analysis discussed above, showing somewhat higher readings of ρ and Kendall τ. The Gumbel copula readings were also similar. Theta was slightly higher using this sample, resulting in readings on Kendall τ and tail dependence, λ_u, to also be a bit higher than in the other periods. The biggest difference was in the student-t copula. For this sample period, the reading on the degrees of freedom, *v*, parameter was much higher for the HY CDX and IG CDX series, though the standard error readings were also much higher, resulting in a much lower, insignificant, t-statistic. Consistent with the other copulas, measures of correlation using ρ and Kendall τ were higher.

6. Conclusion

In this paper, I conduct a study of the comovement between the S&P500 and investment grade and high yield CDX indexes. I study these relationships using DCC-GARCH and copulas which, allowing for a review of equity and credit linkages through multiple lenses and over time. Assessing the results and the consistency of outputs across the approaches allows for a better understanding about whether these asset classes offer diversification potential.

My empirical results consistently show limited diversification potential of equity and CDX indexes. DCC-GARCH analysis shows a consistently high degree of comovement between S&P500 and HY CDX as S&P500 and IG CDX markets. This approach shows rising correlations over time aside from brief episodes over the last decade that coincide with major market shocks. Additionally, copula analysis shows consistently elevated measures of correlation through the lens of correlation metrics and Kendall's τ, a measure of rank correlation. Consistent with the other approaches, comovement is greater in the second half of the data sample than in the first half. Further, the Gumbel copula suggests a high degree of upper-tail dependence across all markets and time periods.

In general, results were consistent with the initial hypothesis, though the degree of comovement was higher than anticipated. Surprisingly, measures of comovement were only slightly lower for IG CDX returns than HY CDX when compared to S&P500 returns. All analytical approaches suggest that the degree of comovement has moved higher since the inception of CDX indexes.

There are several avenues of possible future research that stem from this paper. First, given high correlations, research could investigate the potential to interchangeably use S&P500 and CDX markets as hedges in portfolios based on trading volumes, liquidity, and transaction costs. While Boyarchenko et al. (2019) found a shift in the hedging behavior of dealers post_GFC, additional research could investigate the alternative drivers of higher correlation between equity and credit markets. One possible explanation is the increase in liquidity and trading volume of CDX, which has led to greater usage and adoption by investors and risk managers, leading to more limited arbitrage opportunities. One challenge is that trading volume and open interest data are not available until 2011, which is after the period when correlation appears to have increased most. Another consideration is that the period of study following the GFC, when correlations appear to have risen, was one of accommodative monetary policy and very low interest rates, in part driven by quantitative easing (QE) programs by the Federal Reserve. Finally, it may be worth examining whether the increase in passive investing in both fixed income and equity markets has impacted these trends.

References

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *The review of financial studies, 19(4)*, 1191-1239.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *The review of economics and statistics*, 498-505.

Boyarchenko, N., Costello, A. M., & Shachar, O. (2019). The long and short of it: The post-crisis corporate CDS market. *FRB of New York Staff Report 879*.

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *The Journal of Finance, 58(6)*, 2321-2350.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial Econometrics, 4(4)*, 537-572.

Chen, J., Chollete, L., & Ray, R. (2010). Financial distreses and idiosyncratic volatility: An empirrical investigation. *Journal of Financial Markets, 13(2)*, 249-267.

Chen, L., Collin-Dufresne, P., & Goldstein, R. S. (2009). On the Relation Between the Credit Spread Puzzle and the Equity Premium Puzzle. *The Review of Financial Studies, 22(9)*, 3367-3409.

Chen, L., Lesmond, D. A., & Wei, J. (2007). Corporate yield spreads and bond liquidity. *The Journal of Finance, 62(1)*, 119-149.

Chollete, L., de la Peña, V., & Lu, C.-C. (2011). International diversification: A copula approach. *Journal of Banking & Finance 35*, 403-417.

Chollete, L., de la Peña, V., & Lu, C.-C. (2012). International diversification: An extreme value approach. *Journal of Banking & Finance 36*, 871-885.

Choudhury, T., Kinateder, H., & Neupane, B. (2022). Gold, bonds, and epidemics: A safe haven study. *Finance Research Letters 48*, 102978.

Collin-Dufresne, P., Goldstein, R. S., & Martin, J. S. (2001). The Determinants of Credit Spread Changes. *The Journal of Finance, 56(6)*, 2177-2207.

Collin-Dufresne, P., Junge, B., & Trolle, A. B. (2020). Market structure and transaction costs of index CDSs. *The Journal of Finance, 75(5)*, 2719-2763.

Collin-Dufresne, P., Junge, B., & Trolle, A. B. (2022). How integrated are credit and equity markets? Evidence from index options. *Swiss Finance Institute Research Paper 20-65*.

Culp, C. L., Nozawa, Y., & Veronesi, P. (2018). Option-based credit spreads. *American Economic Review, 108(2)*, 454-88.

Du, D., Elkamhi, R., & Ericsson, J. (2019). Time-varying asset volatility and the credit spread puzzle. *The Journal of Finance, 74(4)*, 1841-1855.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics, 20(3)*, 339-350.

Engle, R. F., & Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. *NBER Working Paper*.

Ericsson, J., Jacobs, K., & Oviedo, R. (2009). The determinants of credit default swap premia. *Journal of financial and quantitative analysis, 44(1)*, 109-132.

Frees, E. W., & Valdez, E. A. (1998). Understanding relationships using copulas. *North American Actuarial Journal, 2(3)*, 143-149.

Fung, H.-G., Sierra, G. E., Yau, J., & Zhang, G. (Summer (2008)). Are the US stock market and credit default swap market related? Evidence from the CDX indices. *Journal of Alternative Investments*.

García-Feijoo, L., Jensen, G. R., & Johnson, R. R. (2012). The effectiveness of asset clasess in hedging risk. *The Journal of Portfolio Management, 38(3)*, 40-55.

Gilchrist, S., & Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American economic review, 102(4)*, 1692-1720.

Greatrix, C., & Rengifo, E. (2012). Government intervention and the CDS market: a look at the market's response to policy announcements during the 2007-2009 financial crisis. *Journal of Applied Finance (Formerly Financial Practice and Education), 22(1)*.

Hartmann, P., Straetmans, S., & de Vries, C. (2004). Asset market linkages in crisis periods. *Review of Economics and Statistics, 86(1)*, 313-326.

Hartmann, P., Straetmans, S., & de Vries, C. G. (2010). Heavy tails and currency crises. *Journal of Empirical Finance 17(2)*, 241-254.

Heinen, A., & Rengifo, E. (2007). Multivariate autoregressive modeling of time series count data using copulas. *Journal of Empirical Finance, 14(4)*, 564-583.

Heinen, A., & Rengifo, E. (2008). Multivariate reduced rank regression in non-Gaussian contexts, using copulas. *Computational Statistics & Data Analysis, 52(6)*, 2931-2944.

Hibbert, A., Pavlova, I., Barber, J., & Dandapani, K. (2011). Credit Spread Changes and Equity Volatility; Evidence from Daily Data. *Financial Review, 46(3)*, 357-383.

Huang, J.-Z., & Huang, M. (2012). How much of the corporate-treasury spread is due to credit Risk? *The Review of Asset Pricing Studies, 2(2)*, 153-202.

IHS Markit. (November 2021). *CDS Indices Primer.*

Longin, F., & Solnik, B. (2001). Extreme correlation of international equity markets. *The Journal of Finance, 56(2)*, 649-676.

McNeil, A. J., Frey, R., & Embrechts, P. (2015). *Quantitative Risk Management: Concepts, Techniques and Tools.* Princeton, NJ: Princeton University Press.

Merton, R. C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. *The Journal of Finance, 29(2)*, 449-470.

Page, S., & Panariello, R. A. (2018). When diversification fails. *Financial Analysts Journal, 74(3)*, 19-32.

Procasky, W. J. (2021). Price discovery in CDS and equity markets: Default risk-based heterogeneity in the systematic investment grade and high yield sectors. *Journal of Financial Markets, 54*, 100581.

Rodriguez, J. C. (2007). Measuring financial contagion: A copula approach. *Journal of empirical finance, 14(3)*, 401-423.

Rugås, N., & Winberg, A. (2015). A study on the relation between VIX, S&P500 and the CDX-index. *University of Gothenburg - School of Business, Economics, and Law, NEG-300 H14 Project Paper*.

Shi, Y., Stasinakis, C., Xu, Y., & Yan, C. (2022). Market co-movement between credit default swap curves and option volatility surfaces. *International Review of Financial Analysis, 82: 102129*.

Sklar, A. (1959). Fonctions de repartition a n dimensions et leurs marges. *Publications de l'Institut de Statistique de L'Universite de Paris 8*, 229-231.

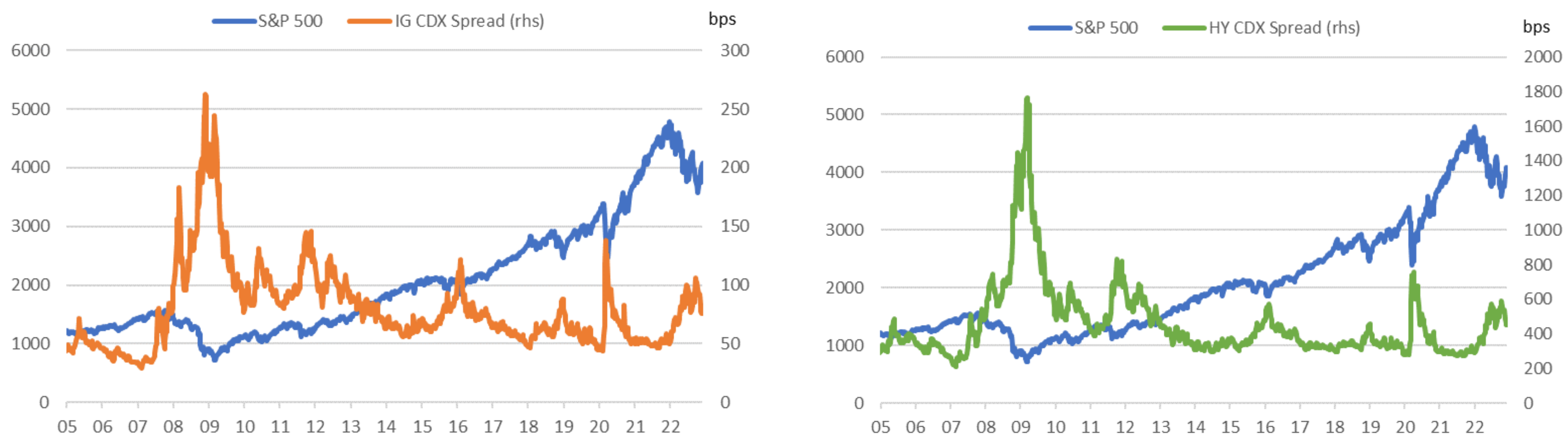

Figure 1: S&P500 Index and CDX Index credit spread

These charts show the S&P500 Index and 5-year on-the-run North America CDX Index spreads. Investment grade CDX and S&P 500 are shown in the left chart while high yield CDX and S&P 500 are shown in the right chart.

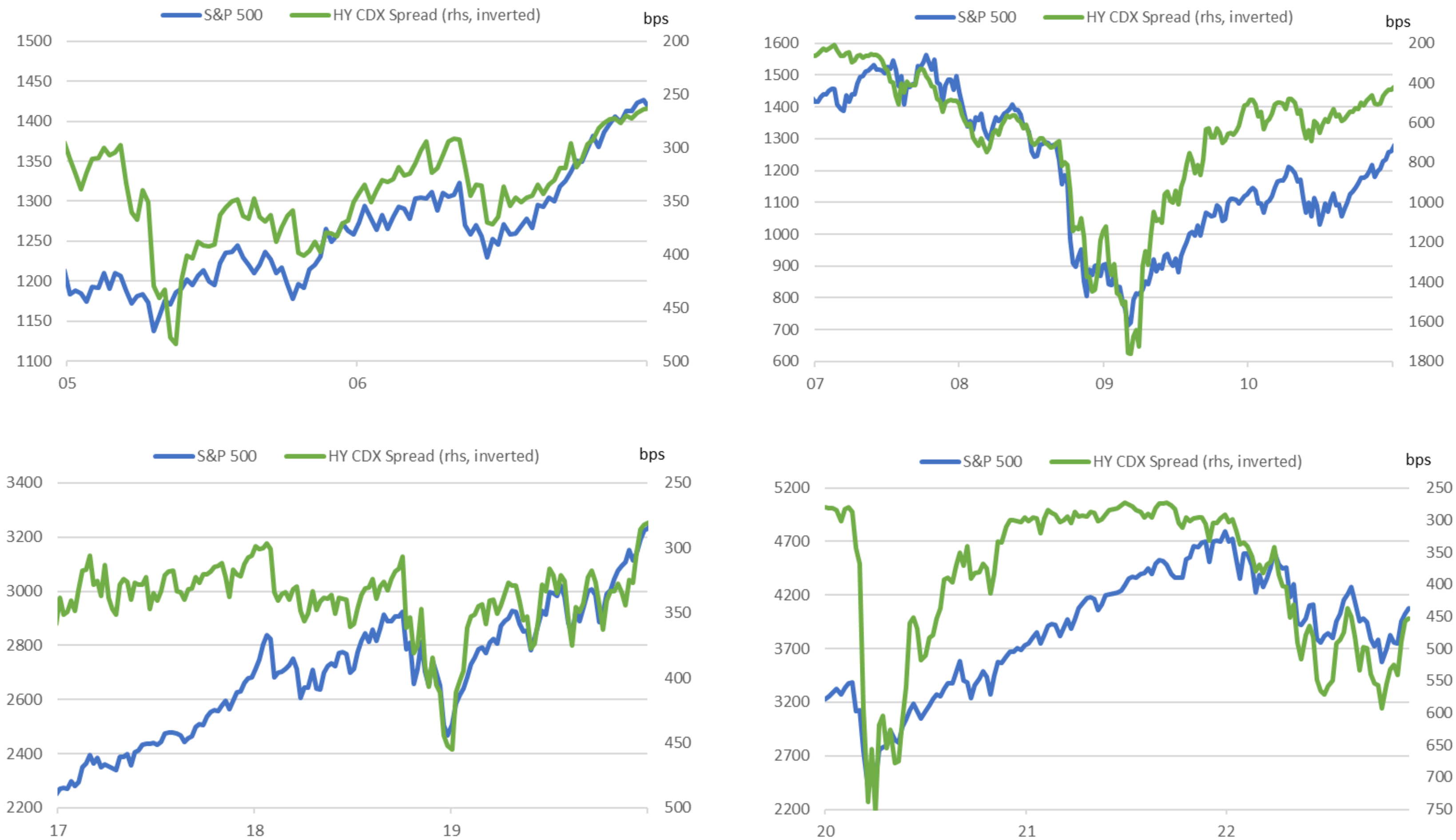

Figure 2: S&P500 Index and high yield CDX Index credit spread

These charts show the S&P500 Index and 5-year on-the-run North America High Yield CDX Index spreads for select periods. In each chart, high yield CDX spreads are shown on the right axis with the scale inverted.

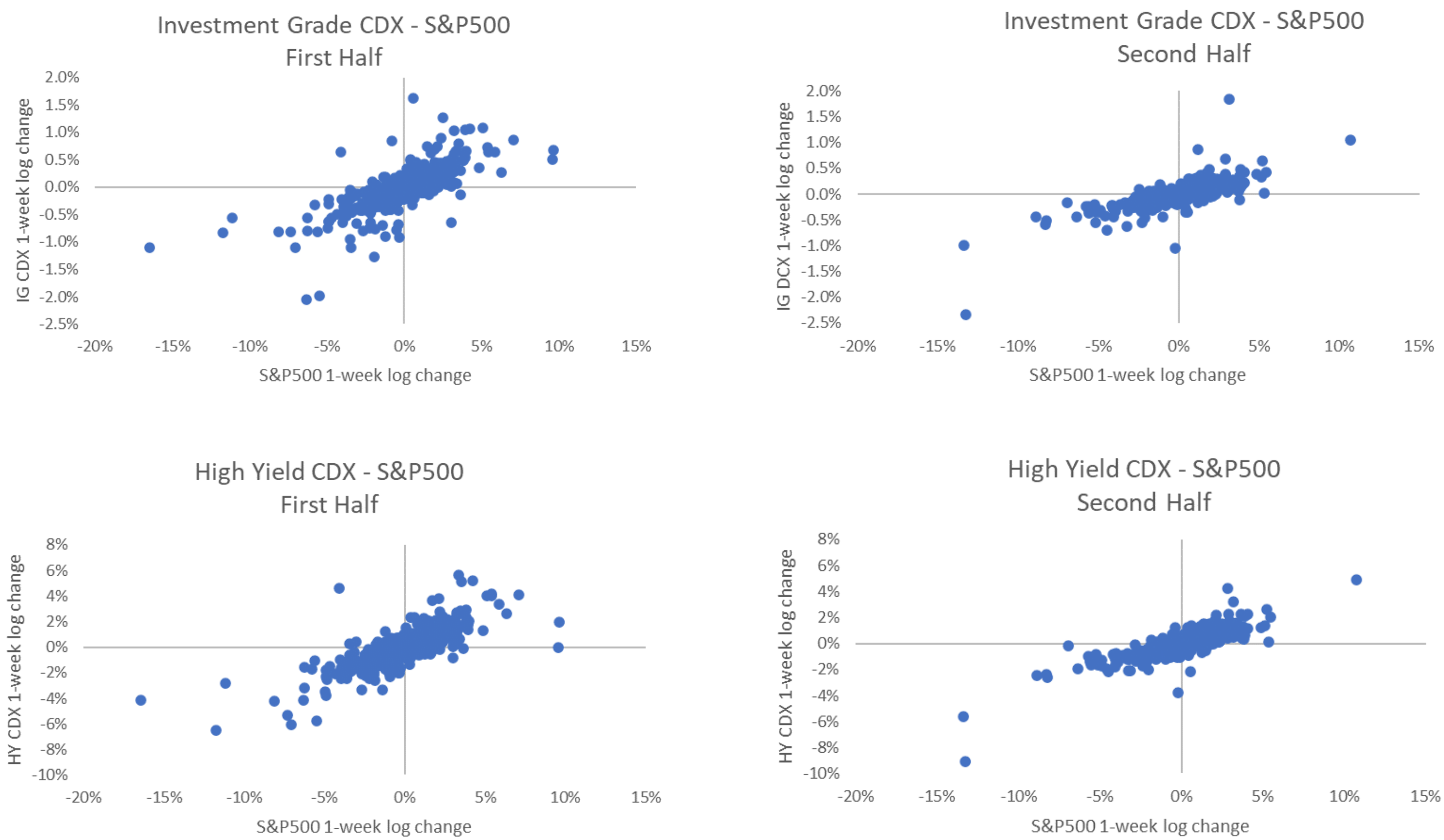

Figure 3: S&P500 Index and high yield CDX Index returns

These charts show scatter plots of returns of the S&P500 Index and CDX Indexes. The top panel shows returns of S&P500 Index and Investment Grade CDX, while the bottom panel shows returns of S&P500 Index and High Yield CDX. Calculations are based on weekly log changes, multiplied by 100. First half covers December 1, 2004 – November 27, 2013. Second half covers November 27, 2013 – November 30, 2022.

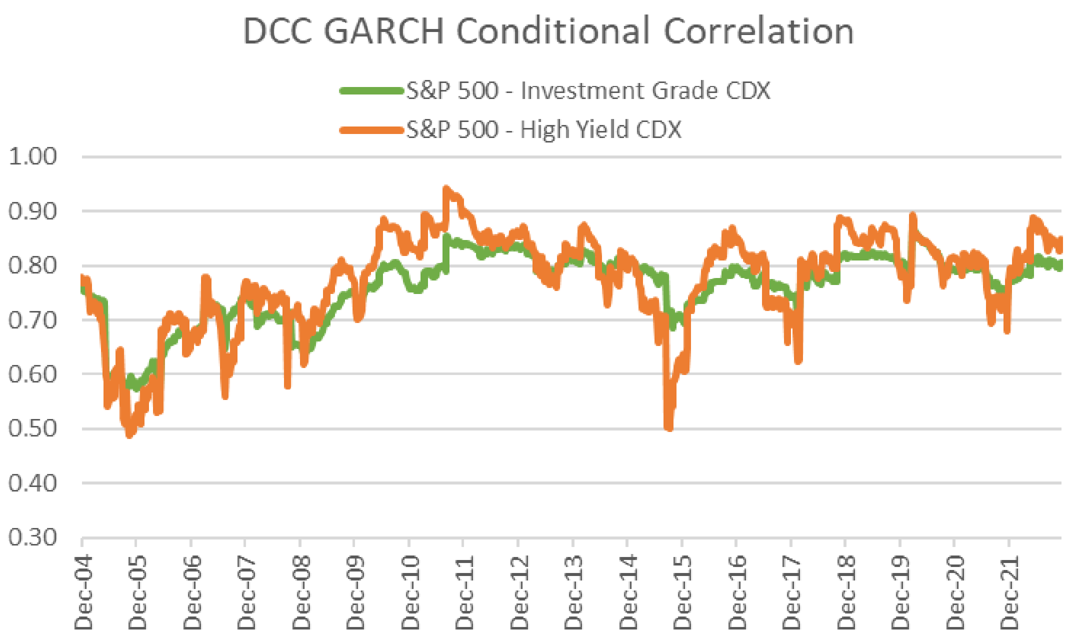

Figure 4: Dynamic Conditional Correlation GARCH – Full sample

The chart shows DCC GARCH conditional correlation between S&P500 Index and 5-year CDX Indexes based on weekly log changes between December 1, 2004 and November 30, 2022

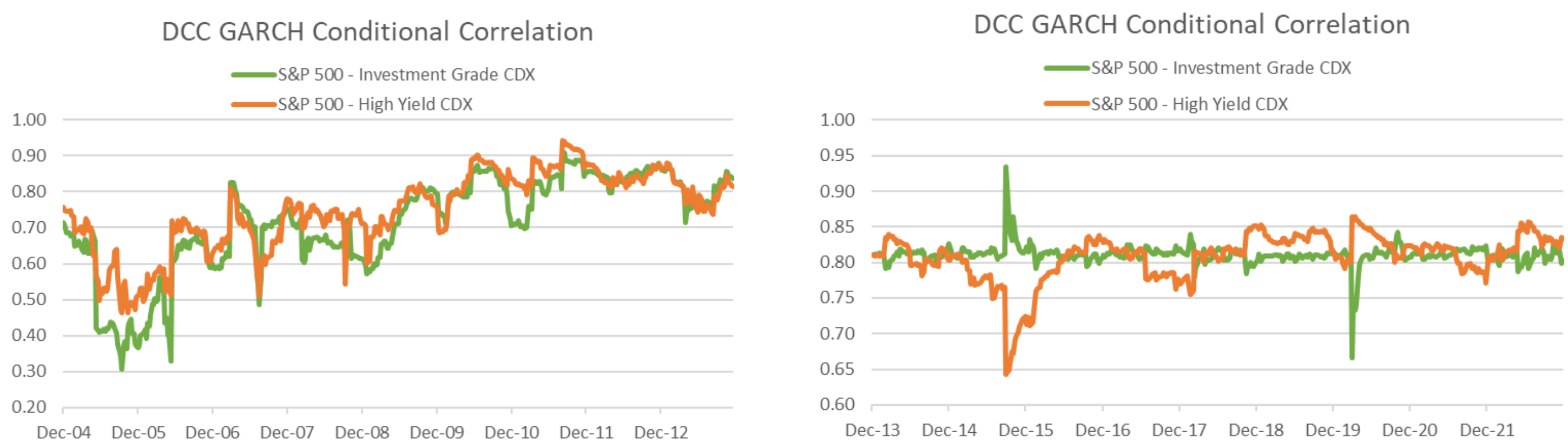

Figure 5: Dynamic Conditional Correlation GARCH – Full sample

The charts show DCC GARCH conditional correlation between S&P500 Index and 5-year CDX Indexes based on weekly log changes. The left chart is based on returns between December 1, 2004 and November 27, 2013 while the right chart is based on returns between November 27, 2013 and November 30, 2022.

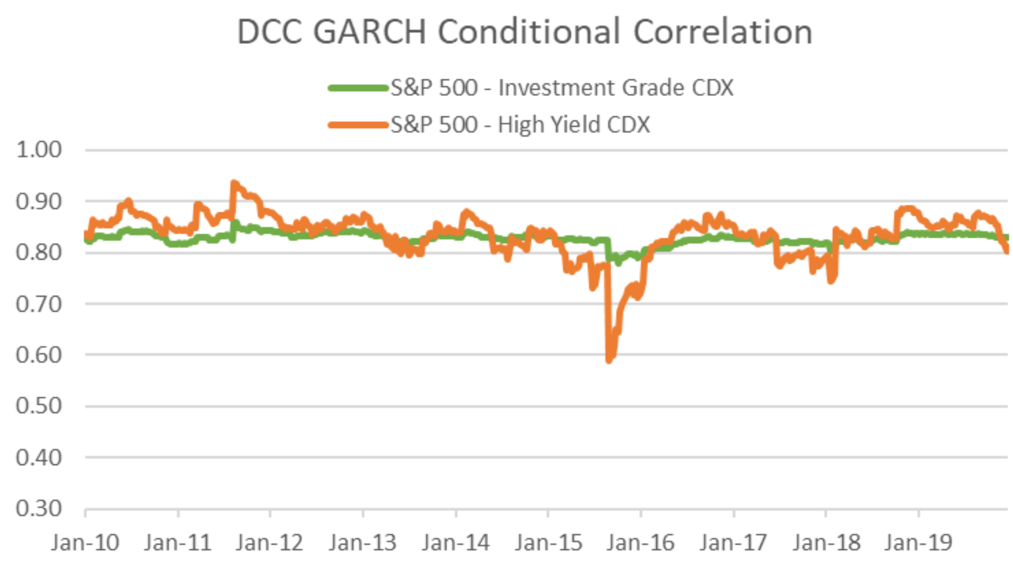

Figure 6: Robustness check – DCC-GARCH conditional correlation

The chart shows DCC-GARCH conditional correlation between S&P500 Index and 5-year CDX Indexes based on weekly log changes. Data cover 2010 through 2019.

	Full Sample			First Half			Second Half		
	SP500	IG	HY	SP500	IG	HY	SP500	IG	HY
Mean	0.131	-0.001	0.037	0.089	-0.003	0.060	0.173	0.000	0.013
Median	0.370	0.012	0.073	0.307	0.015	0.112	0.426	0.006	0.045
Maximum	10.717	1.845	5.668	9.639	1.624	5.668	10.717	1.845	4.875
Minimum	-16.452	-2.341	-9.112	-16.452	-2.052	-6.481	-13.378	-2.341	-9.112
Std. Dev.	2.352	0.309	1.227	2.450	0.364	1.434	2.251	0.242	0.978
Skewness	-1.270	-0.789	-0.698	-1.161	-0.628	-0.324	-1.393	-1.132	-1.818
Kurtosis	10.130	13.837	10.829	9.968	8.535	6.649	10.188	29.882	22.892
Observations	939	939	939	469	469	469	470	470	470

Table 1: Descriptive statistics for S&P500 and CDX Indexes

The table shows descriptive statistics for S&P500 Index, 5-year on-the-run North America Investment Grade and High Yield CDX Indexes. Calculations are based on weekly log change, multiplied by 100. Full sample period is December 1, 2004 to November 30, 2022. First half covers December 1, 2004 – November 27, 2013. Second half covers November 27, 2013 – November 30, 2022.

S&P500 - High Yield CDX					
Copula	Parameter		Full Sample	First Half	Second Half
Normal	Correlation	ρ	0.790	0.786	0.813
		Kendall τ	0.580	0.575	0.604
Student-t	Deg Freedom	ν	6.314	4.650	7.502
		std err	1.431	1.295	2.785
		t value	4.410	3.590	2.690
	Rho	ρ	0.799	0.798	0.819
		Kendall τ	0.589	0.588	0.611
	LogL		483.539	244.148	259.958
	AIC		-963.079	-484.296	-515.917
	SBC		-953.389	-475.995	-507.611
Gumbel	Theta	ϴ	2.244	2.271	2.321
		std err	0.060	0.086	0.088
		t value	37.400	26.360	26.440
	LogL		425.712	214.851	226.165
	AIC		-849.424	-427.701	-450.329
	SBC		-844.579	-423.551	-446.176
		Kendall τ	0.554	0.560	0.569
	Tail dependence	λ_u	0.638	0.643	0.652

Table 2: S&P500 Index and High Yield CDX Index copula statistics

The table reports copula output statistics between S&P500 Index and High Yield CDX returns using normal, student-t, and Gumbel copulas. All CDX Indexes refer to 5-year on-the-run North America CDX Index. Returns are based on weekly log change. Full sample time period is December 1, 2004 to November 30, 2022. First half covers December 1, 2004 – November 27, 2013. Second half covers November 27, 2013 – November 30, 2022.

S&P500 – Investment Grade CDX					
Copula	Parameter		Full Sample	First Half	Second Half
Normal	Correlation	ρ	0.774	0.767	0.794
		Kendall τ	0.564	0.556	0.584
Student-t	Deg Freedom	ν	6.108	5.954	4.597
		std err	1.295	1.756	1.250
		t value	4.720	3.390	3.680
	Rho	ρ	0.786	0.781	0.805
		Kendall τ	0.576	0.571	0.595
	LogL		453.049	221.630	246.237
	AIC		-902.098	-439.259	-488.474
	SBC		-892.408	-430.958	-480.169
Gumbel	Theta	ϴ	2.187	2.179	2.288
		std err	0.059	0.082	0.087
		t value	37.300	26.460	26.150
	LogL		401.932	199.018	216.372
	AIC		-801.863	-396.035	-430.745
	SBC		-797.018	-391.885	-426.592
		Kendall τ	0.543	0.541	0.563
	Tail dependence	λ_u	0.627	0.626	0.646

Table 3: S&P500 Index and Investment Grade CDX Index copula statistics

The table reports copula output statistics between S&P500 Index and Investment Grade CDX returns using normal, student-t, and Gumbel copulas. All CDX Indexes refer to 5-year on-the-run North America CDX Index. Returns are based on weekly log change. Full sample time period is December 1, 2004 to November 30, 2022. First half covers December 1, 2004 – November 27, 2013. Second half covers November 27, 2013 – November 30, 2022.

Descriptive Statistics			
	SP500	IG	HY
Mean	0.002	0.000	0.001
Median	0.004	0.000	0.001
Maximum	0.071	0.009	0.042
Minimum	-0.117	-0.008	-0.065
Std. Dev.	0.019	0.002	0.010
Skewness	-0.966	-0.269	-0.529
Kurtosis	7.113	4.757	8.344
Observations	521	521	521

Copula Analysis				
Copula	Parameter		HY – SP500	IG – SP500
Normal	Correlation	ρ	0.790	0.786
		Kendall τ	0.580	0.575
Student-t	Deg Freedom	ν	6.314	4.650
		std err	1.431	1.295
		t value	4.410	3.590
	Rho	ρ	0.799	0.798
		Kendall τ	0.589	0.588
	LogL		483.539	244.148
	AIC		-963.079	-484.296
	SBC		-953.389	-475.995
Gumbel	Theta	Θ	2.244	2.271
		std err	0.060	0.086
		t value	37.400	26.360
	LogL		425.712	214.851
	AIC		-849.424	-427.701
	SBC		-844.579	-423.551
		Kendall τ	0.554	0.560
	Tail dependence	λ_u	0.638	0.643

Table 4: Robustness check statistics – Descriptive statistics and Copula outputs

The table reports descriptive statistics and copula output statistics between S&P500 Index and Investment Grade CDX returns using normal, student-t, and Gumbel copulas. All CDX Indexes refer to 5-year on-the-run North America CDX Index. Returns are based on weekly log change. Sample period is 2010 through 2019.

Appendix: Copula analysis

The normal (Gaussian) copula can be defined as:

$$C_N(u,v) = \Phi_p(\Phi^{-1}(u), \Phi^{-1}(v)) \quad (10)$$

The correlation parameter, ρ, in the normal copula can range from -1 to 1, with complete dependence at -1 and 1, and independence at 0.

The student-t copula, which is symmetric and shows tail dependence can be defined as:

$$C_t(u,v) = t_{d,p}(t_d^{-1}(u), (t_d^{-1}(v)) \quad (11)$$

The coefficient of tail dependence, degrees of freedom, is expressed as *v* and correlation of ρ. Correlation can range from -1 to 1, with complete dependence at -1 and 1, and independence at 0. Kendall's tau is related to ρ through the formula: $\tau = \frac{2}{\pi}\arcsin(\rho)$.

The Gumbel copula contains upper tail dependence. It can be defined as:

$$C_G(u,v) = \exp\left[-((-\log(u))^{\theta} + (-\log(v))^{\theta})^{1/\theta}\right. \quad (12)$$

The parameter of the Gumbel copula is Θ, which can range from 1 to ∞. As shown in table 5, Θ can be related to Kendall's τ and to λ_u, a measure of upper tail dependence. When τ = 0 there is complete independence between the variables; when τ = 1 there is complete dependence. As λ_u approaches 1, there is increased upper tail dependence.

Parameter	Range	Kendall τ	Kendall τ Range	Tail Dependence λ_u	λ_u Range
Θ	1 to ∞	1-(1/Θ)	0 – 1	$2\text{-}2^{(1/\Theta)}$	0 – 1

Table 5: Gumbel copula parameter and transformations

Note: Kendall τ calculation is based on Frees and Valdez (1998) and λ_u calculation is based on McNeil, et al (2015)

Appendix: Correlation

Correlation is one of the most common measures of assessing comovement in finance given the simplicity of evaluating market linkages across time periods. The drawback, however, is that these measures show the average diversification potential across the entire distribution of data and do not capture changes in market behavior.

The Pearson correlation coefficient, ρ, is defined as the covariance divided by the product of the standard deviations of the two variables:

$$\rho = \frac{Cov(X,Y)}{\sqrt{Var(X) * Var(Y)}} \tag{13}$$

The Kendall rank correlation coefficient, τ, is an alternative rank correlation metric that measures the similarity of the data when they are ranked by quantiles. As can be seen in equation 14 below, Kendall τ expresses the agreement of the variables *x* and *y*. In particular, it measures the probability of concordance minus the probability of discordance. Therefore, if *x* and *y* move in the same direction, τ will be positive and equal to one if the agreement is perfect. If *x* and *y* are moving in opposite directions, τ will be negative and equal to -1 if there is perfect disagreement. If *x* and *y* are independent, τ will equal zero. It is expressed as:

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} sgn(x_i - x_j) sgn(y_i - y_j) \tag{14}$$