Copenhagen Business School

MSc in Advanced Economics and Finance

Master's Thesis

Market Integration between CDS and Equity markets

An Empirical Study on Pricing Discrepancies and Market Efficiency

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Abstract

We contribute to the existing literature on market integration by analyzing influences on the degree of market integration between CDS and equity markets. Using a linear cointegration framework, we find market integration to be higher for European companies, investment grade companies, and during the Covid crisis. Further, we identify that the price discovery process between the stock and the CDS market is characterized by a lead-lag relationship in which the CDS market significantly lags. The lagging role of the CDS market allows for one-week-ahead predictions of CDS spread levels and changes based on company-specific equity returns, option-implied volatility, and liquidity measures as well as macroeconomic indicators. Due to impediments to arbitrage, trading strategies based on mispricings in the CDS market appear unprofitable in our empirical tests. Lastly, our findings indicate that illiquidity in the single-name CDS market causes pricing discrepancies in relation to the equity market, which negatively affects the degree of market integration.

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1 Introduction

General market theory implies that market prices are expected to adjust to newly available information. Consequently, prices in an efficient market contain all available information at any given point in time. Therefore, the ability of a market to instantly incorporate newly available information determines whether the market can be considered efficient. These considerations are central to this thesis.

In particular, we analyze how information is processed in the CDS market in relation to the equity market by assessing the integration of single-name CDS and stock pairs. We conclude that a market pair is integrated when significant cointegration is detected between the two markets. With the inception of the CDS market in 1994 and its subsequent growth in market volume in the early 2000s, the market is still relatively new. In addition, structural changes and regulatory reforms after the financial crisis in 2008 have potential implications on the functioning of the market and, therefore, make an analysis of recent data particularly relevant. As an efficient market should perfectly incorporate new information, a market pair on the same company is theoretically expected to be integrated (Blanco et al., 2005). Furthermore, results from previous research concerning the CDS market indicate that, while the markets appear integrated for some companies, several market pairs do not exhibit this feature (Norden and Weber, 2009; Forte and Lovreta, 2015; Mateev and Marinova, 2017). Thus, a further assessment of the main reasons behind the potential lack of market integration is needed. Moreover, the degree of market integration, measured by the proportion of integrated market pairs, appears to increase during the financial crisis (Narayan et al., 2014). While structurally different from the financial crisis, the recent Covid crisis allows for assessing whether market conditions drive time-varying market integration. In line with previous literature, we find that markets are integrated for only a proportion of market pairs and that this proportion increases during the Covid crisis. In addition, we find that investment grade market pairs are generally more integrated than high yield companies.

Furthermore, previous research analyzes the price discovery process between the two markets and finds that the equity market generally leads the price discovery process over the CDS market (Norden and Weber, 2009; Forte and Peña, 2009; Narayan et al., 2014). We conduct a similar analysis on our sample of 211 European and U.S. companies and find confirming evidence of the stock market's dominant role in the price discovery process.

Moreover, based on the two empirical findings that the degree of market integration increases during the Covid crisis and that the CDS market consistently lags the equity market, we analyze what determines the variation in CDS spreads. This analysis is conducted on both CDS spread levels and changes. In confirming results from previous research, we find that CDS spreads and their changes can be predicted a week ahead using company-specific equity returns, option-implied volatility, and liquidity measures, as well as overall macroeconomic conditions (Da Fonseca and Gottschalk, 2020).

Based on the results of our market integration analysis as well as the determinants of CDS spreads, we develop two trading strategies. These include a signal trading strategy that uses significant variables from the CDS spread prediction analysis and a pairs trading strategy that exploits short-term divergences from the cointegrating relationship between the equity and the CDS market. We find positive gross returns from these strategies, which can be explained by the existence of arbitrage opportunities from imperfectly integrated markets (Blanco et al., 2005). As also suggested by previous research, these apparent arbitrage opportunities prevail due to impediments to arbitrage in the form of trading costs (Kapadia and Pu, 2012) – net of trading costs, the arbitrage opportunities cease to exist.

In summing up our main results, we, first, find that equity and CDS markets are only integrated for a fraction of our sample companies. Second, the stock market consistently leads the CDS market, suggesting that the latter market is somewhat inefficient at timely incorporating new information. Third, the degree of market integration depends on macroeconomic conditions, region, and credit rating. Fourth, arbitrage opportunities arise through the lack of integration but appear to not be exploitable due to impediments to arbitrage. To conclude, the lack of market integration for a proportion of companies prevails since the arbitrage opportunities it creates cannot be exploited. In particular, the inefficiency of the single-name CDS market is likely to arise from a lack of liquidity.

The analysis can be summarized in one main research question and four sub-questions.

1.1 Research Questions

What influences the degree of market integration between the equity and CDS markets?

1. Using cointegration as a measure of market integration, how integrated are the two markets, and does the level of integration change depending on region, credit rating, and market conditions?

2. What characterizes the price discovery process between the two markets?

3. The CDS market is found to have a lagging role, although less so during crisis periods. What variables determine the levels and the changes of CDS spreads, and how can this help explain mentioned findings?

4. Given the systematic short-term market disconnections, can these inefficiencies be utilized to construct profitable trading strategies?

1.2 Delimitations

The geographic scope of data used for answering the research questions is limited to U.S. and European companies. Further, only companies that are part of the CDX and iTraxx indices are included for liquidity reasons. This is explained in further detail in our data selection section (section 4.1).

The time scope of the data used is January 2, 2014, to December 31, 2021. Since the CDS market has evolved significantly in the past 10 to 15 years, older data may be inaccurate in describing the current features of the market. Further, regulatory changes in contractual terms for CDS may result in some noise in the data. These changes are discussed in detail in section 2.3 on the fundamentals and the historical evolvement of the CDS market.

In this paper, we define markets as being integrated when a cointegrating relationship exists between prices in the markets. Further, when measuring each market's contribution to price discovery, we use four commonly applied measures. These include assessing the significance of the equilibrium correction term in the VECM, the Gonzalo-Granger measure, the Hasbrouck measure, and a Granger causality analysis. A discussion of methods used in previous literature is provided in section 2.2. Further, we use a linear framework to estimate potential cointegration. Critics and limitations of using a simple linear approach are discussed in section 2.2.7. Nevertheless, it is still the most commonly used approach (see section 2.2).

When discussing trading costs, we simplify by only considering trading costs related to bid-ask spreads. Bid-ask spreads are expected to have the most sizeable effects for the purposes of our trading strategy, while they vary both depending on company and over time. Other trading costs are assumed to be negligible in comparison.

Lastly, our trading strategies use a static approach of having a training window for setting up and fitting the models and a testing window for applying the strategy. Consequently, the strategies do not incorporate new information that emerges during the testing period. A more dynamic procedure to set up a trading strategy could better integrate those and lead to a more accurate and profitable strategy. Thus, our return estimates can be considered conservative estimates. This is discussed in further detail in section 5.5.2.

2 Literature Review

This section summarizes findings from previous research and discusses the implications of these findings for choices made in this thesis. First, we consider previous literature on general market theory needed to set expectations for market efficiency and liquidity effects. Second, we discuss previous market integration results. Finally, we review literature on credit default swaps and the credit default swap market including historical structural changes and their influence.

2.1 Market Theory

2.1.1 Market Efficiency

The topic of market efficiency is central to nearly all discussions of financial markets. It is essential to specify general assumptions and definitions in relation to efficient markets as these are fundamental for how we interpret the results of our market integration analysis. In the following section, we distinguish between short-run and long-run returns whereas short-run returns are daily or weekly, while long-run returns are defined as returns over more than a year. Starting with a theoretical assumption of efficient markets, we can derive the expected return of an asset as follows. Using consumption-based pricing, we can price an asset with a payoff x as

$$p_t = E_t \left[\beta \frac{u'(c_{t+1})}{u'(c_t)} x_{t+1} \right] \tag{2.1}$$

where $\frac{u'(c_{t+1})}{u'(c_t)}$ captures the relative marginal utility of consumption tomorrow instead of today, and β captures impatience of the investor. As such, the price of an asset depends on the investor's consumption choice c_t, c_{t+1}, and the payoff of the asset x_{t+1}. Defining $\beta\frac{u'(c_{t+1})}{u'(c_t)}$ as the stochastic discount factor m, we get

$$p_t = E_t(m_{t+1}x_{t+1}) \tag{2.2}$$

In the case of no uncertainty, we use $\frac{1}{R_f}$ as our discount factor and get the following price

$$p_t = \frac{1}{R_f} x_{t+1} \tag{2.3}$$

From the definition of gross returns as $R_{t+1} \equiv \frac{x_{t+1}}{p_t}$, we can rewrite the risk-free rate as

$$R^f_{t+1} = \frac{x_{t+1}}{p_t} = \frac{x_{t+1}}{\frac{1}{R_f} x_{t+1}} = R_f \tag{2.4}$$

Further, the risk-adjusted price for an asset i can be expressed as the discounted expected future payoff

$$p^i_t = \frac{1}{R^i} E_t(x_{t+1}) \tag{2.5}$$

Yielding an expected return of

$$E_t(R^i_{t+1}) = E_t \left(\frac{x^i_{t+1}}{\frac{1}{R^i} E_t(x^i_{t+1})} \right) = R^i \tag{2.6}$$

Based on this the return of an asset depends solely on its specific risk profile and the general consumption and risk aversion of investors. If expectations of payoffs change, investors will buy or sell the asset until the condition is satisfied again. That is, if the expected payoff tomorrow x^i_{t+1} increases, the price today p^i_t increases, such that the return R^i remains at the risk-adjusted level. Only if general investor consumption or risk aversion changes R^i will change, yet this is not expected in the short term. Therefore, we can expect that in efficient markets, short-term price changes are represented by random deviations in the expected payoff, such that the price in the next period can be approximated by

$$p_{t+1} = p_t + \varepsilon_{t+1} \tag{2.7}$$

As equation 2.7 shows, short-run future prices in an efficient market can be approximated by a random walk, which is also the definition of the *efficient market hypothesis* (Cochrane, 2009). Notably, according to the efficient market hypothesis, prices in an efficient market follow a random walk and reflect all available information.

Based on stock market returns from 1926 to 1960, Fama (1965) tests the efficient market hypothesis and finds strong empirical support for the random walk hypothesis, arguing that looking for patterns in past returns will not yield abnormal future returns. Further, he argues that in an efficient market, a fundamental stock analysis will only yield superior returns if the investor has information that is not already implicit in current market prices. While several authors support this view (see, e.g., Cootner, 1962; Kendall and Hill, 1953), the random walk hypothesis has been subject to much scrutiny over the past 60 years.

The leading alternative hypothesis has been the idea of stock prices following mean-reverting processes, allowing investors to forecast future returns based on past returns. Fama and French (1988) argue that mean-reverting components in stock prices exist, which cause negative autocorrelation in returns. The evidence holds for long-term returns in their 1926-1985 sample, although mostly for portfolios of small firms and most evidently for data before 1940. After that, the price components become less significant. The evidence for mean reversion in short-run returns is weak for the entire sample period. Poterba and Summers (1988) find similar evidence of mean reversion in long-run stock returns. These results are disputed by several authors who argue that they do not persist when correcting for small sample biases, are not robust to outliers and alternative distribution assumptions, and that they, similar to empirical results by Fama and French (1988), only hold in the pre-second world war period (Kim et al., 1991; McQueen, 1992; Richardson, 1993; Richardson and Stock, 1989). The discussion prevails in more recent literature. Chaudhuri and Wu (2003) argue that stationary returns exist when allowing for structural breaks in the data while Borges (2010) finds that this is only true for some countries, making a general conclusion challenging. Lastly, Kumar Narayan et al. (2016), argues that due to the heterogeneity of firms, aggregating stock prices may be spurious. Consequently, they use firm-level stock data in a GARCH model that allows for structural breaks and find stationary stock prices for 63 out of 156 firms.

Overall, no clear consensus exists on the degree to which a random walk can express stock returns. More recent literature, using more sophisticated statistical models, finds more robust evidence for stationarity in stock returns, but the results are still not overwhelming and seem to depend on regions and time periods considered. The analysis of this thesis contributes to the discussion of market efficiency through the analysis of two different but strongly connected markets. Analyzing two connected markets allows for studying timing differences in reactions to news and information flows across markets. Timing differences imply predictability in the lagging market, which is inconsistent with the random walk hypothesis and, thereby, the efficient market hypothesis. One reason for a market to not be efficient is a lack of liquidity, motivating a more thorough discussion in the following section.

2.1.2 Market Liquidity

Two overall streams of research exist in terms of relating market efficiency to liquidity. The first stream considers how different prices for buying and selling stocks lead to illiquid markets, whereas the second focuses on the link between liquidity and excess returns.

Within the first stream of research, Glosten and Milgrom (1985) examine the situation where a trade consists of three players: a buyer, a seller, and a middleman. The seller and the buyer can be either informed, traders or liquidity providers. In a case of informational asymmetries, such as in a market where the potential of insider trading exists, the middleman faces an adverse selection problem. The informed trader will only agree to trade because he has information which is not reflected in the price offered by the middleman. The middleman can transfer these costs to a liquidity provider by offering prices with a sufficient bid-ask spread. Hence, the bid-ask spread becomes at least partially an informational phenomenon. Further, it implies that even if a seemingly inefficient market allows for observable abnormal returns, the realizable returns from engaging in such a market may be lower. Consequently, realizable prices still follow martingales. Using a model of sequential auctions, Kyle (1985) reaches a similar conclusion. This stream of study has implications on the degree to which observable returns in a market can effectively be converted into realizable gains and how liquidity and informational flaws affect this conversion. These considerations are central to our analysis as engaging in CDS trades may seem to allow for abnormal returns, which are not realizable once illiquidity costs in the form of wide bid-ask spreads are accounted for.

In contrast, the second research stream concerning this topic is more empirical in nature. It considers how liquidity limitations in some markets may pose a risk for investors, for which they demand a premium to bear. Pástor and Stambaugh (2003) create a liquidity measure that examines how sensitive individual stock returns are to changes in aggregate liquidity. Looking at U.S. stock returns from 1966 to 1999, they conclude that stocks with a high sensitivity to changes in liquidity provided significantly higher returns than less exposed stocks over the 34-year period, even when adjusting for exposure to size, value, and momentum factors. Acharya and Pedersen (2005) expand on this by providing a theoretical framework that explains why investors should worry not only about a security's performance and tradeability in market downturns but also about how it performs when liquidity dries up. More specifically, the required return of a security for which the liquidity has a high covariance with the overall market liquidity should be higher. This is also tested empirically on U.S. stock data, concluding that a liquidity-adjusted CAPM better explains cross-sectional return differences. Lee (2011) tests the liquidity-adjusted pricing model in a total of 50 countries, confirming that liquidity risk is priced separately from market risk worldwide. Testing the covariance between liquidity for our sample companies and the overall market liquidity is outside the scope of this paper, yet it is nonetheless essential to keep the findings of this stream of literature in mind when analyzing the cause of abnormal returns. This is not only true for liquidity risk in the stock market but also in the CDS market, as systematic and individual liquidity may play an important role in this market too.

Having established theoretical expectations as well as summarized empirical findings in relation to market efficiency and liquidity, the following section discusses previous findings on the topic of market integration.

2.2 Market Integration

2.2.1 Credit Risk

In theory, credit risk should be correctly reflected across all prices of financial claims on an arbitrary firm in efficient financial markets (see section 2.1.1 on market efficiency). Since prices in the CDS, bond, and stock markets directly depend on the market value of a firm's assets, Norden and Weber (2009) argues that a strong relationship should exist between these markets. However, as previous empirical analyses have shown, structural differences between markets, such as market participants, liquidity, and the overall structure, prevent financial assets from pricing in information simultaneously. Instead, these structural differences create a lead-lag relationship in which the lead-lag roles depend on the speed at which each market can reflect new information in its prices (Forte and Peña, 2009).

Among the first researchers, Merton (1974) analyzes the fundamental relationship between credit markets and the stock market on a corporate level. The Merton (1974) credit risk model postulates that a firm's credit risk is linked to the company's probability of default which is effectively measured by the probability of a firm's assets falling below a certain level – its default boundary. As crucial inputs, the model uses the company's assets, modeled by a geometric Brownian motion assuming constant asset volatility and its capital structure. It can be shown that the price of the firm's risky debt is equal to the price of a risk-free bond plus the price of a put option on the firm's debt claims. The value of the credit risk is then derived from the value of the option, which can be calculated based on the standard Black and Scholes (1973) option formula. Based on the Merton model, a vast stream of academic research has investigated this relationship. Moreover, the introduction of new financial products, such as credit derivatives and particularly credit default swaps, has led to a further reexamination of this relationship as CDS spreads are assumed to be a purer measure of credit risk (Mateev and Marinova, 2017).

Ötker-Robe and Podpiera (2010) argue that CDS spreads are a superior proxy for credit risk since the selection of the risk-free rate and its term structure adds a significant degree of discretion to the extraction of credit risk from corporate bonds[1]. On the contrary, CDS spreads are based on arbitrage-free pricing (Ötker-Robe and Podpiera, 2010). The standardized terms for setting up a CDS contract on a reference entity significantly reduce potential noise stemming from a bond's indenture terms. Further, while there is clear evidence of a liquidity premium in corporate bond prices Ötker-Robe and Podpiera (2010) argues that there is conflicting evidence on whether or not CDS contracts contain such a premium. However, as outlined in section 2.3.7, empirical evidence points toward the inclusion of a liquidity risk premium in CDS. Lastly, among others, Blanco et al. (2005) and Zhu (2006) find that CDS spreads respond more efficiently to changes in credit conditions than corporate bond yields. The above mentioned arguments is part of the motivation behind our focus on the credit default swap market rather than the bond market for a market integration analysis. Specifically, the CDS market should in theory provide an accurate price of the credit risk of a company.

The following sections discuss previous literature on market integration between the CDS market and other markets.

2.2.2 CDS vs. Bonds

Our literature review on market integration between the CDS market and other markets begins with a review of previous research between the traditional bond market and the relatively new CDS market. Its sharply increasing popularity and the subsequent standardization of CDS contracts have strengthened focus on the CDS market.

In understanding the market integration between the bond and CDS market, Blanco et al. (2005) investigate the lead-lag relationship between changes in CDS spreads and credit spreads,

[1] Credit risk is calculated by subtracting the risk-free rate from a bond's yield.

derived from corporate bonds following the approach by Duffie (1999). Applying a Vector Error Correction Model (VECM) to a sample of 33 U.S. and European companies, the authors find CDS contracts to take a leading role over bond spreads. The existence of cointegration between the two measures shows strong evidence in favor of a long-run parity relation as an equilibrium condition. Further, the leading role combined with CDS being a more pure measure of credit risk suggests CDS prices to be the more valid indicator (Blanco et al., 2005).

In a similar setup, Zhu (2006) applies a VECM to 24 international companies and finds CDS spreads and bond spreads to both be important in reflecting credit conditions and information, although the VECM suggests a leading position of the CDS market.

2.2.3 CDS vs. Bonds vs. Stocks

By adding stock returns to their analysis, Longstaff et al. (2003) incorporate the stock market in their market integration research. The authors use a Vector Auto-Regressive model (VAR) to assess the price discovery process between the bond, CDS, and equity markets on weekly data for 68 firms from March 2001 to October 2002 (see also Longstaff et al., 2005, for additional research on the topic). Their empirical results suggest that both the stock and the CDS market have leading positions over the corporate bond market. Interestingly, no clear leading role in the price discovery process is found between the stock and the CDS market. While the stock market tends to lead on an aggregate level, the CDS market still leads for a considerable fraction of reference entities and as such motivates a further investigation between the two markets.

While following the VAR approach by Longstaff et al. (2003), Norden and Weber (2009) also empirically investigate the connection between financial markets and their role in reflecting default-risk related information in asset prices. However, the analysis by Norden and Weber (2009) puts particular emphasis on the factors that influence the strength of a lead-lag relationship. First, a leading role of the equity market in the price discovery process is found. Further, results suggest that the CDS market reacts more quickly and significantly to the stock market than the bond market. The strength of a lead-lag relationship is mainly influenced by a firm's average credit quality and the liquidity of corporate bonds but not by its market capitalization (Norden and Weber, 2009). Moreover, a stronger degree of market integration is found for U.S. rather than non-U.S. companies. Lastly, the cointegration analysis of CDS and bonds in a VECM setup reveals CDS spreads to be the primary contributor to the price discovery process between the two markets, which confirms previous findings by Longstaff et al. (2003), Blanco et al. (2005), and Zhu (2006).

Forte and Peña (2009) also analyze market integration between the bond, CDS, and equity markets by considering a VECM approach, although their work differs from previous research by using stock market-implied credit spreads[2] instead of stock returns. They argue that stock market-implied credit spreads is a more appropriate measure as other relevant factors to credit risk might be omitted by using simple stock returns, e.g., factors from the Merton (1974) model. Using a sample of U.S. and European firms, the empirical analysis confirms previous results by finding a leading role of equity markets over CDS and bond markets in the price discovery process. It further indicates that the CDS market is leading compared to the bond market.

2.2.4 CDS vs. Stocks

While the lagging role of the bond market against both the CDS and the stock market in the context of price discovery has been consistently confirmed by empirical research including those in section 2.2.2 and 2.2.3, previous literature does not commonly agree on whether equity or CDS markets are leading and, hence, motivates further empirical analysis.

Acharya and Johnson (2007) find empirical support that suggests a significant information flow from CDS to stock markets. The analysis is performed on a sample of U.S. reference entities from January 2001 to October 2004. The authors assume information reflected in the stock market to be the "benchmark" for public information. Further, the analysis is performed by constructing a measure of "CDS innovations" stemming from the residuals of regressing CDS spreads on its lagged values and an interaction term with the corresponding stock price. Their findings can be summarized as follows. First, there exists significant information revelation in CDS prices in the form of revisions of quotes or insider trading. Secondly, a more severe informational flow is found for reference entities with deteriorating credit conditions during the sample period, and entities with above-average CDS spreads (reflecting higher default risk). Moreover, the CDS innovations can be explained by several indicators of insider information, such as the number of banks with ongoing lending relationships with the reference entity. Also, the information flow is found to be asymmetrical as it is only statistically significant around adverse credit events but not improving credit conditions. Despite insider information in the CDS market, no evidence of an adverse market impact is found on prices or liquidity.

The role of public and private news revelations in CDS markets is also investigated by Norden (2017) using an international sample during the period from 2000 to 2006. He not only finds that news intensity significantly affects CDS spreads prior to rating announcements but also that private information plays a significant role in CDS spreads around credit rating events. The empirical results by Norden (2017) are consistent with the conclusions by Acharya and Johnson (2007) regarding insider trading in the CDS market as anticipative changes in CDS spread are significantly correlated with the reference entity's number of bank relationships.

Fung et al. (2008) investigate market integration between the U.S. stock and CDS markets by

[2] Following the approach by Forte (2011).

using CDS indices – both the CDX.NA.IG and CDX.NA.HY – and the S&P500 stock index over a period from 2001 to 2007. Given the concentration of sophisticated market participants and that credit default swaps only depend on the firm's credit conditions, the authors expect the CDS market to lead the stock market. However, using a VAR approach to assess the lead-lag relationship, the authors find the relationship depends on credit quality. Particularly, the stock market tends to be leading the investment grade segment of the CDS market but is lagging in the price discovery process against the high yield CDS market. The authors intuitively explain this by the fact that high yield companies are more volatile and exposed to credit events and, therefore, the market for insurance derivatives, i.e., CDS, is larger and more efficient in pricing in changes in credit quality (Fung et al., 2008). Following this, Fung et al. (2008) argue that credit protection on high credit quality companies is not as widespread given their lower risk. Finally, market volatility in both the investment grade and the high yield CDS market seems to be leading to stock market volatility.

Using both weekly and daily data from an extensive sample of 800 companies, a study by Hilscher et al. (2015) provides evidence that stock returns are leading CDS returns. In applying a VAR framework, it is found that lagged stock returns have statistically significant predictive power in explaining CDS returns for up to several weeks, but not vice versa[3]. In contrast to previous papers, the authors conclude that informed trading is primarily taking place in global stock markets rather than in the CDS market.

In following a different approach than other empirical literature, Kapadia and Pu (2012) define a firm-level market integration measure based on the frequency of arising arbitrage opportunities across the equity and CDS market. Empirical findings suggest that short-term pricing discrepancies between firms' equity and CDS markets appear frequently and that a significant fraction of these discrepancies is anomalous. The considerable lack of integration between the two markets can, according to the authors, be attributed to its impediments to arbitrage which prevent institutional investors, e.g., hedge funds, from exploiting mispricings that would eliminate pricing anomalies. These impediments include liquidity issues and idiosyncratic risk. A simple trading strategy based on the empirical findings produces positive excess returns, which supports the explanation that market frictions, such as illiquidity, prevent market participants from taking advantage of these opportunities.

In a sample of Asia-Pacific countries, Da Fonseca and Gottschalk (2020) analyze the co-movement of CDS and equity markets (and volatility markets) both at a firm and index level. By applying the commonly used Vector Auto-Regressive model (VAR) and a classical Granger causality test[4], an approach we also apply to assess our non-cointegrated sample, the leading

[3]Significant predictability up to the fifth lag for daily stock returns and predictability up to the fourth lag in weekly specifications is found.

[4]See section 3.2.2.

role of the stock market against the single-name CDS market is confirmed at the firm level. On the contrary, index level data provide less clear evidence as index CDS spreads tend to lead the corresponding stock market. A further discrepancy is found when considering volatility. On a firm level, the stock market again leads compared to realized volatility but implied volatility of CDS index options appears to be leading across the three markets. The reason for this discrepancy lies in the use the different measures of volatility – implied volatility on the index level and realized volatility on the firm-level due to the lack of liquid single-name options.

The evidence on a corporate level is backed by empirical findings of Scheicher and Fontana (2010). Using sovereign CDS for 10 Euro-zone countries between 2006 and 2010, the results suggest a leading role of the stock market compared to the CDS market, especially for countries of higher credit risk. However, Eyssell et al. (2013) find a leading role of Chinese sovereign CDS compared to stock returns.

In summing up previous literature, no consistent leading role can be determined by previous empirical analysis. However, on an aggregate level, evidence points toward the stock market to be the main driver in the price discovery process since a leading role of the CDS market is primarily concentrated around credit events (see Acharya and Johnson, 2007; Norden, 2017). Our analysis aims to further investigate the price discovery process between the CDS and the stock market using more recent data on a larger number of companies. The use of recent data and a larger number of sample companies allows us to make conclusions that better capture current market conditions and their potential influence on the price discovery process.

2.2.5 CDS vs. Volatility

A further key factor in explaining credit risk within a structural credit risk model, e.g., the Merton (1974) model, is a firm's asset volatility. As neither the market value nor the volatility of a firm's assets can be obtained at a reasonable and valuable frequency, asset volatility is widely approximated by either realized or option-implied volatility based on a firm's share price. Higher equity volatility leads to more pronounced swings in the process of firm value over time. An increase in volatility makes it more likely for a reference entity to hit its default boundary, which translates into more credit risk and wider credit spreads (Blanco et al., 2005).

Zhang et al. (2009) use high-frequency data of stock prices to calculate historical realized volatility and jumps and assess their effect on CDS spreads. Approximately 50% of the CDS spread level can be solely explained by using short-term (one week) and long-term (one year) realized volatility measures, while adding jump risk to their linear model can add an additional 19% of explanatory power. The study distinguishes itself from previous literature by incorporating both short-run and long-term measures and thereby tackling the common issue of assuming volatility to be constant over time (Zhang et al., 2009). Moreover, adding balance sheet information and macroeconomic indicators increases the explanatory of variation in CDS spreads to 73%. Their use of both short-run and long-term measures of volatility motivates this paper to use two different time horizons for implied volatility in our determinants of CDS spreads analysis.

Motivated by the similar payoff characteristics of CDS and specific options, primarily out-of-the money put options[5], Cao et al. (2010) investigate the link between option-implied volatility and credit default swaps. Using a large sample of 301 companies, the empirical results indicate implied volatility to be a strongly significant explanatory variable in the time-series variation in CDS spreads. Furthermore, when comparing implied and realized volatility Cao et al. (2010) find s strictly dominating role of implied volatility. The subsequent investigation identifies implied volatility to be more efficient in forecasting future realized volatility than historical realized volatility and, further, that the option-embedded volatility risk premium is significantly correlated with CDS spreads. In assessing the robustness of their empirical findings, they conclude the link between credit default swaps and implied volatility to be more powerful the lower the reference entity's credit rating, the more volatile the CDS, and the more liquid the firm's options.

Schneider et al. (2010) assess the economic implications of the implied loss given default and jumps in default risk on CDS spreads using a large sample of U.S. entities. Among other findings, clear evidence of a link between market volatility (VIX) and short-term and long-term default factors is found, confirming a link between CDS spreads and volatility not on a firm but on a market level.

Evidence from the study by Kapar and Olmo (2011) who use a cointegration framework suggests a leading role of both equity option-implied volatility and the VIX, a measure of market risk, compared to CDS spreads. The study uses monthly CDS data for a European sample from 2005 to 2010. By allowing for a structural break in the long-run cointegration relationship, the authors conclude that after the financial crisis, CDS spreads tend to move more independently from market variables (VIX) but a leading relationship of the implied volatility remains.

Overall, previous empirical literature find a consistent leading role of both firm-level and market volatility in the price discovery process. These results contribute to the overall evidence of a leading stock market over the CDS market as discussed in the literature review on the market integration between the CDS and stock market (section 2.2.4). As historical realized volatility as well as implied volatility is derived from stocks and their options, a leading role of the these variables are expected over the CDS market as well. However, as mentioned in Cao et al. (2010) liquidity in the option market can substantially affect the leading role of implied volatility compared to CDS spreads. The effect of liquidity on price discovery is relevant for

[5]Both deliver a liquid and cost-efficient way to provide downside protection on a reference entity.

conclusions made in this paper as well.

2.2.6 CDS during Crisis Periods and Market Turmoil

The key role of the CDS market during the subprime mortgage crisis in 2007-08 and the subsequent regulation and standardization of CDS contracts initiated a vast stream of research investigating whether the crisis has structurally changed cross-market integration and affected the price discovery process.

Narayan et al. (2014) apply a panel VECM (PVECM) setup in combination with the Gonzalo and Granger (1995) and Hasbrouck (1995) measure to assess cointegration and price discovery between the CDS and the stock market by using a sample of 212 companies. The overall leading role of the stock market is confirmed in the price discovery process. However, the authors find a more dominant role of the CDS market for investment grade reference entities compared to companies with lower credit quality. Further, evidence of both a size-related and sectoral effect on price discovery is found. Related to the effect of the financial crisis, their findings can be summarized as follows. All sample firms support the leading role of the stock market in both the pre-crisis and crisis period, whereas the stock market's dominance in the price discovery was stronger during the financial crisis. The results are robust to size and sectoral effects.

In an event study, Trutwein et al. (2010) asses if and how market stress impacts the relationship between equity and CDS markets. During benign times, severe CDS movements or even jumps are statistically significant anticipated by the stock market in the form of positive abnormal returns two to five days prior to the credit event. Moreover, the results are even stronger for events associated with improving credit quality, indicating a degree of asymmetry in the link. During the subprime crisis, however, the relationship changed as changes in the spread level significantly impacted stock returns during the time. Further, a spread widening negatively impacted stock returns during the crisis, although the effect is statistically significant only for the high yield subsample. Trutwein et al. (2010) explain the insignificance in the investment grade subsample with a potentially lower relative importance of improvements in credit quality than the importance of overall market conditions during the crisis.

Empirical results by Breitenfellner and Wagner (2012) point towards significant time variation in both the lead-lag relation between CDS and equity markets as well as the determinants of CDS spreads. The authors extend a VAR model with exogenous explanatory variables (VARX) and apply it to the European iTraxx CDS index universe to assess the relationship. Before the financial crisis, no significant leading role of either the CDS or the stock market is found across all sub-indices. During the crisis, however, a significant lead of the stock market is observed across all sub-indices suggesting a more efficient price discovery process. In the post-crisis period, a two-sided information flow is documented, whereas the financial sector even show a leading role in the CDS market. The fact that they find two structural breaks in the cross-market link empirically underlines the theory of time-varying market integration.

Several findings in this strain of research are important for this paper. The findings that that the price discovery relationship differs between the financial crisis period and the periods before and after that motivates this paper to conduct analyses on crisis and pre crisis periods as well (Narayan et al., 2014; Breitenfellner and Wagner, 2012). The importance of a crisis and pre crisis split in the analysis is further emphasized by previous findings of time varying market integration (Breitenfellner and Wagner, 2012). Findings by Trutwein et al. (2010) on the assymetric effects of crisis periods between credit ratings motivates a split into sub samples based on this characteristic. Moreover, the finding by Breitenfellner and Wagner (2012) that the relationship seems to change after the financial crisis motivates an analysis on even more recent data.

2.2.7 Critics of a linear Cointegration Approach

Although it is commonly used and empirical results are able to detect a long-run equilibrium relationship, empirical studies by Ngene et al. (2014) and Chan-Lau and Kim (2004) argue that a simple VECM approach and a following linear cointegration test is insufficient to assess the relation between asset markets thoroughly. Ngene et al. (2014) argues that non-linear links between markets are overseen when relying on a linear modeling framework as time-varying volatility in markets might distort linear relationships. In tackling the issue, Ngene et al. (2014) apply a threshold cointegration assessment and test it against its standard linear equivalent. Empirical results suggest that the price discovery process is dependent on time-varying conditions, including financial, economic, liquidity, and other factors, that are not well captured in a linear framework.

Gatfaoui (2017) applies a quantile cointegrating regression approach to more accurately assess the relation of extreme CDS values (or quantiles) and the stock market as well as time-varying variance and autocorrelation. While a significant response of the CDS market to both equity prices and volatility is found across quantiles, its sensitivity is remarkably varying between quantiles which underlines risk asymmetry and heteroskedastic patterns in the CDS market (Gatfaoui, 2017).

While non-linearity as well as time-varying variance and autocorrelation is not accounted for in this paper, the findings from previous research on this topic are important to mention. Specifically, applying non-linear approaches may increase the likelihood of detecting cointegrating relationships. This is outside the scope of this paper.

2.2.8 Trading Strategies

Empirical results on cross-market integration and the relation between credit and market risk are important when constructing different trading strategies (see e.g. Crouch and Marsh, 2005). Figuerola-Ferretti and Paraskevopoulos (2013) investigate the cointegration relationship between market risk, measured by the VIX, and 47 of the most liquid iTraxx Europe index constituents during the period of 2004 to 2009. The paper uses a VECM framework and finds a long-run equilibrium with significant short-term divergences. The results suggest a dominant position of the VIX in the price discovery, implying the CDS market adjusts after the new information has already been reflected in the VIX. Based on the cointegrating relation, Figuerola-Ferretti and Paraskevopoulos (2013) set up a pairs trading strategy and find positive abnormal returns which are robust to out-of-sample testing and transaction costs. Our analysis follows the approach by Figuerola-Ferretti and Paraskevopoulos (2013), as we try to capitalize on the found evidence of short-term divergences of different asset prices for cointegrated companies (see section 5.6).

Kapadia and Pu (2012) use their empirical findings of frequent pricing discrepancies between the stock and the CDS market to set up an investment strategy based on convergence trades. Furthermore, on average, the strategy can generate positive abnormal excess across firms that are statistically significant with an annualized Sharpe ratio of up to 0.45. Kapadia and Pu (2012) conclude, however, that significant impediments to arbitrage as well as the overall risk profile of the strategy prevent institutional investors from taking advantage of the lack of market integration.

2.2.9 Determinants of CDS Spreads

In light of the mostly lagging role of the CDS market compared to the stock market regarding price discovery, various previous literature continue their analysis by investigating the determinants of CDS spreads. Further, the analysis is empirically motivated by the insufficient explanatory power of theory-backed determinants of credit risk, e.g., the Merton (1974) model (Kapadia and Pu, 2012).

Blanco et al. (2005) uses both firm- and market-related variables and conclude that while all included variables are statistically significant, overall explanatory power leaves around 75% of the variation of CDS spread levels unexplained. Explanatory power decreases when using CDS spread changes rather than levels as the dependent variable. Da Fonseca and Gottschalk (2020) adds realized volatility derived from high-frequency data on stock prices to their linear panel model and finds similar explanatory power in both the CDS levels and CDS changes regressions. Ericsson et al. (2009) conducts an analysis on the explanatory power of leverage and volatility variable and find significance of both determinants.

In a variation of the linear model, the study by Zhang et al. (2009) puts particular emphasis on the influence of stock market volatility and jump risk on CDS spreads. By including both realized volatility derived from high-frequency data and jump risk, the authors can explain around 69% of the variation in CDS levels.

Moreover, Wang et al. (2013) find that 29% of the variation of CDS spread levels can solely be explained by the variance risk premium, whereas the addition of common firm- and market variables add a combined 21% to the 29% explained by the variance risk premium.

An analysis of CDS spreads using a similar framework but using a distinct set of variables is conducted in this paper. Given the frequently mentioned topic of CDS market liquidity, particularly given the decline of the market in the post financial crisis period, we distinguish our analysis from previous literature by including measures of CDS liquidity in our linear framework.

2.3 Credit Default Swaps

This section provides important fundamental information on the functioning of the CDS market. The market is fairly new but has still undergone substantial regulatory and practical changes in the past 20 years. These considerations are important when analysing the market integration between this market and the equity market.

2.3.1 Definition

The most widely known and traded credit derivative is the Credit Default Swap (CDS), an over-the-counter-traded contract that provides the owner with insurance against a contingent credit event of the underlying company, i.e., the reference entity (Hull, 2018). A credit event is triggered when the reference entity fails to meet its debt-related obligations, such as, for example, the failure of interest payment in time (Augustin et al., 2014). While a credit event is evaluated on a case-by-case basis, a credit event can be of one of the following categories: bankruptcy, failure to pay, obligation default or acceleration, repudiation or moratorium, and restructuring.

The buyer of the CDS, which we refer to as the protection buyer, makes periodic payments, usually quarterly or semi-annual, to the protection seller throughout the contract duration or until a credit event is triggered. These periodic payments are conventionally referred to as the CDS spread, which is a percentage of the insured notional amount specified in the contract. In case of a credit event, the CDS contract can be settled either by cash settlement or by physical delivery, whereas the former is the industry convention[6]. In the case of physical delivery, the protection buyer has the right to deliver bonds among a set of deliverable reference obligations that contain the same debt ranking as specified in the CDS contract and a face value equal to the notional amount to the protection seller. Noteworthy, the listed reference obligations typically have the same debt seniority but may sell for a different percentage of face value at the time of the credit event (Hull, 2018). In exchange for the CDS spread payments, the protection seller promises to pay the face value, i.e., the notional amount, for the delivered bonds. With cash settlement, no exchange of debt claims takes place but only the actual incurred losses occurred by the protection buyer are paid in cash by the protection seller. The incurred loss is determined by the mid-market price of the cheapest to deliver bond through a two-stage auction (Hull, 2018). The periodic payments stop once a credit event occurs, and the contract is settled. *Figure 1* illustrates the different cash flows occurring from both parties of the CDS contract.

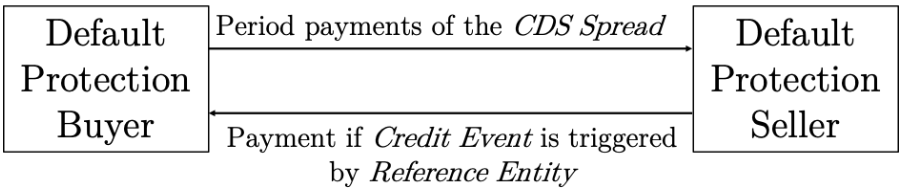


Figure 1: CDS Cash Flows.

As part of the physical settlement, the option of the protection seller to transfer the cheapest-to-deliver (CTD) bond among the reference obligations to the contract seller can be interpreted as a put option (Hull, 2018). The value depends on the documentation clause specified in the contract as it determines the range of acceptable reference obligations. For the Full Restructuring (CR) clause, any obligation with a maturity of up to 30 years can be delivered as part of the settlement. Given the infrequent trading and the resulting illiquidity discount of these debt claims, the value of the CTD option increases significantly. Under the Modified Restructuring (MR) clause, any debt restructuring of the reference entity is still considered a credit event, but the range of possible deliverable reference obligations is restricted to those with maturities within 30 months of the contract's remaining duration. A further narrowing of the obligations under the Modified-modified Restructuring (MMR) clause distinguishes between allowing bonds with maturities within 60 months of the contract's remaining duration in case of a debt restructuring and within 30 months for other credit events. In contrast, a CDS contract, labeled as No Restructuring (XR), can completely rule out restructuring as a credit event. Due to the

[6]Physical delivery as a settlement option has been ruled out with the introduction of the Big Bang and Small Bang protocols for the American and European CDS markets in 2009.

disappearance of the CTD option in case of a restructuring under the XR clause, Berndt et al. (2007) find a 6% to 8% restructuring premium of the CDS spread for XR-labeled contracts.

As outlined in the section on data selection (section 4.1), we follow the approach by Junge and Trolle (2015) to select CDS contracts with contract terms that are the industry standard based on regulatory reforms – modified-modified restructuring (MMR) clause for Euro-denominated contracts and no restructuring (XR) clause for USD-denominated contracts.

2.3.2 The CDS Market

After the inception of the CDS market following the invention of the CDS contract by J.P. Morgan in 1994, the market experienced a modest growth until the late 1990s, with a gross notional amount outstanding of approximately US$180bn in 1997 (Augustin et al., 2014). While CDS are part of the OTC market, they are subject to some regulations and guidance from the International Swaps and Derivatives Association (ISDA). The ISDA also acts as the organizer of the various regional Credit Derivatives Determination Committees (DC) that examine credit events and other related situations (Augustin et al., 2014). The first standardized contract was publicized by ISDA in 1999, which subsequently released new additions or amendments to contractual specifications of CDS, such as the Restructuring Supplement in 2001.

In the early 2000s, the market experienced significant growth following a new set of ISDA CDS contract definitions in 2003 and overall increased trading in the broader credit derivative space, including credit derivative index products (Aldasoro and Ehlers, 2018). Subsequent years of triple-digit growth up to the unfolding of the financial crisis led to the market size peaking at approximately US$61.2 trillion of gross notional amount outstanding at the end of 2007 (Augustin et al., 2014).

The years of exponential growth were followed by an extraordinary decline of the market during the unfolding of the financial crisis, given the CDS market's key role in it. Its crucial role and size led to calls for increased transparency and resilience (Committee on the Global Financial System, 2009). Initially used as a tool for risk management as outlined in Shan et al. (2014), the global financial crisis shed light on the downsides of the little regulation in the credit derivative markets. The most disruptive response in regulation came from the Big Bang and Small Bang protocols for the American and European CDS markets, respectively, in the first half of 2009. Their main target was to improve the efficiency and transparency of the CDS market by further standardizing contract and trading conventions. Among other changes, the standardization of coupon payments for U.S. single-name CDS to either 100 or 500 basis points (bps) represented a key change in regulation. Any difference to the par spread[7] is settled through an upfront

[7] *"The spread of a CDS contract that ensures the PV of the expected premium payments (fee leg) equal the PV of the expected default payment payments (contingent leg)."* (IHS Markit, 2021, p. 40)

payment. Further, restructuring is no longer considered a credit event in the U.S. market, and physical delivery was excluded as a settlement option, leading to cash settlement becoming the industry standard for which settlement prices were determined through a two-stage auction process. This change followed concerns about market squeezes resulting from situations where the net notional amount outstanding exceeds the number of deliverable cash bonds (Augustin et al., 2014). A final noteworthy change was the inclusion of the auction settlement mechanism into the CDS contract and the full transfer of responsibility in assessing whether a credit event was triggered to the Credit Derivatives Determination Committees (DC).

The latest substantial regulatory change in the CDS market was proposed and initiated by ISDA in 2014, mainly concerning European financial and global sovereign CDS. In brief, government intervention was added as a new credit event applicable to financial entities, and senior CDS will only be triggered based on whether the senior bonds of the reference entity are restructured.

These changes, specifically since the financial crisis, may have important structural effects on the CDS market and therefore also its integration with the equity market. Much research on the topic uses data from before the financial crisis, motivating a thorough analysis using recent market data.

2.3.3 The CDS Market in Figures

The massive collapse of the CDS market during the global financial crisis and the subsequent increase in regulation has changed the market remarkably. As Aldasoro and Ehlers (2018) sum it up, market participants steadily lowered their exposures, higher reporting requirements and more standardized contracts increased transparency, and mandatory central clearing and higher margin requirements have lowered counterparty risk. As a result, the CDS single-name and the CDS index market steadily declined. Figure 2 shows the decline in the gross notional amount outstanding for both the single-name and CDS index market from 2014 to 2019. While both markets are in decline, it is worth noting that the CDS index market shrank at a significantly lower rate and nowadays makes up more than 50% of the entire CDS market. Further, as the recent Global CDS Market study by ISDA (2019) shows, only five major CDS indices – CDX.NA.IG, CDX.NA.HY, iTraxx Europe, iTraxx Europe Crossover, and iTraxx Europe Senior Financials – account for more than 90% of the total CDS index market activity. Since 2016, the single-name market has also stabilized at around US$4trn of gross notional outstanding. Figure 3a underlines the trend observed in the single-name space, as market activity and the number of transactions steadily declined since 2014. In contrast, the index CDS market remained more resilient over the same period (see Figure 3b). Moreover, contracts increasingly concentrate around five years of maturity as the volume of longer-term contracts continuously declined after the financial crisis (Abad et al., 2016). The overall decline in volume of the single-name CDS market motivates an analysis on recent data.

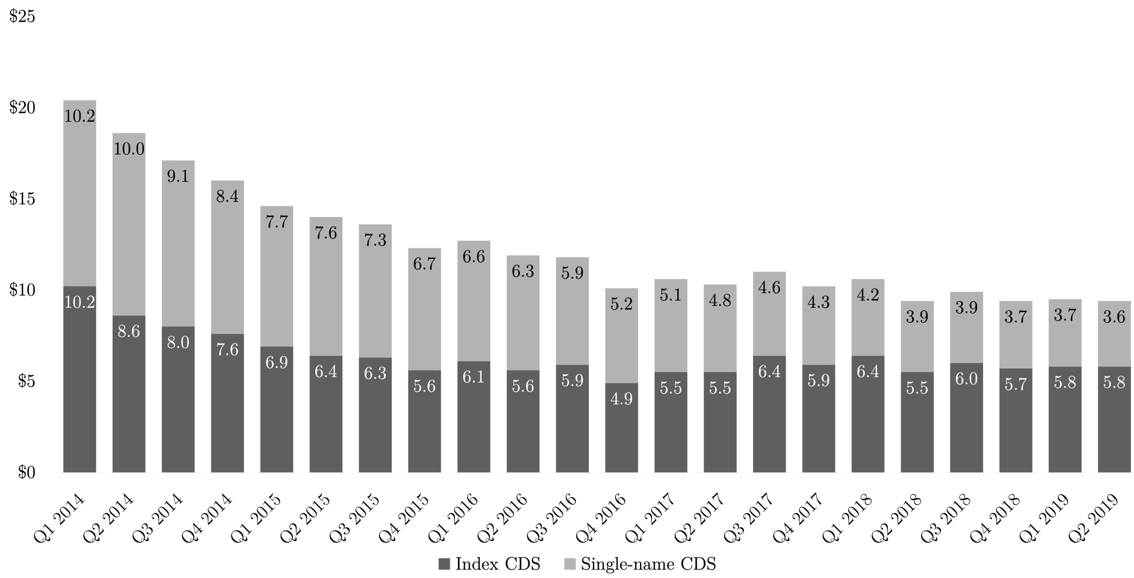
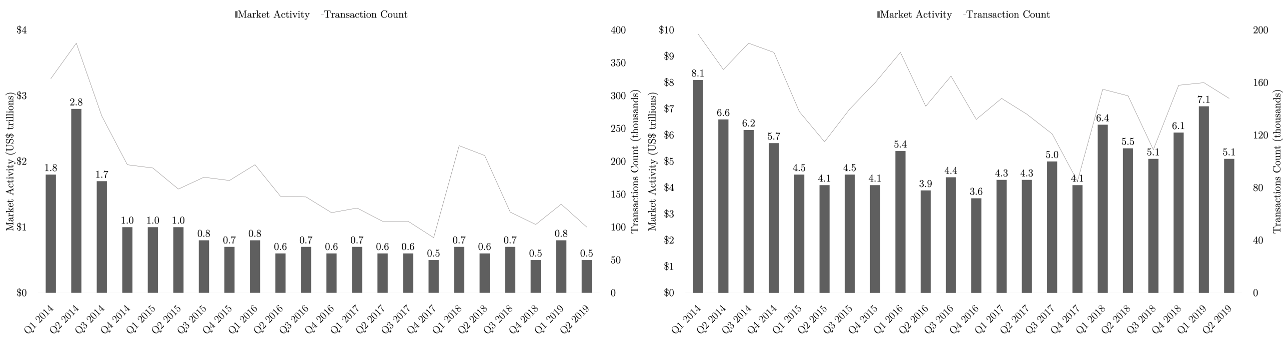


Figure 2: CDS market share.

The graph shows the gross notional amount outstanding for both the single-name CDS and the index CDS market from 2014 to 2019.
Source: ISDA (2019)



(a) Single-name CDS market activity and transaction count

(b) Index CDS market activity and transaction count

Figure 3: CDS market activity and transaction count.

The two figures show the CDS market activity in US$ trillion and the number of executed transactions in thousands for the single-name CDS and the index CDS market from 2014 to 2019. As defined by ISDA, market activity only includes transactions that lead to a different risk position between the two contract parties. It is measured by executed notional of these transactions.
Source: ISDA (2019)

2.3.4 CDS Indices

While the index CDS market also faced a severe contraction in market size in the post-financial crisis period, it nowadays is the largest and most active part of the credit derivative market as preferences of market participants shifted from company-specific exposure to hedging credit risk on an aggregate level through index CDS (see Figure 2).

An index CDS is a standardized contract on a diversified equally-weighted basket of underlying companies (Collin-Dufresne et al., 2020). The reference obligations are credit default swaps. Maturities range from one to ten years, whereas five years is the most liquid (Junge and Trolle, 2015). In exchange for periodic, fixed coupon payments, the protection seller commits to providing default protection on each index constituent. As with single-name CDS contracts, the periodic payments are fixed to either 100 bps or 500 bps with an upfront payment equal to the present value of the contract. The major index CDS provider is IHS Markit, which administrates the most prominent products, including the CDX and iTraxx indices focused on North America and the rest of the world. The recent Global CDS Market study by ISDA (2019) shows that the five major CDS indices – CDX.NA.IG, CDX.NA.HY, iTraxx Europe, iTraxx Europe Crossover, and iTraxx Europe Senior Financials – account for more than 90% of the overall index CDS market activity.

The index constituents are selected based on criteria set by IHS Markit, which primarily focus on liquidity, respective business sectors, and geographical location. CDX and iTraxx indices are rolled twice a year in March and September. If necessary, index constituents are replaced based on the index-specific criteria and requirements, and reference obligations are updated during the process. The newly launched index series is referred to as being on the run while the outdated index continues to trade off the run. As with government bonds, a drop in liquidity and market activity is observed in the off-the-run series after the index is rolled (Junge and Trolle, 2015).

In case of a credit event by one of the index constituents, the protection buyer and the protection seller can trigger the contract. The triggered company is stripped out of the contract, and the protection buyer receives the loss given default (1-Recovery Rate), as with a regular single-name CDS contract. Furthermore, a new version of the index is launched, excluding the relevant entity. The weight of the stripped-out entity reduces the notional amount on the new version of the index, and the CDS premium is paid on the reduced notional going forward.

Due to the importance of liquidity in the CDS market and the large liquidity differences between CDSs included in an index and those not included, we focus our analysis on companies included in indexes. This is discussed in further detail in the data selection section (section 4.1).

2.3.5 Pricing CDS Contracts

The Credit Default Swap (CDS) contract provides the owner with insurance against a contingent credit event of the underlying company, i.e., the reference entity (Hull, 2018). The protection buyer makes periodic CDS premium payments, usually quarterly or semi-annual, to the protection seller throughout the term of the contract or until a credit event is triggered. The CDS spread is a percentage of the insured notional amount specified in the contract. In case of a credit event, the CDS contract is settled in cash, i.e., the protection seller pays out the loss given default, 1 − Recovery Rate, determined by the mid-market price through an auction process.

CDS contracts can be priced in multiple ways, for example, through an arbitrage-free pricing model by setting up a portfolio comprising a default-free and a defaultable floating-rate par bond (Duffie, 1999). The net cash flows of going long the former and short the latter correspond to the credit spread. The net payments coincide with the payment structure of a CDS contract whether a credit event occurs or not and, hence, the CDS spread must equal the credit spread over the risk-free rate on the long-short portfolio in the absence of arbitrage. Noteworthy, this pricing approach is only an approximation as several market frictions can prevent the equation from holding precisely in practice.

Another pricing approach results from the structural credit risk model introduced and shaped by the work of Black and Scholes (1973) and Merton (1974). These models assume default occurs when a firm's asset value, which is assumed to evolve randomly over time, plunges below a defined default boundary. Credit spreads in structural models are determined mainly by leverage, asset volatility, and macroeconomic conditions. While widely applied to model credit risk, the approach suffers from its inaccuracy in empirically explaining the magnitude of credit spreads, referred to as the *Credit Spread Puzzle* (Augustin et al., 2014). Du et al. (2013) use time-varying volatility in trying to explain the *credit risk puzzle* in structural credit risk models and finds that exchanging constant asset volatility, as assumed in the classic Merton (1974) model, with time-varying asset volatility can solve the puzzle partially. Motivated by these results, we include option-implied volatility for two different durations (30 days and 90 days) into our analysis on the determinants of CDS spreads in section 5.4.

In a reduced-form model, the default time follows a Poison process based on an underlying probability distribution. The most widely used approach is from Jarrow and Turnbull (1995). However, given the latent default process, the model does not consider other macroeconomic determinants of credit spreads.

The cash flows of a CDS contract are commonly split into the premium leg and the protection leg. The CDS par spread is then resulting from solving the following equation

$$PV(\text{premium leg}) = PV(\text{protection leg}) \tag{2.8}$$

In the reduced-form model, the conditional probability of a default occurring between $[t, t + \Delta t]$

can be written as

$$PV(\tau < t + \Delta t | \tau \geq t) = \lambda(t)\Delta t \tag{2.9}$$

with $\lambda(t)$ being the default intensity derived under the risk-neutral measure. Hence, the survival probability to maturity at time T, conditional on the reference entity not defaulting up to the valuation time t_V, $Q(t_V, T)$, is characterized by

$$Q(t_V, T) = e^{-\int_{t_V}^{T} \lambda(s)ds}. \tag{2.10}$$

To obtain the CDS par spread, both the present value of the premium leg and the protection leg have to be equal at inception. Following the approach from Duffie and Singleton (1997) and assuming the risk-free rate r_t and the default intensity λ to follow an independent stochastic process, the term structure can be specified exogenously. By assuming a continuous payment of the premium s for simplicity, the premium leg $P(s, T)$ can be obtained by

$$P(s, T) = E\left[s \int_0^T e^{-\int_0^t r_s + \lambda_s ds} dt\right] \tag{2.11}$$

Further, the protection leg can be written as

$$P(w, T) = E\left[w \int_0^T \lambda_t e^{-\int_0^t r_s + \lambda_s ds} dt\right] \tag{2.12}$$

whereas w is the expected loss to a bondholder in case of a credit event. Finally, the CDS par spread is obtained from equating equation 2.11 and 2.12

$$s = \frac{E\left[w \int_0^T \lambda_t e^{-\int_0^t r_s + \lambda_s ds} dt\right]}{E\left[\int_0^T e^{-\int_0^t r_s + \lambda_s ds} dt\right]} \tag{2.13}$$

Since the CDS par spread is only used for quoting purposes and CDS contracts trade with a fixed coupon and an adjustable upfront payment, it is worth noting how to translate the par spread into the contract's corresponding upfront payment $U(t)$

$$U(t) = (s - c) * PVBP(t) \tag{2.14}$$

$$PVBP(t) = e^{-\int_0^t r_s + \lambda_s ds} \tag{2.15}$$

whereas c is the fixed coupon rate, and $PVBP(t)$ is the present value of a basis point.

2.3.6 CDS Returns

As outlined in the previous section, there are multiple approaches to pricing CDS contracts. Consequently, there are multiple ways in which academic literature calculates returns on these contracts. The lack of available actual transaction prices for specific CDS contracts presents the main challenge in accurately calculating CDS returns (Berndt and Obreja, 2010). The available spread quotes on a reference entity obtained from IHS Markit are based on at-market spreads for newly issued CDS contracts with a fixed maturity. Therefore, CDS returns must be approximated based on the data available.

With the introduction of the Big and Small Bang protocols in 2009 (see section 2.3.2) and the henceforth standardization of coupons in CDS contracts, the cash-flow structure of credit default swaps has changed remarkably. In brief, CDS contracts are no longer issued at zero initial investment but priced through a varying upfront payment, while the periodic coupon rate is fixed over the term of the agreement. Therefore, par spreads for CDS no longer represent the actual price of the contract but instead are only used for quotation. Given the significant change in the cash-flow structure of the contracts, it becomes more appropriate to no longer calculate returns based on CDS spreads but rather on CDS upfront prices, given that ignoring the price paid for the contract can have a significant impact on returns (Augustin et al., 2020).

The different existing return calculation approaches vary significantly in their complexity and, more importantly, their accuracy compared to actual CDS returns (Augustin et al., 2020). Ericsson et al. (2009) approximates CDS returns by the simple change in credit spreads over a given period

$$R_{t,t+1} = \Delta s_{t+1} = s_{t+1} - s_t \tag{2.16}$$

In their paper on analyzing information flows between the stock and CDS market, Hilscher et al. (2015) approximate the return on a credit insurance contract by the percentage change of the quoted CDS spread for a given fixed maturity

$$R_{t,t+1} = \frac{\Delta s_{t+1}}{s_t} = \frac{s_{t+1} - s_t}{s_t} \tag{2.17}$$

which can also be expressed as the first difference in the logarithm of the CDS spread

$$R_{t,t+1} = \Delta \log s_{t+1} = \log \frac{s_{t+1}}{s_t} \tag{2.18}$$

In addition, they apply the approach by Berndt and Obreja (2010) and Bongaerts et al. (2011) to multiply the change in quoted CDS spreads with a fixed annuity factor. In Berndt and Obreja (2010), the excess return of a defaultable risky bond over the return of a risk-less bond, i.e., the credit risk, is equal to minus the CDS return times the value of a t-year risky annuity.

The defaultable annuity can be calculated using the risk-free rate and the risk-neutral survival probability, which they simplify by assuming a constant risk-neutral default intensity. Lastly, the authors argue that the risk-neutral default intensity can be directly obtained from the quoted CDS spread.

He et al. (2017) and Kelly et al. (2019) add an additional component to the return calculation to reflect the carry component stemming from the coupon payments (Augustin et al., 2020).

The change in the cash-flow structure and the usually non-zero value at the initiation of a CDS contract logically calls for a calculation approach that takes this structure into account more accurately. As shown in Augustin et al. (2020), the correlation between actual CDS returns and the approximations based on the above-introduced approaches is as low as 20% in their empirical test.

Augustin et al. (2020) therefore propose an alternative, pure cash flow-based approach to calculate CDS returns by first deriving the CDS upfront price and then computing returns based on these prices.

The upfront price of the CDS, P_t, is the difference between the present value of the protection leg, π_t^s, and the premium leg, π_t^b,

$$P_t = \pi_t^s - \pi_t^b \tag{2.19}$$

given by

$$\pi_t^s = (1 - R) \sum_{i=1}^{n} DF_t(t_i - t)[Q_t(t_{i-1} - t) - Q_t(t_i - t)] \tag{2.20}$$

and

$$\pi_t^b = c \sum_{i=1}^{n} DF_t(t_i - t) Q_t(t_i - t) \Delta_i \tag{2.21}$$

Following the standard ISDA convention and assuming an exponential distribution with mean $\frac{1}{\lambda_t}$, with λ_t for the constant default intensity to determine the random time of default, simplifies the formula to

$$P_t = (s_t - c) \sum_{i=1}^{n} DF_t(t_i - t) \Delta_i e^{-\lambda_t (t_i - t)} \tag{2.22}$$

from which the CDS return is easily obtained by

$$R_{t,t+1} = \frac{P_{t+1} - P_t}{P_t} \tag{2.23}$$

However, as this approach is computationally involved and slow in computation time (Augustin et al., 2014), the authors propose a simple approximation that delivers highly accurate return approximations compared with the above-presented CDS return approach. Furthermore, by having a correlation of at least 99% with the true cash-flow-based approach, the authors' approximation outperforms the previously introduced approaches in terms of accuracy. Following their approach, the CDS price is obtained by converting the quoted CDS spread using the below formula

$$\tilde{P}_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left[1 - e^{-\left(r_t + \frac{s_t}{1-R}\right)(T-t)}\right] \tag{2.24}$$

using the directly observable values for the quoted CDS spread (s_t), the fixed coupon (c), the expected recovery rate (R) and the ($T - t$)-year risk-free rate (r_t). The CDS return is consequently obtained by

$$\tilde{R}_{t,t+1} = \frac{\tilde{P}_{t+1} - \tilde{P}_t}{\tilde{P}_t} \tag{2.25}$$

Given the empirical results regarding calculation accuracy and the particular importance of accurate computation of CDS returns when assessing investment strategies, as stressed by the authors, we follow the suggestion by Augustin et al. (2020) in using an approximation of a true cash-flow-based approach to compute CDS prices and subsequent returns. While we adopt the approximation of converting quoted CDS spreads to CDS upfront prices given by equation 2.24, a different approach to calculate returns is used to evaluate the performance of our trading strategies in section. Compared to the return calculation in equation 2.25, we include a notional in the price used for the calculation.

As in Junge and Trolle (2015) who propose a similar true cash-flow-based approach to compute CDS returns, we assume that 100% of the notional is required in collateral on top of the upfront price when investing in the CDS. This is assumed to be the case for both sides of the contract. Further, returns are calculated by the percentage change in the collateral and the CDS upfront price. A side effect of this is that it significantly reduces the volatility of the CDS return component. We assume a zero interest rate on the posted collateral.

2.3.7 Liquidity in the CDS Market

As section 2.1.2 on market liquidity shows, incomplete market activity can be considered a substantial market friction that prevents markets from being efficient. These inefficiencies often lead to an incomplete integration of information into asset prices and considerably higher transaction costs.

Given the development of the CDS market in the aftermath of the financial crisis, especially the sharp shrinkage of the single-name segment, a thorough investigation of the CDS market from a liquidity perspective is important. Among the early papers addressing this topic, Longstaff et al. (2005) investigate the default and non-default components within CDS spreads. Their results indicate that even for the highest rated investment grade companies, more than half of the spread can be attributed to default risk. While they also find a significant non-default component that can be partly attributed to the liquidity in CDS markets, they conclude that CDS spreads can be interpreted as a pure measure of credit risk. The findings are empirically confirmed by Fabozzi et al. (2007) who find no liquidity premium in CDS spreads in their paper.

However, more recent empirical literature finds contradicting evidence that CDS spreads indeed are a function of liquidity. Tang and Yan (2007) measure liquidity through a ratio of CDS spread volatility to the number of quotes on the contract. The results indicate that CDS spreads contain an 11% liquidity premium of the mid quote, which the contract seller earns. Findings are confirmed by Bongaerts et al. (2011) who find strong evidence for an expected liquidity premium, measured by the bid-ask spread earned by the protection seller. Bühler and Trapp (2009) develop an extension to the reduced-form CDS pricing model by incorporating a liquidity measure of bid-ask spreads. The authors find a liquidity premium of approximately 5% of the mid-quote.

By using the contract's depth[8] as a proxy for liquidity, Qiu and Yu (2012) find that even though higher liquidity on average leads to a decrease in CDS spreads due to competition, it may also increase CDS spreads as the number of dealers can work as a proxy of asymmetric information. That is, a higher number of dealer quotes may imply that dealers are in possession of information that the general market does not have. Further, liquidity is concentrated around the investment grade/high yield cutoff. Moreover, excess market volatility in CDS returns compared to fundamental firm volatility is explained by the illiquidity in the CDS market according to Bao and Pan (2013).

Systematic liquidity risk in the CDS market is investigated by Junge and Trolle (2015) who construct a tradable liquidity factor from the divergence of the CDS index level from its implied no-arbitrage value, computed by replicating the index using single-name CDS contracts. The authors find that liquidity risk, on average, makes up 24% of CDS spreads and, further, that the impact of contract-specific liquidity risk becomes less severe after accounting for systematic liquidity risk (Junge and Trolle, 2015).

Furthermore, market liquidity is considered a primary contributor to short-term pricing discrepancies between the stock and CDS market (Kapadia and Pu, 2012). By defining a market integration measure on a firm-level based on the frequency of arising arbitrage opportunities across the equity and CDS market, the authors find a highly significant and economically important influence of illiquidity on market integration. In particular, a one standard deviation

[8] The depth of a CDS contract counts the number of dealers who provide quotes on a reference entity.

move in liquidity is, on average, associated with a 9.5% move in the variability of equity-credit market integration (Kapadia and Pu, 2012). Especially the dry-up of the CDS market during the financial crisis led to the disconnecting of markets for more volatile and riskier firms. Given the focus of this paper on market integration, liquidity is further investigated in this context as part of the empirical analysis.

3 Econometric Theory

This section explains the econometric theories and methodologies applied in the paper. The methods and the practical implications from these are important for the considerations made in our empirical analysis.

3.1 Stationarity

Within time series modelling the stationarity of a series has important implications for assumptions and methods applicable. For a stationary time series, the mean, variance, and autocorrelations can be approximated by time averages, meaning that for all t and $t-s$

$$E(y_t) = E(y_{t-s}) = \mu \tag{3.1}$$

$$E[(y_t-\mu)^2] = E[(y_{t-s}-\mu)^2] = \sigma_y^2 \qquad [var(y_t) = var(_{y-s} = \sigma_y^2] \tag{3.2}$$

$$\begin{aligned} E[(y_t-\mu)(y_{t-s}-\mu)] = E[(y_{t-j}-\mu)(y_{t-j-s}-\mu)] = \gamma_s \\ [cov(y_t, y_{t-s}) = cov(y_{t-j}, y_{t-j-s}) = \gamma_s] \end{aligned} \tag{3.3}$$

We consider an AR(1) model with the white noise term ε_t

$$y_t = a_0 + a_1 y_{t-1} + \varepsilon_t \tag{3.4}$$

For a stationary time series we require $a_1 < 1$ such that the time series mean-reverts over time. In the case of $a_1 = 1$ the process is non mean reverting causing it to go to infinity as time goes to infinity Enders (2015).

In order to formally test the stationarity of a time series, we can use the Dickey-Fuller test. The test uses equation 3.4 from which it subtracts y_{t-1}. Doing this gives

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{3.5}$$

where $\gamma = a_1 - 1$ allowing for us to test the null hypothesis of $\gamma = 0$, which is equivalent to testing if $a_1 = 1$. The test can be conducted using OLS, after which the t-statistics can be compared to critical values from the Dickey-Fuller distribution reported by Dickey and Fuller (1979).

While the simple Dickey-Fuller test assumes that the ε's are uncorrelated, adding lagged values of Δy as regressors allows for us to relax that assumption. Further, we can add drift and trend terms to the equation in order to more accurately describe the time series process we are assessing

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{3.6}$$

where a_0 and $a_2 t$ are drift and trend terms, respectively. F-statistics from the regression are used to test the joint hypothesis of $a_0 = \gamma = a_2 = 0$ by comparing to critical values provided by Dickey and Fuller (1981) (Enders, 2015).

3.2 Vector Autoregressive Model (VAR)

Within a multivariate setting, where we are uncertain about which variable is indeed exogenous, a Vector Autoregressive (VAR) model can be used to help select the relevant variables and to let the data specify the dynamic structure of the model. Within a VAR model, each variable is treated symmetrically (Enders, 2015) and allows each potential endogenous variable to be affected not only by past realizations of its own sequence but also by current and past realizations of all other variables in the model. Equation 3.7 and 3.8 display a bivariate VAR model of order p (the order is determined by the lag length) as this will also be used later on in our analysis.

$$y_t = \alpha_{10} + \gamma_{10} z_t + \sum_{j=1}^{p} \beta_{1j} y_{t-j} + \sum_{j=1}^{p} \gamma_{1j} z_{t-j} + \varepsilon_{yt} \tag{3.7}$$

$$z_t = \alpha_{20} + \gamma_{20} y_t + \sum_{j=1}^{p} \beta_{2j} y_{t-j} + \sum_{j=1}^{p} \gamma_{2j} z_{t-j} + \varepsilon_{zt} \tag{3.8}$$

The setup further assumes that both time series y_t and z_t are stationary (see section 3.1) and the error terms ε_{yt} and ε_{zt} are uncorrelated as well as white noise with a constant standard deviation of σ_y and σ_z, respectively. The lag length p is chosen such that all dynamics are captured in the model and there is no remaining autocorrelation in the error term, i.e, the error terms ε_{yt} and ε_{zt} are white noise. In practice, information criteria (such as the AIC or BIC) can be chosen to determine the length of the model. As described in Enders (2015) the model allows for feedback effects across y_t and z_t whereas the error terms ε_{yt} and ε_{zt} also have an indirect contemporaneous effect across variables. Due to the contemporaneous effects from y_t

on z_t and vice versa, the system of equation can no longer be estimated by simple OLS as it would suffer from a simultaneity bias but can be transformed into matrix notation. However, we can move from a structural VAR model to a reduced form VAR model by transforming the system of equations such that we have no contemporaneous effects among y_t and z_t but contemporaneously correlated errors (see Enders, 2015). The equations in the reduced form model can then be estimated by OLS which provides consistent and efficient estimates when assuming normality of the error terms (alternatively Maximum Likelihood (ML) estimation can be applied). As with other univariate AR models, the stationarity of the VAR(p) model is checked by assessing that the characteristic roots all lie inside the unit circle. Again as mentioned in section 3.1 this can be tested by applying the Dickey-Fuller test or its augmented version (see Dickey and Fuller, 1979).

3.2.1 VAR in Differences

Given the non-stationary nature of our main data – CDS spreads and equity prices – it is convenient to briefly look at the theory behind VAR models of first differences as this model will be used for data pairs between CDS and equity prices that are not cointegrated as tested by the Johansen test (see Johansen, 1988). As it is possible to write a VAR model in first differences even if the data are integrated of order one $I(1)$ but not cointegrated, this allows to perform further analysis such as testing for Granger causality (see section 5.3.2) as the standard F-distribution is valid to use.

3.2.2 Granger Causality

To assess causality, one possible approach is to test whether the past realizations of one variable statistically significant explain another variable within a VAR framework. Continuing in our bivariate VAR model with p lags (see 3.9 and 3.10 transformed from a structural form in section 3.2 to a reduced form model), a variable z_t does **not** *Granger cause* y_t if and only if all coefficients γ_{1j} on the lagged variables of z_t (i.e. z_{t-1} to z_{t-p}) are equal to zero, vice versa (Enders, 2015)

$$y_t = \alpha_{10} + \sum_{j=1}^{p} \beta_{1j} y_{t-j} + \sum_{j=1}^{p} \gamma_{1j} z_{t-j} + \varepsilon_{yt} \tag{3.9}$$

$$z_t = \alpha_{20} + \sum_{j=1}^{p} \beta_{2j} y_{t-j} + \sum_{j=1}^{p} \gamma_{2j} z_{t-j} + \varepsilon_{zt} \tag{3.10}$$

A corresponding hypothesis test using a appropriate null hypothesis H_0 can be set up to test for causality. Further, if all variables in the VAR model are in fact stationary, a Wald test or a Likelihood Ratio (LR) test can be applied to test the imposed restrictions. Again, given the non-stationary nature of our dataset the test will later be applied on a VAR in difference model to ensure stationarity and consequently validity of the Granger test. The appropriate number of lags p to include in the test should result from having no remaining autocorrelation in the error terms and can be obtained from using information criteria (such as AIC and BIC). For a variable to *Granger cause* another variable, the variable should help explain another variable while the opposite should not be. More formally, for y_t to *Granger cause* z_t we would need to reject the null hypothesis of y_t not affecting z_t but should not reject the null hypothesis of the opposite test that z_t is not affecting y_t.

Two general problems in addition to specifying the correct number of lags is that the conclusion of the test is affected by the information set used in the regression models. For example, a third not included variable x_t that causes both y_t and z_t could distort the results of the test leading to false conclusions.

3.3 Panel Data & Pooled Ordinary Least Squares (POLS)

Panel data can be described as having data on the same cross section over time allowing us to assess dynamic relationships of variables over time. The following section provides a brief overview over the main assumptions and characteristics of a pooled OLS model to build the foundation for further empirical analysis in later sections.

A basic pooled OLS model can be written as

$$y_t = \mathbf{x_t}\boldsymbol{\beta} + u_t, \quad t = 1, 2, ..., T \tag{3.11}$$

whereas we are able to add a subscript i (y_{it}) when referring to a particular cross section observation (see Wooldridge, 2010). The first two sufficient assumption for a correctly specified model are as following

Assumption 1. ***POLS.1:*** $E(\mathbf{x_t}'u_t) = 0, \quad t = 1, 2, ..., T$

Assumption 2. ***POLS.2:*** $rank\left[\sum_{t=1}^{T} E(\mathbf{x_t}'\mathbf{x_t})\right] = K$

Furthermore, to use the common OLS statistics it must be ensured that there is (a) homoskedasticity and (b) no serial correlation leading to

Assumption 3. ***POLS.3:*** *(a)* $E(u_t^2\mathbf{x_t}'\mathbf{x_t}) = \sigma^2 E(\mathbf{x_t}'\mathbf{x_t}), \quad t = 1, 2, ..., T$ *where* $\sigma^2 = E(u_t^2) \forall t$; *(b)* $E(u_t u_s \mathbf{x_t}'\mathbf{x_s}) = \mathbf{0}, \quad t \neq s, t, s = 1, ..., T$

POLS.3(a) assumes full homoskedasticity while POLS.3(b) requires the conditional covariances of the error terms to be zero. It follows from POLS.1 and POLS.2 that the estimator is consistent and unbiased.

Further, it is appropriate to apply methods that account for potential breaches of the assumptions listed above. We use heteroskedasticity robust standard errors to tackle the issue as outlined in more detail in Newey and West (1987).

3.3.1 Random Effect Models

Unobserved effects in panel data models can significantly influence the accuracy of model predictions. Consequently, a variety of unobserved effects models have been developed. The standard unobserved effects model can be written as by equation 3.12

$$y_{it} = \mathbf{x_{it}}\boldsymbol{\beta} + c_i + u_{it}, \quad t = 1, 2, ..., T \tag{3.12}$$

where c_i represents the unobserved effect. Discussions often center around whether the unobserved effect is random or fixed and, consequently, can be estimated.

In the random effect framework, strict exogeneity and orthogonality is assumed between c_i and $\mathbf{x_{it}}$.

Assumption 4. ***RE.1:*** $E(u_{it}|\mathbf{x_{it}}, c_i) = 0, \quad E(c_i|\mathbf{x_{it}}) = E(c_i) = 0 \quad t = 1, 2, ..., T$

Further, the unobserved effect is included into the error term, u_{it}, allowing for equation 3.12 to be rewritten as

$$y_{it} = \mathbf{x_{it}}\boldsymbol{\beta} + v_{it}, \quad \text{where} \quad v_{it} = c_i + u_{it} \quad t = 1, 2, ..., T \tag{3.13}$$

$$E(v_{it}|\mathbf{x_{it}}) = 0, \quad t = 1, 2, ..., T \tag{3.14}$$

In case of serial correlation in the new error term, v_{it}, stemming from

$$E(v_{it}, v_{is}) = \sigma_c^2 \neq 0 \tag{3.15}$$

a GLS transformation using the below assumptions (RE.1-3) can be applied to eliminate the serial correlation and to obtain an unbiased and efficient estimator.

Assumption 5. ***RE.2:*** *rank* $E(\mathbf{X_i'}\boldsymbol{\Omega}^{-1}\mathbf{X_i}) = K$, *where* $\boldsymbol{\Omega}^{-1} = E(\mathbf{v_i}\mathbf{v_i'})$

Assumption 6. ***RE.3:*** $E(\mathbf{u_i}\mathbf{u_i'}|\mathbf{x_i}, c_i) = \sigma_u^2\mathbf{I_T}, \quad E(c_i^2|\mathbf{x_i}) = \sigma_c^2$

First, define

$$\lambda = 1 - \left[\frac{\sigma_u^2}{\sigma_u^2 + T\sigma_c^2}\right]^{\frac{1}{2}} \tag{3.16}$$

and then the data are transformed by

$$y_{it} - \lambda \bar{y}_i = \beta_0(1-\lambda) + \beta_1(x_{it1} - \lambda \bar{x}_{i1}) + ... + \beta_K(x_{it1} - \lambda \bar{x}_{iK}) + (v_{it} - \bar{v}_i) \tag{3.17}$$

Finally, the model can be estimated by OLS.

3.3.2 Fixed Effect Models

While the unobserved effect in the random effect model is treated as a random variable, it is treated as a fixed parameter which can be estimated for each observation i in the fixed effect framework (Wooldridge, 2010). Equation 3.12 can therefore be rewritten as

$$\mathbf{y_i} = \mathbf{X_i}\boldsymbol{\beta} + c_i\mathbf{j_T} + \mathbf{u_i}, \tag{3.18}$$

where $\mathbf{j_T}$ is a $T \times 1$ vector of ones (Wooldridge, 2010). As in the random effect framework, we again assume strict exogeneity conditional on the unobserved effect whereas we allow $Ec_i|\mathbf{x_i})$ to be any function of $\mathbf{x_i}$ (see FE.1).

Assumption 7. ***FE.1:*** $\quad E(u_{it}|\mathbf{x_i}, c_i) = 0, \quad t = 1, 2, ..., T$

Similar to a first differencing approach, we we apply a data transformation prior to estimation to remove a part of the unobserved error component. For the fixed effects transformation, we first average equation 3.18

$$\bar{y}_i = \mathbf{\bar{x}_i}\boldsymbol{\beta} + c_i + \bar{u}_i \tag{3.19}$$

and further subtract equation 3.19 from equation 3.12

$$y_{it} - \bar{y}_i = (\mathbf{x_{it}} - \mathbf{\bar{x}_i})\boldsymbol{\beta} + u_{it} - \bar{u}_i \tag{3.20}$$

which can be also written as

$$\ddot{y}_{it} = \mathbf{\ddot{x}_{it}}\boldsymbol{\beta} + \ddot{u}_{it}, \quad t = 1, 2, ..., T \tag{3.21}$$

The demeaning process has successfully removed the unobserved effect, c_i, from equation 3.21. In order to apply pooled OLS techniques on the transformed model, the pooled OLS assumptions (POLS.1-3) need to be satisfied. If the following two additional assumptions FE.2 and FE.3 are fulfilled, the FE estimator is consistent in estimating the transformed data.

Assumption 8. ***FE.2:*** $\quad rank\left[E(\mathbf{\ddot{X}_i'\ddot{X}_i})\right] = K$

Assumption 9. ***FE.3:*** $\quad E(\mathbf{u_i u_i'}|\mathbf{x_i}, c_i) = \sigma_u^2\mathbf{I_T}$

3.3.3 Clustered Standard Errors

While panel data models are popular and widely used in finance Petersen (2009) finds that around 42% of researchers do not adjust their model's standard errors for dependence. Petersen (2009) splits his analysis into investigating unobserved firm effects, i.e., correlation of a company's residuals over time, and cross-sectional dependence. We focus on the first type of bias due to its relevance in our later application of pooled OLS models. Overall, it can be shown that standard errors are systematically underestimated when using classic OLS, Fama-MacBeth, and even Newey-West standard errors even though the bias of the ladder is small (Petersen, 2009).

OLS standard errors in panel data often suffer from the violation of assuming independent errors. Petersen (2009) relaxes this assumption, splits up the residuals in a firm-specific component and an idiosyncratic component, and further assumes that the independent variable also contains a firm-specific component. By combining these assumptions, Petersen (2009) shows how to correct OLS standard errors by tackling the issue of the residual's correlation within a cluster.

3.4 Cointegration

Generally, variables are said to be cointegrated if they are integrated of the same order (larger than 0) and at the same time have a common stochastic trend. More specifically, a linear combination of them should be stationary. Formally, we can start by considering a set of cointegrated economic variables such that the long-run equilibrium can be described by

$$\beta_1 x_{1t} + \beta_2 x_{2t} + ... + \beta_n x_{nt} = 0 \tag{3.22}$$

If β describes the vectors $(\beta_1, \beta_2, ..., \beta_n)$ and x_t describes $(x_{1t}, x_{2t}, ..., x_{nt})'$, the long run equilibrium is given by

$$\beta x_t = 0 \tag{3.23}$$

The equilibrium error e_t is then defined as

$$e_t = \beta x_t \tag{3.24}$$

In order for the variables to be cointegrated we require that the equilibrium error process is stationary.

3.4.1 Testing for Cointegration

One way of testing whether a set of variables are cointegrated is by using the Johansen procedure. The procedure can be considered an n-variable generalization of the Dickey-Fuller test, where A_1 is an $(n \cdot n)$ matrix of parameters

$$x_t = A_1 x_{t-1} + \varepsilon_t \tag{3.25}$$

Differencing the equation gives us:

$$\Delta x_t = \pi x_{t-1} + \varepsilon_t \tag{3.26}$$

Where $\pi = (A_1 - I)$ and I is an $(n \cdot n)$ identity matrix. As we did for the Dickey-Fuller test we can expand this equation to allow for p-order autoregressive processes

$$\Delta x_t = \pi x_{t-1} + \sum_{i=1}^{p-1} \pi_i \Delta x_{t-i} + \varepsilon_t \tag{3.27}$$

where $\pi = -\left(I - \sum_{i=1}^{p} A_i\right)$ and $\pi_i = -\sum_{j=i+1}^{p} A_j$. The rank of π is the number of independent cointegrating vectors.

In order to make conclusions about the rank of π we need to obtain estimated values of the characteristic roots of π. The estimates of the characteristic roots are defined as $\hat{\lambda}_i$. Having T observations, the following two test statistics are used to estimate the number of characteristic roots that are insignificantly different from unity

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} ln(1 - \hat{\lambda}_i) \tag{3.28}$$

$$\lambda_{max}(r, r+1) = -T\, ln(1 - \hat{\lambda}_i) \tag{3.29}$$

Here λ_{trace} has the null that the number of cointegrating vectors is less than or equal to r against an alternative of more than r cointegrating vectors. Setting $r = 0$ allows for us to test if there are more than 0 cointegrating relationships. If we do not reject the null, we are unable to conclude that the number of cointegrating vectors is larger than zero. If we reject the null in equation 3.28 we can continue investigating the exact rank of π.

λ_{max} has the null of exactly r cointegrating vectors against an alternative of $r+1$ cointegrating vectors. We proceed by first setting $r = 1$ and then only continuing if we reject the null. If we for some r fail to reject the null, we can conclude that the rank of π and thereby the number of cointegrating vectors is equal to that particular value for r. Importantly, the rank of π should be lower than n in order for cointegrating relationships to exist. In the case of $r = n$ the x's are all stationary, which contradicts the condition that variables in a cointegrating relationship need to be integrated of an order larger than zero (Enders, 2015)

When testing for cointegrating relationships we use the critical values for λ_{trace} and λ_{max} simulated by Osterwald-Lenum (1992).

3.4.2 Vector Equilibrium Correction Model (VECM)

As explained in section 3.2.1 VAR models can be estimated on nonstationary data by using the first difference. Another approach is to estimate a Vector Equilibrium Correction Model (VECM), which builds on a cointegrating relationship between variables while allowing for them to be nonstationary. By building on a cointegrating relationship, the model incorporates long-run relationships between the variables, which are useful for analyzing certain features of these processes. This is discussed in section 3.4.3.

Using the same methodology as when estimating a VAR model (see section 3.2), we can estimate a two-variable VECM

$$\Delta y_t = \alpha_1 + \lambda_1 V_{t-1} + \sum_{j=1}^{p} \beta_{1j} \Delta y_{t-j} + \sum_{j=1}^{p} \gamma_{1j} \Delta z_{t-j} + \varepsilon_{yt} \tag{3.30}$$

$$\Delta z_t = \alpha_2 + \lambda_2 V_{t-1} + \sum_{j=1}^{p} \beta_{2j} \Delta y_{t-j} + \sum_{j=1}^{p} \gamma_{2j} \Delta z_{t-j} + \varepsilon_{zt} \tag{3.31}$$

with $V_{t-1} = y_{t-1} - \alpha_0 - \beta_0 z_{t-1}$. As such the model is very similar to a VAR model with the main difference being the equilibrium correction term (Juselius, 2006).

3.4.3 Measures of Informational Discovery

Once the VECM has been specified the parameters and their significance can be used to make inferences as to which of the components in the cointegrating system that are permanent. Components not considered permanent are transitory. Generally, permanent components have long-run adjustment effects on other components of the system. The permanent components can also be interpreted as the processes in which the informational discovery of the system happens. Relating this to the VECM model in 3.30 and 3.31, the significance of the parameters on the equilibrium correction terms V_{t-1} can be used to determine where the informational discovery happens. If λ_1 is significantly different from zero, z contributes to the information discovery. Similarly, if λ_2 is significantly different from zero, y contributes to the informational discovery. If both λ's are significant, both parameters contribute to the informational discovery. In addition to the suggestions above, Gonzalo and Granger (1995) propose the Gonzalo-Granger

(GG) measure to determine where the informational discovery in a cointegrating relationship happens

$$GG = \frac{\lambda_2}{\lambda_2 - \lambda_1} \tag{3.32}$$

with$\lambda_1 \neq \lambda_2$. The value GG measure gives an estimation of the proportion of the informational discovery which happens in the y process (still referring to the specific system of equation 3.30 and 3.31). Consequently, the remaining proportion $(1 - GG)$ happens in the z process.

Another measure of informational discovery is the Hasbrouck model of *information shares* (Hasbrouck, 1995), which is developed specifically for determining contributions to price discovery of securities trading in multiple markets. The measure is based on the idea that price innovation variance is a measure of the information intensity of the particular price process. The proportion of the innovation variance that can be attributed to the particular market defined as the *information share*. In cases where prices are contemporaneously determined, the model can only be used to set bounds for the information share's and not to estimate the exact proportions. These bounds are given by

$$HAS_1 = \frac{\lambda_2^2 \left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2} \tag{3.33}$$

$$HAS_2 = \frac{\left(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2} \tag{3.34}$$

where σ_1^2, σ_2^2, and σ_{12} represent the covariance matrix of the residuals ε_{yt} and ε_{yz} in equation 3.30 and 3.31, respectively. HAS_1 and HAS_2 set the bounds for the information share of the y process. Baillie et al. (2002) argue that the average of the bounds can be used as an estimate of the price discovery, even when price innovations are correlated.

4 Data

4.1 Selection Criteria

Our dataset contains quoted CDS spreads, equity prices, and corresponding firm-, liquidity- and macroeconomic-related information from January 2, 2014, to December 31, 2021. The sample contains investment grade and high yield companies across the U.S. and Europe. Daily data for the period from 2014 to 2021 is obtained from two primary data sources – CDS-related information is obtained from IHS Markit, the leading data provider for credit pricing data, while equity prices, option-implied volatility, and macroeconomic indicators, are obtained from Bloomberg.

Our dataset is selected through the use of some pre-set rules to ensure a high quality of the data and omit potential biases and misspecifications in our empirical analysis. First, we restrict our analysis to five-year CDS contracts as those have consistently been the most liquid and actively traded throughout our sample period and the existence of the CDS market (Zhang et al., 2009; Junge and Trolle, 2015; Mateev and Marinova, 2017). We use CDS contracts on senior, unsecured debt with quarterly premium payments and, further, follow the approach by Junge and Trolle (2015) to select contracts with contract terms that are the industry standard during our sample period. In particular, we use Euro-denominated contracts with a modified-modified restructuring (MMR) clause for our European subsample and USD-denominated contracts with no restructuring (XR) clause for the U.S. subsample. Moreover, all obligors in our sample, investment grade and high yield, are constituents of either the CDX or the iTraxx index family. This approach is also applied by Kapadia and Pu (2012) as it ensures continuity in price quotes which is particularly relevant when working with daily data. Furthermore, the decision is motivated by the fact that the liquidity of a single-name CDS contract is among the main selection criteria for being included in a CDS index (IHS Markit, 2021). Moreover, single-name CDS also become more liquid as a result of being an index constituent due to investment strategies, such as relative-value trading and index arbitrage.

Given the focus of our paper on market integration and information spillovers across the CDS and the equity market data availability and its quality must also be ensured for equity prices. Therefore, the remaining companies are further filtered based on whether the reference entity is trading publicly and has a frequently traded stock price. Several reasons cause a company to be excluded from our sample, whereas mergers, takeovers, leveraged buyouts (LBOs), and a privately held company are the most prominent causes. Noteworthy, the size of our high yield subsample is particularly impacted by applying these rules, while the European sample shrink the most from excluding reference entities not trading publicly. In 2014 a total of 430 companies were included in the four indexes used. Removing companies that are not part of the indexes in years up until and including 2021 and companies that are not publicly traded shrinks the sample to 245 companies.

The extensive length of our dataset allows us to obtain a statistically significant and economically relevant contribution from a company to our empirical analysis even if data are missing for a particular, short period. Consequently, we base our decision on the following quantitative rule: for a reference entity to be included in our sample, at least 62.5% of the required data points must be available throughout the sample period. This corresponds to five out of eight years. Further, for the period from January 2, 2014, to December 31, 2018, the pre-crisis period, and for the period January 1, 2019, to December 31, 2021, the crisis period, at least 60% and 66% of the required data must be available, respectively. This corresponds to three out of five years for the pre-crisis period and two out of three years for the crisis period. Applying these rules shrinks the dataset from 245 to 211 companies, which corresponds to the companies used for our empirical tests.

4.2 Summary Statistics

Completing the data selection process described in section 4.1 and manually matching the IHS Markit data on CDS to firm characteristics obtained from Bloomberg results in a final sample of 211 companies. Geographically, the set is divided into 95 European and 116 U.S. companies. Further, the sample consists of 145 investment grade-rated companies (AAA, AA, A, and BBB) and 66 high yield-rated entities (BB, B, and CCC). Specifically, we have 81 and 64 U.S. and European investment grade entities, respectively, and 35 and 31 U.S. and European high yield entities, respectively.

The significant variation in the number of companies between our investment grade and high yield subset results from the applied data selection process and structural differences in how the respective indices are constructed. In comparison, both the U.S. IG (CDX.NA.IG) and the European IG (iTraxx Europe) have 125 constituents, and their high yield equivalents the CDX.NA.HY and the iTraxx Crossover are composed of only 100 and 75 companies, respectively. Moreover, the latter index was extended from only 60 to 75 companies in September 2014 (Series 22). The resulting smaller starting sample combined with the application of our selection rules results in a smaller final high yield sample.

Table 1 provides summary statistics of CDS spreads, firm size[9], equity-option implied volatility[10], and CDS bid-ask spreads by geographic region, credit rating, and divided into our defined pre-crisis and crisis period. In computing these statistics, we follow Kapadia and Pu (2012) by first averaging over our sample period for every company followed by averaging across obligors. In addition, a correlation matrices for the European and U.S. sample are provided in the appendix, see Table A.1 and Table A.2.

The overall mean CDS spread is 125 basis points (bps), whereas the mean for the investment grade and high yield subset is 56 bps and 277 bps, respectively. Noteworthy, there is a substantial difference in the mean CDS spread between the U.S. (147 bps) and Europe (99 bps) samples resulting from few but severe outliers, as can be seen when comparing the maximum CDS spread of these two sets. Further, the medians lie considerably closer (U.S.: 69 bps; Europe: 70 bps).

The average firm size of an investment grade company is \$63.49 billion, compared to \$10.75 billion for the high yield subsample. Also, the average size differs between U.S. and European

[9]Firm size is the market capitalization measured in USD billions.

[10]90-day at-the-money call/put implied volatility based on the Listed Implied Volatility Engine (LIVE) calculator from Bloomberg.

Table 1: Summary statistics.

The sample consists of 211 European and U.S. companies over the period from January 2, 2014 to December 31, 2021. The sample contains 145 investment grade and 66 high yield companies across the U.S. and Europe. Geographically, the set is divided into 95 European and 116 U.S. companies. Firm size is measured by market capitalization in U.S.% billions. Equity volatility is measured by 90-day equity-option implied volatility.

	Five-year CDS spread (bps)				
	Mean	Median	Min	Max	Std. Dev.
All	125.27	68.76	6.20	6553.31	61.13
Europe	99.22	70.41	10.64	3598.61	43.53
U.S.	146.60	68.61	6.20	6553.31	75.54
Investment grade	56.28	51.43	6.20	772.95	21.36
High yield	276.83	187.40	15.78	6553.31	148.50
Pre-crisis	129.11	69.65	9.76	6553.31	54.12
Crisis	119.34	62.32	6.20	5941.78	49.16

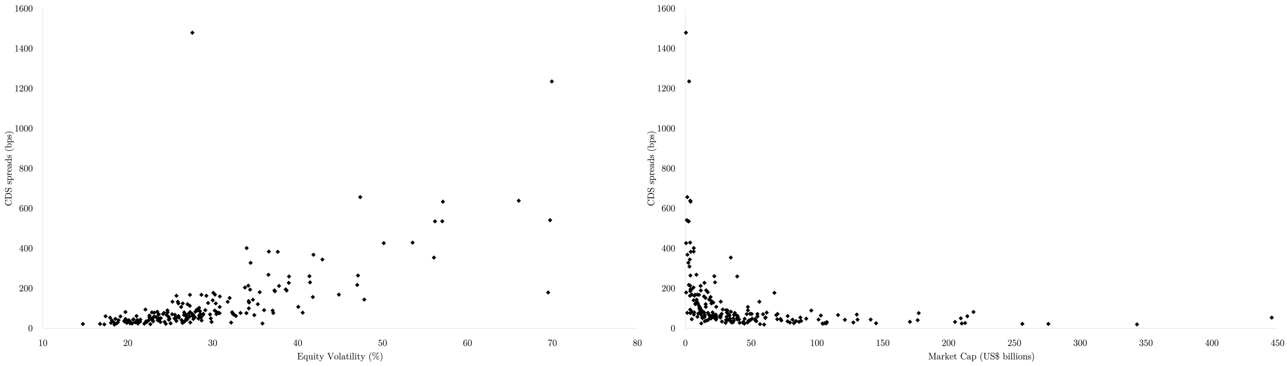
	Firm Size (U.S.$ billions)				
	Mean	Median	Min	Max	Std. Dev.
All	46.99	26.79	0.05	669.12	12.14
Europe	41.06	26.54	0.34	417.82	9.86
U.S.	51.85	27.14	0.05	669.12	14.01
Investment grade	63.49	39.72	1.38	669.12	15.70
High yield	10.75	7.44	0.05	180.58	4.33
Pre-crisis	44.81	26.65	0.10	527.49	8.09
Crisis	50.82	26.35	0.05	669.12	9.52

	Equity volatility (%)				
	Mean	Median	Min	Max	Std. Dev.
All	30.35	26.98	2.20	716.02	12.00
Europe	27.01	25.95	9.01	349.36	7.36
U.S.	33.06	27.72	2.20	716.02	15.75
Investment grade	25.51	24.66	7.58	150.26	9.79
High yield	41.50	34.73	2.20	716.02	17.07
Pre-crisis	26.24	24.08	7.58	255.47	5.82
Crisis	37.08	31.03	2.20	716.02	14.23

	CDS bid-ask spread (bps)				
	Mean	Median	Min	Max	Std. Dev.
All	35.80	6.25	1.17	2466.67	15.82
Europe	31.89	5.79	2.00	763.08	12.94
U.S.	39.00	6.93	1.17	2466.67	18.17
Investment grade	6.04	5.55	1.17	104.23	2.55
High yield	101.18	92.08	19.61	2466.67	44.97
Pre-crisis	33.15	5.72	1.17	1433.33	10.31
Crisis	40.36	6.68	1.25	2466.67	18.86

companies with $51.85 billion and $41.06 billion, respectively. Figure 4b plots the mean CDS spread against the mean firm size and shows that larger companies have lower CDS spreads and, hence, lower credit risk. This not surprising since larger firms typically are more mature and stable in their businesses.

Furthermore, as expected, non-investment grade companies show a higher average implied volatility which is consistent with the Merton (1974) structural model and the findings by Kapadia and Pu (2012). In particular, the mean implied volatility for the investment grade set is at 25.51%, whereas the high yield sample shows an average of 41.50%. Implied volatility across geographic regions is relatively similar, with 33.06% for the U.S. and 27.01% for Europe. This is further illustrated in Figure 4a.



(a) CDS spread vs. equity volatility.

(b) CDS spread versus market capitalization.

Figure 4: Summary statistics.

For each company, the figures plot the mean CDS spread over the period January 2, 2014, to December 31, 2021, against the company's mean equity volatility and market capitalization, respectively. Equity volatility is measured by 90-day equity-option implied volatility.

When looking at our data over time – pre-crisis vs. crisis – we find a consistent and supporting pattern that confirms the general increased volatility and uncertainty in capital markets as a result of the Covid-19 outbreak. The market turmoil stemming from health concerns, disrupted supply chains, and lockdown forced closed production plants led to an increase in overall market volatility and firm-level implied volatility (26.24% pre-crisis vs. 37.08% crisis). Consequently, we should see higher mean CDS spreads during the crisis period as. That is, as implied in the Merton (1974) model, higher implied volatility also increases the firm's probability of breaching its default boundary resulting in a higher default probability. This is also explained by Blanco et al. (2005). Surprisingly, we see lower average CDS spreads during the crisis period. However, as seen in Figure 5, around the outbreak of the pandemic at the beginning of 2020, we see steeply increasing CDS spreads which fits the theoretical explanation. The subsequent normalization in CDS spreads after that, and lower levels during 2019 might explain the lower mean level during the crisis period. The pattern is confirmed by the 30-day realized CDS volatility.

Figure 5: Average 5-year CDS spread and average 30-day realized volatility.

The figure plots the average 5-year CDS spread in basis points (lhs) and the average 30-day realized CDS volatility in percentage (rhs) over the period January 2, 2014, to December 31, 2021.

4.2.1 Liquidity and Macroeconomic Conditions

Predominantly used in section 5.4 to explain the composition of CDS spreads and then further in section 5.5 to construct a signal trading strategy, our dataset also contains measures of liquidity for CDS spreads and several macroeconomic indicators to measure the overall state of the economy.

Liquidity

For our analysis, we consider two different measures of credit market liquidity. First, we use the quotes depth of a single-name CDS contract which measures the number of contributors that submit quotes on a contract to Markit for each trading day. Given the reporting requirement by Markit, market participants are required to document their quotes. The more quotes are submitted, the higher the liquidity of the CDS contract. These data are obtained from IHS Markit, which provides the average daily quotes depth for each of our sample CDS contracts. The measure is frequently used in economic literature as a proxy for CDS liquidity, for example by Gala et al. (2010) and Kapadia and Pu (2012).

The second measure of liquidity is the CDS bid-ask spread obtained from IHS Markit, which reports the daily average for each of our sample single-name CDS contracts. These data points are calculated based on so-called dealer runs[11]. Further, these quotes are converted using the ISDA Standard Model into quotable spreads for comparability across different quoting conventions (ISDA and Markit Group Limited, 2021). This liquidity proxy is widely applied in market liquidity analyses across all major asset classes, including the CDS market (see Zhang et al., 2009; Kapadia and Pu, 2012; Zhang and Zhang, 2013; Junge and Trolle, 2015).

Geographically, the descriptive statistics on the CDS bid-ask spreads do not remarkably differ between the European and U.S. subsample, especially because one large outlier in the U.S. sample drags up the U.S. average. In contrast to splitting by geography, splitting our data by credit rating shows significant differences across all metrics shown in Table 1. The mean bid-ask spread is approximately 17 times higher for the high yield subgroup than for the investment grade companies. A structural wider bid-ask spread is confirmed by the notable difference in the median (IG: 5.55 bps vs. HY: 92.08 bps).

Macroeconomic Conditions

In order to measure if and how macroeconomic conditions influence single-name CDS spreads, we include three macroeconomic indicators in our dataset. This is specifically used our analysis of determinants of CDS spreads in section 5.4.

In addition to firm-specific volatility approximated by option-implied volatility, we add the Chicago Board Options Exchange (CBOE) volatility index (VIX) as a proxy for overall market volatility. The VIX is based on the S&P 500 index (SPX) and estimates expected volatility by averaging the weighted prices of S&P 500 put and call options over a wide range of strike prices. As shown by Schneider et al. (2010), overall equity market volatility is positively correlated with both short- and long-term default factors that consequently have an impact on the valuation of credit default swaps. Moreover, a positive relationship between credit spreads and the VIX index is found by Greatrex (2008) and Collin-Dufresne et al. (2001). Noteworthy, Collin-Dufresne et al. (2001) use bond data instead of CDS spreads and find only an asymmetric relationship between the VIX and credit spreads, i.e., a spread widening as a response to increases in the VIX but no reaction to declines of the index level. Even though the correlation between the VIX and its European equivalent, the VSTOXX, is close to one[12] we decide to perform our analysis on the European subsample by using the VSTOXX. Though calculated slightly differently, the VSTOXX estimates market volatility based on the Euro Stoxx 50, Europe's major blue-chip index, and therefore appears as the obvious choice for our empirical analysis.

[11] Electronic messages on price quotes from dealers to buy-side clients.
[12] We estimate a correlation of 0.87 over our sample period.

Furthermore, as we follow the approach by Da Fonseca and Gottschalk (2020) and Blanco et al. (2005) in section 5.4 to explore the determinants of CDS spreads (see also Zhang et al., 2009; Ericsson et al., 2009; Collin-Dufresne et al., 2001), we include the spot interest rate as well as the slope of the yield curve to our dataset. In our analysis, we approximate the risk-free rate by using both USD and EUR OIS swap rates for a 3-month tenor, a measure also used by Junge and Trolle (2015) to approximate unsecured funding costs (see also Filipović and Trolle, 2013). The selection slightly differs from what Blanco et al. (2005), Zhang et al. (2009), and Da Fonseca and Gottschalk (2020) have used as they rely on either 2-year or even 10-year U.S. Treasury yields. Furthermore, we construct a proxy for the slope of the term structure by combining the 3-month OIS swap rates with its 10-year equivalent (10-year rate minus 3-month rate). Daily data is obtained from Bloomberg.

5 Methodology and Empirical Results

5.1 Stationarity

5.1.1 Methodology

If equity and CDS markets both react efficiently to changes in underlying risk and new information, we expect any pair of these series to be linearly cointegrated. In addition, checking for cointegrating relationships allows us to get an idea of the lead-lag relationship between stock prices and CDS spreads. As nonstationary time series are required for a cointegrating relationship, we first test the stationarity of the respective par spread and stock price series for each of the 211 companies. Like Figuerola-Ferretti and Paraskevopoulos (2013) we use an augmented Dickey-Fuller test to assess stationarity. When choosing the number of lags included in the test, there is a trade-off between the loss of power that comes from adding too many lags and the risk of bias from remaining autocorrelation when choosing a too parsimonious model. Therefore, we use the Akaike information criterion (AIC) to select the number of lags included for each time series. Further, we allow for a drift and trend term in the tests to account for any potential existence of these features in the series. This leads to the following specifications for the augmented Dickey-Fuller test

$$\Delta \text{log} CDS_{i,t} = a_0 + \gamma \text{log} CDS_{i,t-1} + a_2 t + \sum_{j=2}^{p} \beta_j \Delta \text{log} CDS_{i,t-j+1} + \varepsilon_t \tag{5.1}$$

$$\Delta \text{log} STOCK_{i,t} = a_0 + \gamma \text{log} STOCK_{i,t-1} + a_2 t + \sum_{j=2}^{p} \beta_j \Delta \text{log} STOCK_{i,t-j+1} + \varepsilon_t \tag{5.2}$$

where log$CDS_{i,t}$ and log$STOCK_{i,t}$ is the log of the par spread and stock price of company i at time t, a_0 is the drift term, a_2t is the trend term, and p represents the number of lags selected based on AIC. The joint null hypothesis is that $a_0 = \gamma = a_2 = 0$, which is tested using F-statistics from the regressions.

5.1.2 Empirical Results

Out of the 422 series tested, none of the tests were able to reject the null at a 5% significance level. This provides a sufficiently strong indication of nonstationarity to allow us to proceed with tests for cointegration for all companies. The results are robust to dividing the sample into crisis and pre-crisis subsamples. This is particularly important as structural changes in a sample can affect the results of unit root tests Mateev and Marinova (2017). The results of the F-tests can be found in Table B.1 in the appendix. The finding of no rejections to the null of nonstationarity is similar to those by (Figuerola-Ferretti and Paraskevopoulos, 2013) who use the test on both index and single-name CDS spreads.

5.2 Cointegration

5.2.1 Methodology

The use of cointegration as a way of checking for market integration is used in much of the previous research on the topic (see Blanco et al., 2005; Forte and Peña, 2009; Norden and Weber, 2009; Figuerola-Ferretti and Paraskevopoulos, 2013; Narayan et al., 2014; Mateev and Marinova, 2017). The idea is that a linear combination of two nonstationary processes, such as the stock price and the CDS spread, should result in a stationary process if they share a common stochastic trend.

Like Mateev and Marinova (2017) and Forte and Peña (2009), we use the Johansen procedure to test for a cointegrating relationship between each of the 211 pairs of CDS spreads and stock prices.

The test is based on a differenced p-order VAR model

$$\Delta x_t = \pi x_{t-1} + \sum_{i=1}^{p-1} \pi_i \Delta x_{t-i} + \varepsilon_t \tag{5.3}$$

where $\pi = -(I - \sum_{i=1}^{p} A_i)$ and $\pi_i = -\sum_{j=i+1}^{p} A_j$. A_i and A_j are (2×2) matrices of the logCDS and log$STOCK$ parameter values and I is a (2×2) identity matrix. Δx_t is a (2×1) matrix containing the values of the differenced logCDS and log$STOCK$ at time t. As also noted in previous literature, data on CDS spreads at a daily frequency suffer from staleness for some companies (Zhang et al., 2009). Thus, we use end-of-week data for our primary analysis of cointegration and the subsequent price discovery process. This leaves us with 2088 weekly data points for the full period, while we have 1304 and 784 weeks of data for the crisis and pre-crisis subsamples, respectively. As discussed in the data section, some companies may have fewer observations due to missing data points in either the stock price or the CDS spread. In addition, to consider the proportion of companies with cointegrating stock prices and CDS spreads in the overall sample, we also consider this proportion for different subgroups. Specifically, we divide the companies into high yield vs. investment grade, European vs. U.S., and lastly, we consider crisis and pre-crisis periods. These splits are also used in previous research and can be motivated by different specifications in CDS contracts across regions and credit rating group[13] (see e.g., Norden, 2017; Blanco et al., 2005; Mateev and Marinova, 2017; Kapadia and Pu, 2012).

The Johansen Trace Test requires an autoregressive order, p, of at least 2. We use the AIC selection criteria to determine the value of p on an individual company basis, although since the test requires that $p \geq 2$, we use two as the autoregressive order in our VAR model when the AIC-selected VAR model is of autoregressive order 1.

Once the autoregressive order is selected for each company, the Johansen procedure is performed on the model with the specification shown in equation 5.3. For each company, characteristic roots of π, defined as $\hat{\lambda}_i$, are estimated. This determines the number of cointegrating relationships for that particular company. We compare λ_{trace} in the below equation to critical values for $r = 0$ simulated by Osterwald-Lenum (1992).

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} ln(1 - \hat{\lambda}_i) \tag{5.4}$$

If the null of zero rank, $r = 0$, is rejected in the test above, we proceed with the test below, using the same estimates of the characteristic roots as in the previous test:

$$\lambda_{max}(r, r+1) = -T\, ln(1 - \hat{\lambda}_i) \tag{5.5}$$

Here we use $r = 1$. If the null of $r \leq 1$ is rejected, we conclude that π has full rank, which indicates that no cointegration exists between the CDS spread and stock prices for that particular company. If the null is not rejected, this indicates that π has a reduced rank of 1 such that exactly one cointegrating relationship between the two variables exists.

[13] See section 2.3 for further details on the contractual specifications of CDS.

5.2.2 Empirical Results

Table 2 summarizes the results of the Johansen Trace cointegration test by reporting the number of companies for which we find cointegration both at the 10% and the 5% level of significance. The table summarizes results for the entire sample and for different subgroups based on geographic region, credit rating, and time, i.e., pre-crisis vs. crisis period. Results on a company basis are reported in Table B.2 in the appendix.

Table 2: Johansen Trace test for cointegration.

Results of the Johansen Trace test for cointegration. Results are reported using a 10% and a 5% significance level. The table summarizes results for the entire sample and for different subgroups based on geographic region, credit rating, and time, i.e., pre-crisis vs. crisis period.

	Significance Level: 10%			Significance Level: 5%		
	Companies	Cointegrated	Percent	Companies	Cointegrated	Percent
Full Sample	211	77	36.5%	211	50	23.7%
Europe	95	44	46.3%	95	34	35.8%
U.S.	116	33	28.4%	116	16	13.8%
IG	145	56	38.6%	145	37	25.5%
HY	66	21	31.8%	66	13	19.7%
Crisis '19-'21	209	87	41.6%	209	60	28.7%
EU crisis	94	44	46.8%	94	31	33.0%
U.S. crisis	115	43	37.4%	115	29	25.2%
IG crisis	144	70	48.6%	144	50	34.7%
HY crisis	65	17	26.2%	65	10	15.4%
Pre-crisis '14-'18	211	20	9.5%	211	16	7.6%
EU pre-crisis	95	14	14.7%	95	9	9.5%
U.S. pre-crisis	116	6	5.2%	116	7	6.0%
IG pre-crisis	145	6	4.1%	145	5	3.4%
HY pre-crisis	66	14	21.2%	66	11	16.7%

At the 10% significance level, the stock prices and CDS spreads are cointegrated for 77 out of 211 companies in the 2014-2021 sample period, corresponding to 37%. Our results are slightly lower than the 62% and 61% found by Norden and Weber (2009) and Forte and Lovreta (2015) for their samples of 58 and 92 firms but also a higher than the 24% found by Mateev and Marinova (2017) in their sample of 109 European firms. Their respective samples include observations from 2000 to 2002, 2002 to 2008, and 2008 to 2016. As discussed in section 2.3, the CDS market has significantly evolved over the past 20 years, and it is, therefore, not surprising to see slight changes in the tested relationship over time. The general finding that a significant proportion of the companies have cointegrating relationships between the two markets is in line with expectations as these markets price features and information on the same underlying companies. Considering the above presented previous results, there seems to be a general tendency for the markets to have become less cointegrated over the past 20 years, coherent with the sharp shrinkage of the single-name CDS market in the post-financial crisis period (see section 2.3.2). As the single-name market has become less liquid after the financial crisis, it is not surprising that the market no longer follows the stock market as closely, making it more challenging to detect movements towards a long-run equilibrium and, thereby, cointegration. Thus, although the two markets are clearly integrated to some degree, as seen by the proportion of cointegrated companies, the market integration seems to be less evident than it was in results reported by Norden and Weber (2009) and Forte and Lovreta (2015) from before the financial crisis of 2007-08.

When considering differences across geographic regions, we find 46% of the European companies to be cointegrated while only 28% of companies from the U.S. market show a statistically significant cointegrating relationship. Our findings of a higher proportion of cointegrated markets for European firms contradict the results by Norden and Weber (2009), who find a higher proportion of cointegrating relationships for U.S. companies (75%) than they do for European firms (57%). Again, however, changes in the CDS market over the past 20 years are likely to make these numbers slightly incomparable. In addition, their U.S. sample only consists of 20 companies against 116 U.S. companies in our sample. These results make general conclusions about whether European or U.S. companies have a higher market integration between the CDS and equity markets challenging. While our results suggest that European markets are more integrated, Norden and Weber (2009) suggest the opposite. Moreover, Mateev and Marinova (2017) only found cointegration for 24% of the companies in their sample of 109 European firms from 2008 to 2016, which is lower than the 28% we find for U.S. companies in our 2014-2021 sample. As discussed, the market has undergone large regulatory changes over the past 10-15 years, which may have also caused changes in the degree to which markets are cointegrated when comparing U.S. and European companies (see section 2.3 for a summary of regulatory changes in the CDS market).

Considering differences across credit ratings, we also observe a slight difference between the proportions of cointegrated companies with investment grade (39%) and high yield (32%) ratings. These findings are in line with results from Wang et al. (2013) who find that CDS returns are generally more sensitive to lagged equity returns for investment grade firms than for non-investment grade firms. However, it contradicts the idea that the high yield CDS market should be more integrated with the stock market because of the potentially higher relevance of credit insurance for these companies. This idea is supported by Fung et al. (2008) who also argue that since high yield companies are more volatile and exposed to credit events, the market for CDS, therefore, is larger and more efficient in pricing in changes in credit quality. Nonetheless, our findings are somewhat in line with the above-mentioned previous findings and indicate that the investment grade single-name CDS market is more integrated with the stock market than the high yield market. The table of summary statistics, Table 1, shows that bid-ask spreads of high yield companies are significantly higher than for investment grade companies, indicating that liquidity is lower for this subsample. The liquidity differences may be a reason for the difference in the degree of cointegration between the two credit rating groups.

The most considerable difference among the subsamples is found between the pre-crisis and crisis periods, which splits the sample into the periods from 2014 to 2018 and 2019 to 2021, respectively. 42% of our companies have a cointegrated equity and credit risk market during the crisis period, while only 10% during the pre-crisis period. These results are in line with findings by Narayan et al. (2014), who find that CDS markets become more involved in the price discovery process during the financial crisis. A likely explanation is that the single-name CDS market becomes more relevant during crisis times, as investors have a higher incentive to protect against credit risk. Consequently, it would increase liquidity in the CDS market, allowing it to follow movements from the equity market more closely. In addition, during crisis times, the risk of default becomes more relevant to the price of a stock, and hence the CDS market is more closely followed by participants of other markets, including the stock market. That is, not only the size of future cash flows or earnings matters but also the likelihood of whether there will be any at all. Through the discount factor in the stock valuation, the stock price more closely imitates what is priced into a CDS, further justifying why the two markets are more integrated during crisis times.

Interestingly, while we see that the investment grade companies seem to have slightly more integrated markets than high yield companies for the entire 2014-2021 sample period, this finding entirely vanishes if we consider only the pre-crisis period. Only 4% of investment grade companies have cointegrated markets for this period, whereas 21% of high yield companies are cointegrated during the same period. Still considering the credit rating subgroups, but now for the crisis period, the results change entirely, with 49% of investment grade firms having cointegrated markets against only 26% of high yield companies. These findings clearly indicate that during pre-crisis times, investment grade CDS are not as heavily traded, likely a consequence of the low risk of default of the reference entities. However, for high yield companies, there is not as much of a change between pre-crisis and crisis periods, likely since an elevated risk of default exists during both of these periods.

As a side-note, it should be mentioned that it is possible for a company to have a statistically significant cointegrating relationship at the 5% level but not at the 10% level. This results from the threshold for rejecting the null in equation 5.5 to be lower at the 10% level than at the 5% level, and rejection of the null means no cointegration. In general, however, as can also be seen in Table 2, the higher significance level leads to a higher acceptance of cointegrating relationships.

Overall, the cointegration analysis between the stock prices and CDS spreads provides clear evidence that cointegration exists between the two markets. This is especially evident for European companies, investment grade companies, and during crisis times. Going one step further, we see how the market integration vanishes for investment grade firms during pre-crisis periods and increases in times of crisis, while it remains more stable for high yield companies.

5.3 Price Discovery

5.3.1 Methodology

Analyzing the price discovery process involves two consecutive steps. First, we estimate VECM and VAR models. Afterward, we use these models to estimate four different measures to investigate the price discovery process.

Estimating VECM and VAR Models

After testing for cointegration, we set up a VECM for each company. Forte and Lovreta (2015) argue that omitting a significant error correction term is more harmful than including an insignificant one and, therefore, set up the model for all companies in their sample. Following their argumentation, we set up VECMs for the entire sample, although we provide a clear discussion of how our results differ between the overall sample and the companies for which there is a cointegrating relationship between their CDS spreads and stock prices. In addition, we set up VAR models, excluding the error correction term, for those companies that do not show significant cointegrating relationships. The VECMs are specified as follows using the specifications used by Forte and Peña (2009)

$$\Delta\log CDS_t = \alpha_1 + \lambda_1 V_{t-1} + \sum_{j=1}^{p} \beta_{1j} \Delta\log CDS_{t-j} + \sum_{j=1}^{p} \gamma_{1j} \Delta\log STOCK_{t-j} + \varepsilon_{CDS,t} \tag{5.6}$$

$$\Delta\log STOCK_t = \alpha_2 + \lambda_2 V_{t-1} + \sum_{j=1}^{p} \beta_{2j} \Delta\log CDS_{t-j} + \sum_{j=1}^{p} \gamma_{2j} \Delta\log STOCK_{t-j} + \varepsilon_{STOCK,t} \tag{5.7}$$

where the error correction term is $V_{t-1} = \log CDS_{t-1} - \alpha_0 - \beta_0 \log STOCK_{t-1}$. We estimate the VECM for each of the 211 companies. Using VECMs to assess market integration is frequently used in previous research (see e.g., Blanco et al., 2005; Norden and Weber, 2009; Forte and Peña, 2009). Given the non-stationary nature of our data (see section 5.1.2), we use first-differenced data of CDS spreads ans stock prices to set up the VAR models. Thus, the VAR models are specified as

$$\Delta\text{log}CDS_t = \alpha_1 + \sum_{j=1}^{p} \beta_{1j} \Delta\text{log}CDS_{t-j} + \sum_{j=1}^{p} \gamma_{1j} \Delta\text{log}STOCK_{t-j} + \varepsilon_{CDS,t} \tag{5.8}$$

$$\Delta\text{log}STOCK_t = \alpha_2 + \sum_{j=1}^{p} \beta_{2j} \Delta\text{log}CDS_{t-j} + \sum_{j=1}^{p} \gamma_{2j} \Delta\text{log}STOCK_{t-j} + \varepsilon_{STOCK,t} \tag{5.9}$$

Once each model has been estimated, we consider four different indicators to determine the price discovery process between the two markets.

Analyzing Price Discovery

The first of the four measures of price discovery is to consider the VECM model by itself, which is a method also applied by Forte and Peña (2009) in their analysis of market integration between bond, stock, and CDS markets. The method builds on the idea that λ is the coefficient on the error correction term, which causes the process to move back towards its long-run equilibrium. If one price moves without the other, moving the overall process away from its equilibrium, their cointegrating relationship will move the process back to its equilibrium over time. This effect is captured by the λ's. Considering out VECM framework as per equation 5.6 and 5.7, if λ_1 is negative and statistically significant, the stock price makes a significant contribution to price discovery. However, if λ_2 is positive and statistically significant, the CDS spread makes a significant contribution to the price discovery. The results indicate whether there is a sole contributor to the price discovery or whether both markets contribute to the process. This measure is considered for all 211 companies. However, since the measure builds on cointegrating relationships, the companies for which such a relationship exists are discussed separately as well.

The second measure is the Gonzalo-Granger (GG) measure by Gonzalo and Granger (1995). The approach is beneficial for cases where the price discovery does not happen solely in one market, as it provides an estimate of what fraction each market contributes to the price discovery process. The measure for the proportion of price discovery happening in the CDS market is given by

$$GG_{CDS} = \frac{\lambda_2}{\lambda_2 - \lambda_1} \tag{5.10}$$

with $\lambda_1 \neq \lambda_2$. The coefficients on the error correction terms, λ, are obtained from the VECM models in equation 5.6 and 5.7. The remainder, $1 - GG_{CDS}$, measures the stock market's contribution to the price discovery. Noteworthy, estimates above one are assumed to be one, and estimates below zero are assumed to be zero, an approach commonly used in the previous literature (see Blanco et al., 2005; Norden and Weber, 2009; Forte and Peña, 2009). As with the previous measure, the GG measure is calculated for all companies, and results are discussed in the following section 5.3.2, including a discussion of differences in the results between cointegrated and non-cointegrated companies.

The third measure, the Hasbrouck (HAS) model of information shares, is similar to the GG measure in the sense that it provides an estimate of the share each market contributes to the price discovery (Hasbrouck, 1995). However, whereas the GG measure relies solely on the permanent effects incorporated in the error correction term, ignoring the correlation between markets, the Hasbrouck model decomposes the implicit efficient price variance and attributes a more considerable price discovery contribution to the market that contributes most to the price variance. Thus, as argued by Baillie et al. (2002), using the two complementary measures is preferable. As discussed in section 3.4.3, only the lower and upper bounds of the Hasbrouck model can be used in cases where prices are contemporaneously determined. Formulas are provided below

$$HAS_{CDS,lower} = \frac{\lambda_2^2 \left(\sigma_1^2 - \frac{\sigma_{12}^2}{\sigma_2^2}\right)}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2} \tag{5.11}$$

$$HAS_{CDS,upper} = \frac{\left(\lambda_2\sigma_1 - \lambda_1\frac{\sigma_{12}}{\sigma_1}\right)^2}{\lambda_2^2\sigma_1^2 - 2\lambda_1\lambda_2\sigma_{12} + \lambda_1^2\sigma_2^2} \tag{5.12}$$

Importantly, as further argued by Baillie et al. (2002) and subsequently applied by Blanco et al. (2005), Forte and Peña (2009), and Narayan et al. (2014), the average of the two bounds provide an adequate measure of the price discovery contribution. Hence, it provides an estimate to be used along with the GG measure. As with the previous indicators of price discovery, this model is used for all 211 companies, but a separate discussion is provided for the companies that show significant cointegrating relationships.

The fourth and last measure is the Granger causality measure, which we use on the estimated VAR models from equation 5.8 and 5.9. Again, this is a frequently used measure in previous research on the topic (see, e.g., Norden and Weber, 2009; Da Fonseca and Gottschalk, 2020; Blanco et al., 2005). Specifically, we test whether any of the γ_1's are significant in equation 5.8 and the β_2's are significant in equation 5.9. The Wald test is performed using a joint F-distribution. For each company, if any γ_1's are significantly different from zero while at the same time the β_2's are insignificant, the stock price Granger causes the CDS spread, indicating a leading role of the stock in the price discovery, and vice versa. If some γ_1's and some β_2's are significantly different from zero, no Granger causality can be detected, and further, no leading role of either market can be determined. The econometrics of these conclusions are discussed in further detail in section 3.2.2. As also discussed in section 3.2.2, the measure relies on the assumption that the residuals are not correlated. Specifically, this means that applying this method to equation 5.8 and 5.9 for a company for which we have found a cointegrating relationship would yield incorrect results. The omitted error correction term would be contained in the errors causing them to be correlated. Therefore, this method only applies to companies for which we do *not* find a cointegrating relationship when conducting the Johansen Trace test. The same approach is used by Blanco et al. (2005).

5.3.2 Empirical Results

The results from the four different ways of determining how the price discovery happens are reported in this section. This includes an analysis of the significance of the VECM coefficients, the Gonzalo-Granger measure, the Hasbrouck model, and the Granger causality measure.

Significance of VECM coefficients

For the first of the four analyses, Table 3 summarizes the contribution of the stock market and the CDS market to the price discovery process based on the significance of the error correction terms in equation 5.6 and 5.7. As discussed in section 5.3.1, these are only counted if they are significantly different from zero. That is, the stock market contributes if λ_1 is significant and negative, while the CDS market contributes if λ_2 is significant and positive. The table shows results for the entire sample at the top and cointegrated companies only at the bottom. In addition, results are reported for different subgroups based on geographic region, credit rating, and time, i.e., pre-crisis vs. crisis. Further, results are reported at the 10% and 5% significance levels. Results on a company basis are reported in the appendix in Table B.3.

At the 10% level, for all companies in our sample, the stock market contributes to the price discovery for 86% of the companies, while it is the sole contributor for 55% of the companies. The CDS market contributes to price discovery for 33% of companies, while it is the sole contributor for only 2%. Across subgroups, there is a general tendency for the CDS market to be a more substantial contributor to the price discovery during the pre-crisis period than during the crisis period or the entire period. However, even in the pre-crisis period, the contribution is much lower than the stock market's. Furthermore, the stock market appears to be a leading contributor more frequently for the investment grade subgroups. Since the probability of default is lower in the investment grade space, it is not surprising that the price discovery happens more often in the stock market for this group of companies. Fung et al. (2008) argue that high yield companies are more volatile and exposed to credit events and, therefore, the market for insurance derivatives, i.e., CDS, is larger and more efficient in pricing in changes in credit quality than it is for investment grade companies.

Table 3: Price discovery based on the VECM coefficients.

The table summarizes the price discovery assessment based on the VECM coefficients, λ. The different columns represent a sole leading role by the stock market, a sole leading role by the CDS market, a contribution from both markets, and no contribution. Results are provided for the full sample at the top and cointegrated companies only at the bottom. In addition, results are reported by subgroups based on geographic region, credit rating, and time, i.e., pre-crisis vs. crisis. Further, results are reported based on the 10% and 5% significance levels of the error correction term in the VECM.

		Significance Level: 10%				Significance Level: 5%			
	Companies	Stock	CDS	Both	None	Stock	CDS	Both	None
		All Companies							
Full Sample	211	55%	2%	31%	12%	58%	2%	24%	16%
Europe	95	64%	1%	25%	9%	69%	1%	15%	15%
U.S.	116	47%	3%	36%	14%	49%	3%	32%	16%
IG	145	59%	1%	30%	10%	64%	1%	22%	12%
HY	66	47%	3%	35%	15%	45%	3%	29%	23%
Crisis	209	49%	3%	40%	9%	52%	5%	33%	11%
EU crisis	94	57%	1%	34%	7%	64%	3%	23%	10%
U.S. crisis	115	42%	4%	44%	10%	42%	6%	40%	12%
IG crisis	144	58%	3%	35%	5%	59%	5%	28%	8%
HY crisis	65	29%	3%	51%	17%	35%	5%	42%	18%
Pre-crisis	211	48%	9%	12%	30%	43%	9%	7%	42%
EU pre-crisis	95	39%	6%	11%	44%	49%	8%	7%	35%
U.S. pre-crisis	116	41%	11%	9%	38%	36%	9%	5%	49%
IG pre-crisis	145	50%	12%	14%	24%	47%	10%	8%	35%
HY pre-crisis	66	44%	5%	8%	44%	35%	5%	5%	56%
		Cointegrated Companies							
Full Sample	77	55%	0%	39%	6%	58%	2%	32%	8%
Europe	44	64%	0%	30%	7%	74%	0%	21%	6%
U.S.	33	42%	0%	52%	6%	25%	6%	56%	13%
IG	56	61%	0%	34%	5%	65%	3%	24%	8%
HY	21	38%	0%	52%	10%	38%	0%	54%	8%
Crisis	87	56%	2%	38%	3%	60%	3%	33%	3%
EU crisis	44	57%	0%	41%	2%	65%	3%	29%	3%
U.S. crisis	43	56%	5%	35%	5%	55%	3%	38%	3%
IG crisis	70	61%	3%	36%	0%	68%	4%	28%	0%
HY crisis	17	35%	0%	47%	18%	20%	0%	60%	20%
Pre-crisis	20	75%	0%	5%	20%	75%	0%	6%	19%
EU pre-crisis	14	36%	0%	0%	64%	44%	0%	0%	56%
U.S. pre-crisis	6	50%	0%	0%	50%	57%	0%	14%	29%
IG pre-crisis	6	100%	0%	0%	0%	80%	0%	20%	0%
HY pre-crisis	14	64%	0%	7%	29%	73%	0%	0%	27%

The results at the 5% significance level in Table 3 are very similar to those at the 10% level. As expected, slightly more companies have insignificant error correction terms λ. The general findings from the 10% significant level also hold at the 5% significance level.

As discussed in section 5.3.1, an additional separate analysis of cointegrated companies, based on the Johansen Trace test, is conducted. The lower part of Table 3 considers only cointegrated companies. First, considering the 10% significance level, the same general tendencies are evident. Of the 77 companies that have cointegrating relationships for the entire period, the stock market contributes to the price discovery for 94% of the companies, whereas for 55% of the companies, the stock market is the sole contributor. The CDS market is the sole contributor for none of the cointegrated companies, showing an even more precise result than in the overall sample. The CDS market does contribute to the price discovery during the crisis period, although only for a tiny proportion of companies. A further primary difference compared to the entire sample is that the CDS market is the sole contributor in 0% of the cases during the pre-crisis period, meaning that CDS only solely contribute to the price discovery for not cointegrated firms. The results are similar at the 5% level.

Based on the analysis of the VECM coefficients, we conclude that the stock market is a clear leader in price discovery. In some instances, the CDS market contributes but is very rarely the sole leader. This is even more evident in the pre-crisis period, for investment grade companies, and for European companies. A potential explanation for why the stock market leads more in pre-crisis periods and for investment grade firms is that the insurance against default provided by CDS is not as demanded during pre-crisis times and for investment grade firms in general (Fung et al., 2008). Therefore, the CDS may not be traded as much for these subgroups, which affects the information flow into CDS compared to the stock, which trades more frequently. The few cases in which the CDS market leads may be attributed to the amount of false-positive we expect when using 10% and 5% significance levels for our conclusions. The findings in our analysis of the significance of the coefficients in the VECM models are in line with the results of a similar analysis conducted by Norden and Weber (2009). Notably, their results indicate the stock market to be the sole contributor to the price discovery in more cases than the CDS market, while they also find that both markets contribute for some companies.

Gonzalo-Granger measure

The second price discovery measure, the Gonzalo-Granger measure, provides an estimate of the proportion of the price discovery that happens in each market. Table 4 summarizes the results based on the GG measure, whereas the averages company estimates are taken across the entire sample and subgroups. Results on a company level are provided in Table B.4 in the appendix. The results are reported for the entire sample and two subgroups of significantly cointegrated companies, whereas cointegration is assessed based on the Johansen Trace test at the 10% and

5% significance levels.

Table 4: Price discovery based on the Gonzalo-Granger (GG) measure.

The table summarizes the price discovery assessment based on the Gonzalo-Granger (GG) measure. The columns show the average fraction each market, stock and CDS, contributes to the price discovery. Horizontally, the results are reported for the full sample and two subgroups of significantly cointegrated companies. Cointegration is assessed based on the Johansen Trace test at the 10% and 5% significance levels. Vertically, results are provided for different subgroups based on geographic region, credit rating, and time, i.e., pre-crisis vs. crisis. The columns show the average fraction each market, stock and CDS, contributes to the price discovery.

	All Companies			Cointegrated (10%)			Cointegrated (5%)		
	Companies	Stock	CDS	Companies	Stock	CDS	Companies	Stock	CDS
Full Sample	211	75%	25%	77	80%	20%	50	77%	23%
Europe	95	79%	21%	44	83%	17%	34	82%	18%
U.S.	116	72%	28%	33	75%	25%	16	66%	34%
IG	145	78%	22%	56	82%	18%	37	79%	21%
HY	66	79%	21%	21	83%	17%	13	82%	18%
Crisis	209	77%	23%	87	81%	19%	60	81%	19%
EU crisis	94	79%	21%	44	83%	17%	31	82%	18%
U.S. crisis	115	76%	24%	43	80%	20%	29	79%	21%
IG crisis	144	84%	16%	70	85%	15%	50	85%	15%
HY crisis	65	63%	37%	17	66%	34%	10	58%	42%
Pre-crisis	211	67%	33%	20	78%	22%	16	75%	25%
EU pre-crisis	95	73%	27%	14	87%	13%	9	83%	17%
U.S. pre-crisis	116	65%	35%	6	58%	42%	7	65%	35%
IG pre-crisis	145	70%	30%	6	96%	4%	5	93%	7%
HY pre-crisis	66	60%	40%	14	71%	29%	11	67%	33%

For the whole sample period, we see that 75% of the price discovery happens in the stock market, which is in line with the results of the first of our four tests. Further, the subgroup estimates range from 60% to 84%, confirming the leading role of the stock market across all subgroups in the sample. The subgroups for which the stock market leads the most are for the crisis period and for European companies. The findings somewhat contradict the conclusion from the first analysis, which shows that the stock market contributes more during the pre-crisis period. In addition, no considerable difference between high yield and investment grade companies is found in the overall sample based on the GG measure.

Considering only cointegrated companies, Table 4 also reports a similar but slightly more dominant leading role of the stock market compared to findings across all companies. The average price discovery stemming from the stock market across cointegrated companies is 80% and 77% for the 10% and 5% significance levels, respectively. Moreover, the leading role of the stock market is confirmed across all subgroups. The fact that the stock market generally leads more substantially during the crisis period and for the European companies is consistent with findings from the overall sample.

Overall, the results from the GG measure further confirm the leading role of the stock market in the price discovery process. Specifically, results indicate that approximately 75% to 80% of the price discovery occurs in the stock market. Our empirical results are consistent with those by Forte and Peña (2009) who find that 70% of the price discovery is done in the stock market, based on a sample of North American and European companies from 2001 to 2003. Using a sample of North American companies from 2004 to 2012, Narayan et al. (2014) estimate that 60% of the price discovery takes place in the stock market. Although their estimates are slightly lower than ours, they are still aligned with the general tendency of our estimates. In addition, the analysis casts some doubt on the findings from our VECM coefficient test. To recall, results point towards a more dominant role of the stock market during the pre-crisis period and for investment grade companies. Narayan et al. (2014), however, find the stock market to be leading more strongly during the financial crisis, which is consistent with our GG measure-based results for the Covid-19 crisis. Lastly, the Gonzalo-Granger measure and the VECM coefficient tests align on the result that the stock market tends to lead more considerably for European companies.

Hasbrouck model

The third measure of price discovery we consider is the Hasbrouck (1995) model of information shares, which like the two previous measures, builds on the VECM. In comparison to the GG measure, it also considers the variance-covariance matrix of the residuals. Table 5 summarizes the price discovery assessment based on the midpoint of the upper and lower bound of the Hasbrouck (HAS) measure, as suggested by Baillie et al. (2002). Further, the average of the company's midpoint HAS estimates are taken across the whole sample and subgroups. Results on a company level are provided in Table B.5.

Similar to the previous results from the VECM coefficients and the GG measure, the leading role of the stock market in the price discovery is confirmed overall. Further, the CDS market is participating slightly more during the pre-crisis period than in the overall or the crisis period. We again see a tendency toward a more leading stock market for European companies than for U.S. companies.

Table 5: Price discovery based on the Hasbrouck (HAS) measure.

The table summarizes the price discovery assessment based on the Hasbrouck (HAS) measure. The table shows the midpoint between the upper and lower bound of the Hasbrouck measure. The columns show the average fraction each market, stock and CDS, contributes to the price discovery. Horizontally, the results are reported for the entire sample and two subgroups of significantly cointegrated companies. Cointegration is assessed based on the Johansen Trace test at the 10% and 5% significance levels. Vertically, results are provided for different subgroups based on geographic region, credit rating, and time, i.e., pre-crisis vs. crisis.

	All Companies			Cointegrated (10%)			Cointegrated (5%)		
	Companies	Stock	CDS	Companies	Stock	CDS	Companies	Stock	CDS
Full Sample	211	71%	29%	77	75%	25%	50	72%	28%
Europe	95	75%	25%	44	75%	25%	34	76%	24%
U.S.	116	67%	33%	33	74%	26%	16	65%	35%
IG	145	72%	28%	56	77%	23%	37	72%	28%
HY	66	75%	25%	21	75%	25%	13	76%	24%
Crisis	209	69%	31%	87	74%	26%	60	72%	28%
EU crisis	94	73%	27%	44	75%	25%	31	72%	28%
U.S. crisis	115	65%	35%	43	73%	27%	29	72%	28%
IG crisis	144	73%	27%	70	76%	24%	50	76%	24%
HY crisis	65	59%	41%	17	65%	35%	10	56%	44%
Pre-crisis	211	54%	46%	20	72%	28%	16	68%	32%
EU pre-crisis	95	60%	40%	14	80%	20%	9	76%	24%
U.S. pre-crisis	116	49%	51%	6	53%	47%	7	58%	42%
IG pre-crisis	145	55%	45%	6	85%	15%	5	72%	28%
HY pre-crisis	66	51%	49%	14	67%	33%	11	67%	33%

The mid and right panels of Table 5 summarize results for cointegrated companies only. Cointegration is assessed based on the Johansen Trace test at the 10% and 5% significance levels. Overall, the proportional split of the price discovery between the two markets is very similar to the findings from the overall sample, although a trend toward a more leading stock market is detected. Again, the relationship is slightly less clear during the pre-crisis period, especially when considering companies cointegrated at the 10% significance level. Noteworthy, the two markets contribute almost equal shares to the price discovery in the U.S. pre-crisis subgroup. However, the low number of cointegrated companies during the pre-crisis period has to be considered, making a general conclusion challenging. The stock market is still leading more significantly for European companies than for U.S. companies, although not as much for the companies cointegrated at the 10% level.

In conclusion, the proportion of price discovery in the stock market ranges from 71% to 75% based on the Hasbrouck model, while it is 75% to 80% based on the Gonzalo-Granger measure. Hence, results from the three different methods used to interpret the VECM model coincide and complement each other in finding a leading price discovery role for the stock market over the CDS market. Forte and Peña (2009) and Narayan et al. (2014) attribute 61% and 75% of the price discovery to the stock market based on their HAS estimations, respectively. These findings confirm our estimates. In addition, the three measures we use align on a more dominant role of the stock market for European companies compared to U.S. firms, and, further, the HAS and GG measures both indicate that the stock market leads more during the crisis period. This is in line with findings by Narayan et al. (2014).

Granger Causality measure

The last measure we consider, the Granger causality measure, is only considered for non-cointegrated companies based on the Johansen Trace test, given the invalidity of the Granger test for non-stationary residuals. The Granger causality assessment shows potential information flows, in the form of market reactions, from one market to the other, even for non-cointegrated companies.

Importantly, Granger causality does not necessarily imply causality, and specifically, in our case, it is likely that other elements, like company-specific or macro events, are driving the changes in both markets. The Granger causality measures build on the VAR models shown in equation 5.8 and 5.9. Table 6 provides results for non-cointegrated companies at respective 10% and 5% significance levels. To remain consistent in the chosen significance level, the significance level of the Granger causality test matches the matching significance levels from the Johansen Trace test.

In the whole sample group for the entire period, the stock market is Granger causing the CDS market for 25% of the companies at the 10% level, whereas the CDS market is Granger causing the stock market for 16% of the sample. This indicates that the stock market is leading, although not as overwhelmingly as indicated by the previous results from the other measures. The relationship is more clear during the pre-crisis period, with the stock market leading for 37% of the firm while the CDS market leads only for 8% of the sample. During the crisis period, the relationship is reversed, and the CDS market is solely Granger causing the stock market for 28% of the companies, while the stock market is solely causing the CDS market for 16% of companies. Comparing across credit ratings, results indicate that the stock market is leading in more frequently for the high yield and the European companies than for investment grade and U.S. firms.

The results at the 5% level, right side of Table 6, are very similar to those at the 10% level. Again we see that the stock market is leading for the whole sample period, whereas its position is more dominant during the pre-crisis period.

Table 6: Price discovery based on the Granger causality test.

The table summarizes the price discovery assessment based on the Granger causality test for non-cointegrated companies at the 10% and 5% significance levels. The different columns represent the percentage of companies for which the stock Granger causes the CDS, not vice versa; the CDS Granger causes the stock, not vice versa; the significant influence is two-sided; no significant influence is detected. In addition, results are reported for different subgroups based on geographic region, credit rating, and time, i.e., pre-crisis vs. crisis. Further, to remain consistent in the chosen significance level, the Granger causality test's significance level matches the matching significance levels from the Johansen Trace test.

	Significance Level: 10%					Significance Level: 5%				
	Companies	Stock	CDS	Both	None	Companies	Stock	CDS	Both	None
Full Sample	134	25%	21%	28%	27%	161	24%	16%	20%	41%
Europe	51	29%	18%	18%	35%	61	26%	13%	11%	49%
U.S.	83	22%	23%	34%	22%	100	22%	17%	25%	36%
IG	89	17%	24%	33%	27%	108	20%	15%	21%	44%
HY	45	40%	16%	18%	27%	53	30%	17%	17%	36%
Crisis	122	16%	28%	27%	29%	149	17%	32%	15%	36%
EU crisis	50	10%	26%	20%	44%	63	11%	40%	6%	43%
U.S. crisis	72	21%	29%	32%	18%	86	21%	27%	22%	30%
IG crisis	74	23%	23%	30%	24%	94	20%	29%	19%	32%
HY crisis	48	6%	35%	23%	35%	55	11%	38%	9%	42%
Pre-crisis	191	37%	8%	6%	49%	195	29%	4%	3%	64%
EU pre-crisis	81	31%	6%	9%	54%	86	24%	2%	6%	67%
U.S. pre-crisis	110	42%	9%	4%	45%	109	33%	6%	1%	61%
IG pre-crisis	139	30%	9%	4%	58%	140	21%	4%	2%	72%
HY pre-crisis	52	56%	6%	12%	27%	55	49%	4%	5%	42%

As we saw at the 10% level, the relationship reverses during the crisis period. At the 5% level, the reversal is even more pronounced with the CDS Granger causing the stock for 32% of the sample, while the opposite is valid for 17% of the firms. The leading role of the stock market is more evident for high yield and European companies. Norden and Weber (2009) find that the stock market Granger causes CDS spreads for 67% of their sample compared with 44% to 53% for our sample[14]. Although the numbers are slightly different, the overall conclusion that the stock market contributes for a high proportion of companies is consistent with our findings.

Overall price discovery results

Overall, the VECM coefficient analysis, the Gonzalo-Granger measure, the Hasbrouck model, and the Granger causality test point towards a strictly leading role of the stock market in the

[14] Norden and Weber (2009) do not test Granger causality in both directions and, thereby, do not differentiate between whether the stock market is a sole contributor or both markets are contributing to the process. Thus, the number they report corresponds to summing the "Stock" and "Both" columns in Table 6.

price discovery process for both the European and the U.S. market. The Gonzalo-Granger and the Hasbrouck measures suggest that around 75% of the price discovery takes place in the stock market. The Granger causality and the VECM coefficient tests indicate that the relationship may be less clear during crisis periods, although the HAS and GG measures indicate the opposite, making overall conclusions on this topic challenging. All four tests indicate that stocks lead more often for European firms than for U.S. firms, while there is no clear trend depending on the credit quality. Furthermore, our findings are in line with those of previous empirical papers, including Norden and Weber (2009), Forte and Peña (2009), and Narayan et al. (2014).

Based on our empirical results, we continue with the perception that the stock market is leading the price discovery, which motivates the following analysis of the determinants of CDS spreads in the next section 5.4.

5.4 Determinants of CDS Spreads

5.4.1 Methodology

In addition to finding that 37% of our sample have cointegrated relationships, our findings are highly consistent in identifying the dominant role of the stock market in the price discovery process. The VECM coefficient analysis, the Gonzalo-Granger measure (Gonzalo and Granger, 1995), as well as the Hasbrouck measure (Hasbrouck, 1995) all find overwhelming evidence that most of the price discovery takes place in the stock market, both for the full sample and for cointegrated companies, thereby clearly underlining the lagged status of the CDS market. Moreover, the VAR-in-differences framework and the subsequent Granger causality assessment we apply to the non-cointegrated sample companies confirm this view as we consistently find equity prices Granger causing CDS spreads to a higher degree than vice versa. Following these results, we continue our analysis by further investigating the impact of stock prices on CDS spreads in a linear regression framework that, in addition, takes into account other structural factors such as measures for liquidity and indicators of overall macroeconomic conditions.

We closely follow the approach by Zhang et al. (2009), Wang et al. (2013), and Da Fonseca and Gottschalk (2020) but distinguish our analysis by using a slightly different set of explanatory variables to shift our focus towards liquidity concerns in the CDS market[15]. Other papers, such as Collin-Dufresne et al. (2001), focus on credit spreads in the bond markets rather than the CDS market. In addition, our analysis distinguishes itself from previous research by analyzing CDS during two significantly different market states – the pre-crisis period and the Covid-19-

[15] Da Fonseca and Gottschalk (2020) focuses on including the main contributors to credit risk as suggested by the Merton (1974) credit risk model. Zhang et al. (2009) puts particular emphasis on jumps and volatility, whereas Wang et al. (2013) investigates the impact of the variance risk premium on CDS.

related crisis period. As discussed in depth in section 2.3.7, there is a wide range of different empirical analyses that confirm the existence of a significant liquidity premium in CDS both on a firm level (see Tang and Yan, 2007; Bongaerts et al., 2011; Bühler and Trapp, 2009; Qiu and Yu, 2012; Bao and Pan, 2013) and a systematic market-wide level (see Junge and Trolle, 2015). Additionally, the post-financial crisis development of the CDS market further amplified this phenomenon, given the high concentration of market activity in the CDS index segment, which makes up more than 50% of the current market (ISDA, 2019). Further, within the single-name space ISDA (2019) finds that around 45% of market risk transfer activity (MRTA) in CDS comes from trading of only 27 reference entities. These previous findings particularly motivate the usage of liquidity measures in this following analysis.

Below we provide a detailed explanation of the financial and economic motivations behind and expected effects of the variables chosen for determining CDS spreads. This will be followed by the considerations behind setting up the model used for this analysis.

Explanatory Variables

The choice of our selected explanatory variables is motivated by both financial and economic theory (see Merton (1974)) as well as by previous empirical analysis (including Zhang et al. (2009), Wang et al. (2013), Da Fonseca and Gottschalk (2020), Collin-Dufresne et al. (2001) and Blanco et al. (2005)). Considering these sources, we have selected the following explanatory variables to assess the determinants of CDS spreads.

Equity Returns. Da Fonseca and Gottschalk (2020) argue that higher growth in firm value, i.e. higher growth of a firm's equity, should lead to a reduction in the probability of default. Consequently, a negative impact of stock returns on CDS spreads should be expected. However, Blanco et al. (2005) argues that stock returns can be interpreted as a proxy for firm leverage which is a crucial contributor to the firm's default barrier in the structural credit risk models by Merton (1974). As such, higher returns imply higher leverage and consequently should lead to increased credit risk and CDS spreads. Depending on which of these two effects that dominate in practice, the effect of equity returns on par spreads can be either positive or negative.

Implied Equity Volatility. Since short-term volatility in equity prices often significantly differs from long-term volatility as it is time-varying, we include 30-day and 90-day option implied volatility to better capture these dynamics and their potential impact on credit spreads. Higher implied equity volatility leads to more pronounced swings in the process of firm value over time. An increase in volatility makes it more likely for a reference entity to hit its default boundary, which translates into more credit risk and wider credit spreads (Blanco et al., 2005).

Short-term Interest Rate. The influence of the spot interest rate is driven by two different dynamics that make the influence uncertain a priori. On the one hand, a higher spot rate increases the risk-neutral drift in firm value, translating into a lower risk-neutral probability of default (Longstaff and Schwartz, 1995; Collin-Dufresne et al., 2001). On the other hand, it can also signify potential future tightening in monetary policy, which would increase default probabilities (Da Fonseca and Gottschalk, 2020).

Slope of the Interest-Rate Term Structure. As with the spot interest rate, the expected direction of the slope of the interest-rate term structure is unclear a priori. A steepening of the curve could signify higher future inflation and resulting tighter central bank policy leading to a widening in credit spreads (Zhang et al., 2009). However, Blanco et al. (2005) argues that with a mean-reverting short-term rate around the long-run equivalent, an increase in the slope could indicate future rising of short-term rates and, therefore, lower default probabilities. Most previous empirical analyses find a steepening of the curve is associated with lower credit spreads (Ericsson et al., 2009; Zhang et al., 2009).

Market Volatility. An increase in overall stock market volatility is expected to trigger the same dynamics as those for individual firm volatility due to the interconnection between firm and market volatility. Consequently, higher market volatility makes it more likely for a company to hit its default boundary, which results in higher credit spreads (Blanco et al., 2005). As shown by Schneider et al. (2010), overall equity market volatility is positively correlated to both short- and long-term default factors, which consequently have a positive impact on the level of CDS. A positive relationship between credit spreads and the VIX index is found by Greatrex (2008) as well as by Collin-Dufresne et al. (2001).

Bid-Ask Spreads. Used across most asset classes, the bid-ask spreads also play a dominant role in assessing liquidity in the CDS market (Augustin et al., 2014). Various previous empirical papers find the existence of a liquidity premium in CDS spreads. Bongaerts et al. (2011) empirically finds that lower liquidity in the form of wider bid-ask spreads pushes up CDS prices. Bühler and Trapp (2009) incorporate a liquidity measure in the form of bid-ask spreads into their asset pricing model and also find a significant impact on the level of CDS spreads (see section 2.3.7 for a detailed discussion of previous research on liquidity in the CDS market). We expect a positive sign on the bid-ask spreads in our regression.

Quotes Depth. The quotes depth measures the average number of dealers who provide CDS quotes for transactions. Consequently, the more quotes are submitted, the higher the liquidity of the CDS contract. Thus, we expect a negative sign of the quotes depth coefficient. This assumption is in line with empirical findings by Kapadia and Pu (2012) (see also Gala et al., 2010).

Model Setup

In our model we regress CDS spreads on our other primary data, equity prices[16], as well as option-implied volatility, two measures of liquidity, and macroeconomic indicators. Liquidity measures include quotes depth and quoted average bid-ask spreads, while macroeconomic indicators include the risk-free rate as approximated by the 3-month (USD or EUR) OIS swap rates, the slope of the term structure of the risk-free rate (the 10-year USD or EUR OIS swap rate minus the 3-month OIS swap rate), and volatility indexes (VIX or VSTOXX). For this analysis, we use weekly data as suggested by Blanco et al. (2005) to reduce short-term noise, an approach also taken on by Da Fonseca and Gottschalk (2020) and Zhang et al. (2009). Furthermore, we use lagged explanatory data to avoid a simultaneity problem from using contemporaneous data. Zhang et al. (2009) argues that as equity prices (or returns) and volatility are jointly determined with CDS spreads, contemporaneous data could inflate the explanatory power of empirical analyses.

We apply a pooled ordinary least square (OLS) regression to our panel dataset, thereby including a restriction of forcing the model to use the same coefficients across all reference entities as in Da Fonseca and Gottschalk (2020). Moreover, we adopt the approach proposed by Petersen (2009) of using clustered standard errors in order to adjust OLS standard errors for potential biases. This approach is also used by Zhang et al. (2009) and Da Fonseca and Gottschalk (2020), as it specifically adjusts for firm effects in the residual terms by clustering the standard errors based on firm size[17]. Our regression model for analyzing CDS spread levels is given by equation 5.13 and 5.14

$$\begin{aligned}\log CDS_{i,t} = \beta_0 &+ \beta_1 \log RETURN_{i,t-1} + \beta_2 \log IMPVOL30_{i,t-1} + \beta_3 \log IMPVOL90_{i,t-1} \\ &+ \beta_4 RATE_{i,t-1} + \beta_5 SLOPE_{i,t-1} + \beta_6 VIX_{i,t-1} \\ &+ \beta_7 BIDASK_{i,t-1} + +\beta_8 DEPTH_{i,t-1} + \varepsilon_{i,t-1}\end{aligned} \tag{5.13}$$

$$\begin{aligned}\log CDS_{i,t} = \beta_0 &+ \beta_1 \log RETURN_{i,t-1} + \beta_2 \log IMPVOL30_{i,t-1} + \beta_3 \log IMPVOL90_{i,t-1} \\ &+ \beta_4 RATE_{i,t-1} + \beta_5 SLOPE_{i,t-1} + \beta_6 VSTOXX_{i,t-1} \\ &+ \beta_7 BIDASK_{i,t-1} + +\beta_8 DEPTH_{i,t-1} + \varepsilon_{i,t-1}\end{aligned} \tag{5.14}$$

in which CDS spreads ($\log CDS$) are regressed on the one week lagged data of the stock return

[16] For this particular analysis, we use stock returns instead of stock prices as this is a more homogeneous measure than the level of the stock price. By that, we follow the approach taken in previous research, including Da Fonseca and Gottschalk (2020).

[17] See section 3.3.3 for further details on clustered standard errors and its importance when working with financial data in a panel model setup.

($\log RETURN$), 30-day and 90-day implied volatility ($\log IMPVOL30$ and $\log IMPVOL90$, respectively), the bid-ask spread ($BIDASK$), the quotes depth ($DEPTH$), the short-term risk-free rate ($RATE$), the slope of the interest rate term structure ($SLOPE$), and a volatility index (VIX or $VSTOXX$, respectively, depending on the geographic region). By using the CDS spreads' logarithm, we can interpret the coefficients on the explanatory variables as elasticities for those that are also expressed as a logarithm.

In addition to our levels regression, we extend our analysis by also running a regression that uses the changes of the variables. This can be motivated both economically and statistically (Da Fonseca and Gottschalk, 2020; Ericsson et al., 2009). Economically, creating a model that explains changes in CDS spreads rather than their levels provides specific insights as to how CDS spreads vary depending on variations in other variables. Statistically, as argued by Ericsson et al. (2009), applying first differencing, making the nonstationary variables stationary, may be of interest in cases where the dependent and independent variables show significant autocorrelation. Collin-Dufresne et al. (2001) and Zhang et al. (2009) mention similar economically and statistically motivated reasons for also conducting the analysis on the differenced variables. As tested in section 5.1.2, the logs of the stock prices and CDS spreads in our sample are nonstationary, thereby providing statistical incentive for testing determinants of CDS spread changes in our particular analysis. Equation 5.15 and 5.16 show the corresponding regressions of changes for the U.S. and European sample, respectively[18]

$$\begin{aligned}\Delta \log CDS_{i,t} = \beta_0 &+ \beta_1 \log RETURN_{i,t-1} + \beta_2 \Delta \log IMPVOL30_{i,t-1} + \beta_3 \Delta \log IMPVOL90_{i,t-1} \\ &+ \beta_4 \Delta RATE_{i,t-1} + \beta_5 \Delta SLOPE_{i,t-1} + \beta_6 \Delta VIX_{i,t-1} \\ &+ \beta_7 \Delta BIDASK_{i,t-1} + +\beta_8 \Delta DEPTH_{i,t-1} + \varepsilon_{i,t-1}\end{aligned} \tag{5.15}$$

$$\begin{aligned}\Delta \log CDS_{i,t} = \beta_0 &+ \beta_1 \log RETURN_{i,t-1} + \beta_2 \Delta \log IMPVOL30_{i,t-1} + \beta_3 \Delta \log IMPVOL90_{i,t-1} \\ &+ \beta_4 \Delta RATE_{i,t-1} + \beta_5 \Delta SLOPE_{i,t-1} + \beta_6 \Delta VSTOXX_{i,t-1} \\ &+ \beta_7 \Delta BIDASK_{i,t-1} + +\beta_8 \Delta DEPTH_{i,t-1} + \varepsilon_{i,t-1}\end{aligned} \tag{5.16}$$

5.4.2 Empirical Results

Results in Levels

We start with the results on the *levels* regressions. Table 7 summarizes our coefficient estimates for both the entire European and U.S. samples (column (1) and (4)). Noteworthy, if we refer

[18]Following Zhang et al. (2009) and Da Fonseca and Gottschalk (2020), we do not take the first difference but rather keep the returns ($RETURN$) unchanged as it already represents changes in prices.

to the CDS level, it corresponds to the log of the CDS level, given our model specifications from section 5.4.1. In both models, all of our explanatory variables except the 30-day implied volatility ($IMPVOL30$) are highly statistically significant at the 1% level. Using the adjusted R^2, we can explain 67% and 72% of the variation in CDS spreads in the European and U.S. sample, respectively. The magnitude is slightly above but overall in line with other papers such as Ericsson et al. (2009), Zhang et al. (2009) and Da Fonseca and Gottschalk (2020). Moreover, most of the signs on our coefficients are as expected based on economic theory and in line with previous empirical findings.

Table 7: Pooled OLS regression in *levels* for the European and U.S. sample.

Results for pooled OLS regression in *levels* as given by equations 5.14 and 5.13 for the European and U.S. sample. Columns (2)-(3) and (5)-(6) show the split by credit rating for the European and U.S. sample, respectively. t-statistics are reported in parenthesis. t-statistics and the level of significance are calculated based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Europe			U.S.		
	All	IG	HY	All	IG	HY
Intercept	0.31	0.98***	0.76*	-0.22	0.29	1.40
	(0.88)	(2.90)	(1.92)	(-0.48)	(0.80)	(1.50)
Quotes Depth	0.03***	0.03***	-0.01	0.05***	0.06***	0.01
	(4.17)	(7.90)	(-0.27)	(7.71)	(11.68)	(0.77)
Bid-Ask Spread	0.01**	0.09***	0.00	0.01***	0.06***	0.00***
	(3.62)	(12.88)	(2.38)	(9.85)	(11.15)	(4.34)
Return	-0.22***	-0.32***	-0.21**	-0.55***	-0.17**	-0.45***
	(-4.57)	(-7.18)	(-2.08)	(-7.11)	(-2.49)	(-3.91)
Log Implied Volatility (30D)	0.03	0.04	0.04	0.05	0.01	0.10
	(0.57)	(0.64)	(0.71)	(0.36)	(0.16)	(0.67)
Log Implied Volatility (90D)	1.09***	0.73***	1.10***	1.04***	0.79***	0.78*
	(7.37)	(5.51)	(7.08)	(4.02)	(4.70)	(2.18)
3-Month OIS Swap Rate	0.58***	0.64***	0.18	0.22***	0.21***	0.21***
	(6.19)	(8.6)	(0.72)	(10.41)	(11.08)	(6.83)
Swap Curve Slope	0.29***	0.28***	0.25***	0.38***	0.30***	0.44***
	(9.21)	(12.00)	(3.77)	(15.35)	(12.41)	(9.18)
Market Volatility	-0.01***	-0.01***	-0.01	-0.02***	-0.02***	-0.02***
	(-3.67)	(-4.88)	(-1.44)	(-6.74)	(-7.51)	(-4.20)
Adjusted R^2	0.67	0.45	0.60	0.72	0.52	0.54

We find a negative relationship between the firm's stock returns and the level of CDS spreads, which is as expected and in line with previous findings, for example, by Da Fonseca and Gottschalk (2020). Thus, our findings suggest that growth in firm value lowers the probability of default and, consequently, reduces the credit risk.

Higher implied volatility on stock options and, therefore, higher asset volatility has a significant positive impact on the level of CDS spreads, which backs our theoretical prediction and confirms previous results. Higher asset volatility makes it more likely to hit the firm's default boundary, leading to higher credit risk and CDS spreads. Noteworthy, only the 90-day implied volatility is statistically significant, whereas the 30-day implied volatility is insignificant in both samples, which results from the high correlation between the two explanatory variables. In the appendix, Table A.1 and A.2 show the correlation for each pair of variables for the European and U.S. subsample, respectively. The removal of either of the two variables leads the remaining one to become statistically significant. Since we use the logarithm of the CDS spread as our dependent variable, we can interpret the coefficient as the elasticity between implied volatility and CDS spreads. In particular, a one percent increase in the 90-day implied volatility increases the CDS spread by 1.09% and 1.04% for the European and U.S. sample, respectively (controlling for all other variables in the model). The magnitude is in line with empirical results by Da Fonseca and Gottschalk (2020).

Across both samples, there exists a positive relationship between the bid-ask spreads and the CDS spread level. As such, we can empirically confirm the conclusions from other papers that lower liquidity, in the form of bid-ask spreads, drives up CDS spreads (Bühler and Trapp, 2009; Bongaerts et al., 2011).

Surprisingly, however, the coefficient on our second liquidity measure, the quotes depth, does not have the expected negative sign but indicates that a higher number of dealers that submit CDS quotes for transactions leads to higher CDS spreads. While this finding seems puzzling at first, Qiu and Yu (2012) find, in what they call an "asymmetric information" effect, that an increase in liquidity can also increase CDS spreads when the existing number of dealers is high in the market. The authors argue that the number of dealers providing quotes can be interpreted as a proxy for asymmetric information in the CDS market.

While the expected effect of the spot interest rate and the slope of the term structure on credit spreads is ambiguous a priori, our analysis indicates a positive influence of the spot rate on CDS spreads. Thus, the findings support the view by Da Fonseca and Gottschalk (2020) that a higher risk-free rate can be a sign of future tightening in monetary policy, which would increase default probabilities. Other papers, however, typically find a negative impact of short-term interest rates on CDS spreads (see Blanco et al., 2005; Ericsson et al., 2009; Zhang et al., 2009; Da Fonseca and Gottschalk, 2020). Noteworthy, these papers use a different proxy for the risk-free rate which could partly explain the difference in our findings as, for example, Blanco et al. (2005) and Ericsson et al. (2009) use yields on 10-year U.S. Treasury bonds. The coefficients on the slope of the interest-rate term structure, on the other hand, match our expectations by having a positive influence on credit spreads and is also in line with earlier empirical results.

Lastly, the dynamics of the market volatility ($VSTOXX$ or VIX) in our regressions contradict our theory-based prediction and other empirical findings. We find a minimal but statistically significant negative influence of market volatility on CDS spreads. Nevertheless, these puzzling results might be emerging from the inclusion of various explanatory variables and correlation among them as we find a positive correlation between the market volatility and CDS spreads in isolation (see appendix A.1 for correlation matrices).

Furthermore, to better understand potential structural differences between the investment grade and high yield segment of the CDS market, we split the European and U.S. sample by credit rating group. The results for the investment grade and high yield subsamples for both geographic areas can be found in columns (2)-(3) and (5)-(6) of Table 7.

First we consider the European subsample. For investment grade (EU IG) companies, all previously significant explanatory variables remain statistically significant at the 1% level, leaving only the 30-day implied volatility ($IMPVOL30$) insignificant. Moreover, all signs on the coefficients remain the same. The European high yield (EU HY) sample shows some changes compared to the output in column (1). While the intercept stays insignificant, the quotes depth ($DEPTH$) becomes statistically insignificant, and the bid-ask spread ($BIDASK$) is only significant at 10%, indicating that liquidity-related measures are less important for the spread level for EU HY contracts than for its EU IG equivalent. The results appear somewhat puzzling given overall wider bid-ask spreads in the high yield segment, assuming that wider bid-ask spreads is an indicator of lower liquidity in a market. More specifically, we expect liquidity to have a higher influence on prices in markets where liquidity is low, as also suggested by the liquidity premium in the CDS market[19]. Yet, due to the higher overall volatility in the high yield segment and its increased risk of default compared to the investment grade space, bid-ask spreads may not be an accurate liquidity proxy for these companies. In addition, the short-term interest rate becomes insignificant, which is in line with the widely recognized lower sensitivity of high yield bonds to interest rates compared to investment grade bonds. Another macroeconomic indicator, market volatility, is insignificant in explaining high yield CDS spreads, which is somewhat surprising since the high yield space is expected to be more correlated to the equity market and thereby also the volatility of this market. Yet, the insignificance of the VSTOXX may be influenced by the multicollinearity that exists among the variables[20]. Further, the significance of the stock return remains significant for the high yield companies although it drops to being significant at the 5% level compared to 1% for the overall sample.

Moving to the U.S. subsamples, we see that the regression using the U.S. IG group fully reflects the overall findings of the overall U.S. sample (column 4). Each variable previously found

[19]Section 2.3.7 in the literature review provides a thorough explanation of this feature of the CDS market.
[20]See appendix A.1 for a correlation matrix of all variables used in this analysis.

significant remains statistically important at the 1% level, only the p-value on the stock return marginally drops from 1% to 2%. Again, we see more differences when looking into the high yield space, although changes are not as drastic as for the EU HY segment. The quotes depth ($DEPTH$) becomes statistically insignificant, whereas the bid-ask spread ($BIDASK$) remains highly significant, contrary to the EU HY group. Furthermore, 90-day option-implied volatility loses some explanatory power being significant at the 5% level (vs. 1%).

Overall, the regression outputs on the split sample support our initial findings even though the adjusted R^2 of the subsamples is lower than in the regressions on of the entire samples (column (1) and (4)) across both geographic regions. While the European high yield subsample shows some outliers, the previously statistically significant explanatory variables mostly remain significant in explaining the levels of CDS spreads.

Next, we assess how gradually adding different types of explanatory variables – liquidity and macroeconomic conditions – influences the explanatory power of our linear model. Starting by only using our primary data and regressing CDS spreads on stock returns as well as 30-day and 90-day implied volatility explains 39% and 49% of the variation in credit spreads for the European and U.S. sample, respectively (see column (1) and (4) in Table 8). Most interestingly, except for the intercept, only 90-day implied volatility has a statistically significant influence on CDS levels in the U.S. sample. While all signs are in line with our previous findings and our a priori expectations, stock returns and 30-day implied volatility do not statistically explain CDS levels. The same observation can be made for the European group, although stock returns are significant at the 10% level.

By adding our chosen liquidity measures, we can explain an additional 22% and 16% of the variation in CDS spreads for the European and U.S. sample, respectively (see column (2) and (5) in Table 8). In both samples, both liquidity measures are statistically significant at the 1% level, indicating a meaningful contribution to the price level of CDS. The 90-day implied volatility remains significant, whereas the stock returns gain in explanatory power (significant at the 10% in both geographic groups).

Consequently, the addition of macroeconomic indicators (interest rates, the slope of the term structure, and market volatility) further increases the explanatory power of our panel data model for European and U.S. companies by, respectively, 6% and 7% when comparing column (2) with column (3) and (5) with (6) in Table 8.

Table 8: Pooled OLS regression in *levels* for different types of explanatory variables.

Results for pooled OLS regression in *levels* for the European and U.S. sample. Columns (1) and (4) shows the results for regressing the changes of CDS spreads only on stock returns and changes in 30-day and 90-day implied volatility. Columns (2) and (5) shows the results for adding the average bid-ask spread and the quotes depth. By adding the macroeconomic variables, columns (3) and (6) show the results for the full regression as given by equations 5.14 and 5.13, respectively. t-statistics are reported in parenthesis. t-statistics and the level of significance are calculated based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Europe			U.S.		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-0.33	1.07***	0.31	-0.83**	0.93**	-0.22
	(-0.89)	(3.22)	(0.88)	(-2.10)	(2.54)	(-0.48)
Quotes Depth		0.03***	0.03***		0.05***	0.05***
		(3.80)	(4.17)		(7.43)	(7.71)
Bid-Ask Spread		0.01**	0.01**		0.01***	0.01***
		(3.74)	(3.62)		(10.45)	(9.85)
Return	0.18*	-0.10*	-0.22***	0.15	-0.16*	-0.55***
	(1.84)	(-1.71)	(-4.57)	(1.23)	(-1.86)	(-7.11)
Log Implied Volatility (30D)	-0.19*	0.01	0.03	0.01	-0.06	0.05
	(-1.86)	(0.12)	(0.57)	(0.04)	(-0.43)	(0.36)
Log Implied Volatility (90D)	1.61***	0.84***	1.09***	1.54***	0.87***	1.04***
	(8.50)	(5.59)	(7.37)	(6.81)	(3.90)	(4.02)
3-Month OIS Swap Rate			0.58***			0.22***
			(6.19)			(10.41)
Swap Curve Slope			0.29***			0.38***
			(9.21)			(15.35)
Market Volatility			-0.01***			-0.02***
			(-3.67)			(-6.74)
Adjusted R^2	0.39	0.61	0.67	0.49	0.65	0.72

In a final test, we re-run our model and exclude explanatory variables that have shown to be insignificant in our baseline model (column (1) and (3) in Table 7. The results for European and U.S. companies can be found in Table 9. The explanatory power, as measured by the adjusted R^2, the level of significance, and the direction of the relationship remain the same in both samples when excluding the 30-day option-implied volatility.

Table 9: Pooled OLS regression in *levels* excluding insignificant explanatory variables for the European and U.S. sample.

Results for the reduced pooled OLS regression in *levels* for the European and U.S. sample. 30-day option-implied volatility is excluded for the European and the U.S. sample. t-statistics are reported in parenthesis. t-statistics and the level of significance are calculated based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Europe	U.S.
	All	All
Intercept	0.30	-0.23
	(0.87)	(-0.54)
Quotes Depth	0.03***	0.05***
	(4.17)	(7.71)
Bid-Ask Spread	0.01**	0.01***
	(3.62)	(9.96)
Return	-0.22***	-0.55***
	(-4.54)	(-6.67)
Log Implied Volatility (30D)		
Log Implied Volatility (90D)	1.12***	1.09***
	(8.74)	(7.84)
3-Month OIS Swap Rate	0.58***	0.22***
	(6.19)	(11.15)
Swap Curve Slope	0.29***	0.38***
	(9.28)	(15.86)
Market Volatility	-0.01***	-0.02***
	(-3.62)	(-6.00)
Adjusted R^2	0.67	0.72

Results in Changes

To further assess the influence of firm-, liquidity- and macroeconomic-related variables on credit default swaps and to confirm our previous findings, we also conduct an empirical analysis of the changes of CDS spreads, as per equation 5.15 and 5.16. The results for the European and U.S. sample can be found in Table 10.

First and foremost, the regressions in changes show a considerably lower adjusted R^2 compared to its pendant in levels, as the U.S. model can explain only 6% of the variation in CDS spread changes, whereas the European model explains even less with only 2%. However, these results are as expected and in line with previous empirical results as, for example, Zhang et al. (2009) can explain between 1% and 6% and Collin-Dufresne et al. (2001) approximately 5% of the variation in credit spread changes. By conducting a principal component analysis of the residuals, Collin-Dufresne et al. (2001) argue that the low explanatory power likely stems from a systematic effect rather than noise in the data.

Table 10: Pooled OLS regression in *changes* for the European and U.S. sample.

Results for pooled OLS regression in *changes* as given by equations 5.16 and 5.15 for the European and U.S. sample. Columns (2)-(3) and (5)-(6) show the split by credit rating for the European and U.S. sample, respectively. t-statistics are reported in parenthesis. t-statistics and the level of significance are calculated based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Europe			U.S.		
	All	IG	HY	All	IG	HY
Intercept $\times 10^{-2}$	-0.04**	-0.05***	-0.01	0.04**	0.05***	-0.03
	(-2.19)	(-2.98)	(-0.2)	(2.45)	(2.73)	(-0.91)
Δ Quotes Depth $\times 10^{-1}$	-0.22***	-0.21***	-0.24***	-0.04	-0.02	-0.05
	(-11.27)	(-10.48)	(-4.7)	(-1.58)	(-0.82)	(-1.02)
Δ Bid-Ask Spread $\times 10^{-1}$	0.01	-0.14**	0.01	0.02**	0.41***	0.01
	(0.86)	(-2.05)	(0.79)	(3.01)	(5.2)	(1.22)
Return $\times 10^{-1}$	-1.20***	-0.75***	-1.69***	-0.46**	0.54	-0.86***
	(-8.07)	(-4.07)	(-6.88)	(-2.34)	(1.37)	(-4.17)
Δ Log Implied Volatility (30D) $\times 10^{-1}$	-0.07	-0.07	-0.03	-0.17*	-0.32***	-0.12
	(-1.64)	(-1.18)	(-0.62)	(-1.91)	(-3.66)	(-1.04)
Δ Log Implied Volatility (90D) $\times 10^{-1}$	0.11	0.17*	0.26	0.38**	0.64***	0.26
	(1.37)	(1.76)	(1.82)	(2.25)	(3.21)	(1.24)
Δ 3-Month OIS Swap Rate	0.32***	0.34***	0.27***	-0.21***	-0.09***	-0.47***
	(9.57)	(13.85)	(2.94)	(-7.21)	(-2.9)	(-12.28)
Δ Swap Curve Slope	0.09***	0.10***	0.09***	0.17***	0.18***	0.14***
	(18.77)	(19.29)	(7.6)	(36.15)	(31.4)	(14.33)
Δ Market Volatility $\times 10^{-1}$	0.01***	0.01***	0.02***	0.01***	0.01***	0.01***
	(10.97)	(8.99)	(6.49)	(8.32)	(7.91)	(2.74)
Adjusted R^2	0.02	0.02	0.03	0.06	0.05	0.11

The observed effect of stock returns on CDS spread levels is confirmed by our findings for spread changes. For both regions, the sign on the coefficient is negative while the coefficients are both statistically significant at 1%, thereby in line with the theoretical framework by Merton (1974).

However, the effect of implied volatility on spread changes is somewhat surprising and different from our findings on CDS levels. First, both 30-day and 90-day implied volatility is insignificant (p-value of 15% and 19%, respectively) in explaining variation in European CDS spread changes. Yet, this is likely a results of the multicollinearity effects discussed earlier. Results for our U.S. group are more in line, as we find 30-day implied volatility to be insignificant and 90-day implied volatility to have the correct sign and to be statistically significant (5% level). Overall, the signs are mainly in line with economic theory.

Furthermore, our liquidity measures show some inconsistency across the two geographic regions. While the quotes depth is highly significant (1%) in explaining CDS changes in the European sample, the bid-ask spread is not significant. The exact opposite is true for the group of U.S. companies. To recall, both liquidity measures are significant at the 1% level in the levels regression. However, this might be explained by the high degree of autocorrelation in CDS levels.

The remaining macroeconomic indicators are all highly statistically significant at the 1% level, confirming their relevance in explaining credit default swaps. The sign on the short-term interest rate is positive for the European sample but negative for the U.S. sample. As argued before, two contrasting theoretical explanations exist of how interest rates can affect CDS spreads. The negative sign is in line with the explanation by Collin-Dufresne et al. (2001) that a higher spot rate translates into lower risk-neutral probabilities of default which, consequently, leads to lower credit spreads.

On a final note, both geographic groups show a statistically significant intercept at the 5% with a positive sign indicating that no matter which region we look at, a slight upward trend in the percentage changes of CDS is observed over time.

Again, we split both the European and U.S. sample by credit rating group to identify potential structural differences between the investment grade and high yield segment of the CDS market. The results for the investment grade and high yield subsamples for both geographic areas can be found in column (2)-(3) and (5)-(6) of Table 10.

First of all, for both geographic regions, the explanatory power for the high yield groups is higher compared to the investment grade equivalent, especially in the U.S. sample (Europe: 3% vs. 2%; U.S.: 11% vs. 5%). Looking at the investment grade subsamples, the coefficients still show the expected signs and significance levels are similar to those for the overall sample (column (1) and (4)). In particular, the only worsening of significance levels is the insignificance of the stock returns in the U.S. IG group. The results of the European high yield sample are in line with the overall findings for European companies, whereas the average bid-ask spread and the 90-day implied volatility become insignificant in the U.S. high yield group.

Moreover, regressing the changes of CDS spreads only on stock returns and changes in 30-day and 90-day implied volatility (see column (1) and (4) in Table 11) indicates that stock returns in both samples are highly statistically significant (1%) in contrast to our previous findings in levels when only considering the three variables. Again, 30-day implied volatility is insignificant, whereas 90-day implied volatility has the correct sign and is statistically significant (5%). The explanatory power of the regressions is, as expected, low.

Table 11: Pooled OLS regression in *changes* for different types of explanatory variables.

Results for pooled OLS regression in *changes* for the European and U.S. sample. Columns (1) and (4) shows the results for regressing the changes of CDS spreads only on stock returns and changes in 30-day and 90-day implied volatility. Columns (2) and (5) shows the results for adding the average bid-ask spread and the quotes depth. By adding the macroeconomic variables, columns (3) and (6) show the results for the full regression as given by equations 5.16 and 5.15, respectively. t-statistics are reported in parenthesis. t-statistics and the level of significance are calculated based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Europe			U.S.		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept $\times 10^{-2}$	-0.11***	-0.11***	-0.04**	0.00	0.00	0.04**
	(-7.28)	(-7.07)	(-2.19)	(-0.03)	(0.04)	(2.45)
Δ Quotes Depth $\times 10^{-1}$		-0.20***	-0.22***		-0.10***	-0.04
		(-10.59)	(-11.27)		(-3.74)	(-1.58)
Δ Bid-Ask Spread $\times 10^{-1}$		0.01	0.01		0.03***	0.02**
		(0.99)	(0.86)		(4.08)	(3.01)
Return $\times 10^{-1}$	-1.50***	-1.51***	-1.20***	-0.74***	-0.69***	-0.46**
	(-9.34)	(-9.8)	(-8.07)	(-3.90)	(-3.64)	(-2.34)
Δ Log Implied Volatility (30D) $\times 10^{-1}$	-0.03	-0.02	-0.07	-0.19*	-0.20*	-0.17*
	(-0.85)	(-0.58)	(-1.64)	(-1.93)	(-1.98)	(-1.91)
Δ Log Implied Volatility (90D) $\times 10^{-1}$	0.19**	0.19**	0.11	0.44**	0.44**	0.38**
	(2.50)	(2.65)	(1.37)	(2.36)	(2.41)	(2.25)
Δ 3-Month OIS Swap Rate			0.32***			-0.21***
			(9.57)			(-7.21)
Δ Swap Curve Slope			0.09***			0.17***
			(18.77)			(36.15)
Δ Market Volatility $\times 10^{-1}$			0.01***			0.01***
			(10.97)			(8.32)
Adjusted R^2	0.01	0.01	0.02	0.00	0.01	0.06

Adding the bid-ask spreads and the quotes depth increases the explanatory power in both models, but the absolute magnitude of these changes is small (see column (2) and (5) in Table 11). In the U.S. sample, both liquidity measures are significantly correlated with the changes in CDS spreads, while only the quotes depth is significant for the European sample. Yet, the coefficient on the quotes depth is higher than the coefficients on the liquidity measures for the U.S. sample combined, indicating that the influence of liquidity in the European sample may be even larger than it is in the U.S. sample.

Finally, the addition of macroeconomic indicators further increases the explanatory power of our panel data model for European and U.S. companies by respectively 1% and 5% when comparing our full model column (3) and (6) to column (2) and (5), respectively. As argued before, all macroeconomic variables have a strong significant (1%) impact on the changes in CDS spreads, particularly for the U.S. sample.

Results for our reduced baseline model where insignificant explanatory variables are excluded can be found in Table 12. In the model for European companies, we exclude both 30-day and 90-day option-implied volatility[21] and the bid-ask spreads, whereas 30-day implied volatility and the quotes depth are excluded in the group of U.S. companies. All remaining explanatory variables keep the correct sign and remain statistically significant, at least at the previous level.

Table 12: Pooled OLS regression in *changes* excluding insignificant explanatory variables for the European and U.S. sample.

Results for the reduced pooled OLS regression in *changes* for the European and U.S. sample. For the European companies, 30-day, 90-day option-implied volatility and the bid-ask spreads are excluded. For the U.S. sample 30-day implied volatility and the quotes depth are excluded. *t*-statistics are reported in parenthesis. *t*-statistics and the level of significance are calculated based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Europe	U.S.
	All	All
Intercept $\times 10^{-2}$	-0.04**	0.04**
	(-2.13)	(2.34)
Δ Quotes Depth $\times 10^{-1}$	-0.22***	
	(-11.28)	
Δ Bid-Ask Spread $\times 10^{-1}$		0.02**
		(3.00)
Return $\times 10^{-1}$	-1.22***	-0.46**
	(-7.99)	(-2.34)
Δ Log Implied Volatility (30D) $\times 10^{-1}$		
Δ Log Implied Volatility (90D) $\times 10^{-1}$		0.19**
		(2.20)
Δ 3-Month OIS Swap Rate	0.31***	-0.21***
	(9.56)	(-7.2)
Δ Swap Curve Slope	0.09***	0.17***
	(18.61)	(36.44)
Δ Market Volatility $\times 10^{-1}$	0.01***	0.01***
	(12.42)	(8.18)
Adjusted R^2	0.02	0.06

[21] 30-day and 90-day volatility are insignificant for the European sample, even when only one of them is included in the model.

Robustness of model framework

Given the high degree of significance of most of our included explanatory variables and the substantial overall explanatory power, measured by the adjusted R^2, in the CDS levels regression across geographic regions, we further investigate the robustness of our findings. In following Zhang et al. (2009), we apply panel data techniques and re-estimate the CDS levels regression using a fixed effect and random effect framework. The results of both the fixed effect and random effect regressions for the European and the U.S. sample can be found in Table 13[22].

Table 13: Pooled OLS, Fixed Effects, and Random Effects regression in *levels* for the European and U.S. sample.

Results for pooled OLS, Fixed Effects, and Random Effects regression in *levels* for the European and U.S. sample. Columns (1) and (4) shows the results for the pooled OLS model. Columns (2) and (5) shows the results from using a Fixed Effects framework. Columns (3) and (6) shows the results from using a Random Effects framework. t-statistics are reported in parenthesis. t-statistics and the level of significance are calculated based on clustered standard errors. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Europe			U.S.		
	POLS	FE	RE	POLS	FE	RE
Intercept	0.31		1.39***	-0.22		1.93***
	(0.88)		(6.96)	(-0.48)		(3.65)
Quotes Depth	0.03***	0.02***	0.02***	0.05***	0.03***	0.03***
	(4.17)	(5.71)	(5.71)	(7.71)	(7.72)	(7.72)
Bid-Ask Spread	0.01**	0.00*	0.00*	0.01***	0.00***	0.00***
	(3.62)	(2.69)	(2.71)	(9.85)	(5.73)	(5.84)
Return	-0.22***	-0.07	-0.07	-0.55***	-0.35***	-0.35***
	(-4.57)	(-1.61)	(-1.64)	(-7.11)	(-5.99)	(-6.06)
Log Implied Volatility (30D)	0.03	0.00	0.00	0.05	0.05	0.05
	(0.57)	(0.15)	(0.15)	(0.36)	(0.69)	(0.68)
Log Implied Volatility (90D)	1.09***	0.77***	0.77***	1.04***	0.46**	0.47**
	(7.37)	(9.41)	(9.47)	(4.02)	(2.14)	(2.17)
3-Month OIS Swap Rate	0.58***	0.47***	0.47***	0.22***	0.15***	0.15***
	(6.19)	(5.47)	(5.48)	(10.41)	(7.09)	(7.15)
Swap Curve Slope	0.29***	0.26***	0.26***	0.38***	0.23***	0.23***
	(9.21)	(11.53)	(11.55)	(15.35)	(7.58)	(7.68)
Market Volatility	-0.01***	0.00	0.00	-0.02***	0.00	0.00
	(-3.67)	(0.77)	(0.73)	(-6.74)	(-0.28)	(-0.38)
Adjusted R^2	0.67	0.42	0.42	0.72	0.25	0.26

[22] We assess the consistency of the fixed effect and random effect models by conducting a Hausman (1978) test. For the European and the U.S. sample, we reject the null hypothesis at the 1% level indicating inconsistency of the random effect estimator and, hence, conclude a higher consistence of the fixed effect model. Yet, for completeness we include and discuss the results of both models

First of all, all explanatory variables show the expected signs on their coefficients, thereby confirming our previous overall results, shown in column (1) and (4) of Table 13.

Comparing the different regression models for the European sample, the VSTOXX index becomes statistically insignificant in the fixed effects and random effects models. While our pooled OLS model estimates a significant coefficient on this variable, it is negative, which, as we discussed, goes against expectations. As such, the three models align on not being able to confirm economically motivated expectations for the effect of the VSTOXX index. In addition to the change in significance of the VSTOXX, the stock returns become insignificant (p-value: 0.11) in the fixed effects and random effects regressions. This is another minor discrepancy between the models, given its high explanatory power in the pooled OLS model.

Results for the U.S. companies are even more consistent across the three model frameworks. Only the VIX becomes highly insignificant in the fixed effect and random effect models. Again, as explained above, previous findings on the VIX were rather inconsistent and its overall economic effect on CDS spreads limited. The equity returns, in contrast to the European sample, are highly statistically significant at the 1% level.

Overall Results

Overall, our results are in line with our a priori expectations and findings by previous liteature, including Blanco et al. (2005), Ericsson et al. (2009), Zhang et al. (2009), and Da Fonseca and Gottschalk (2020). Noteworthy, market volatility, measures by either the the VSTOXX or the VIX, show some unexpected signs while being highly stastically significant across subgroups (see Table 7). The effect of the risk-free rate differs from previous findings but can be explained both economically (see Da Fonseca and Gottschalk, 2020) and by the fact that we use a different proxy for the risk-free rate than other papers.

The regression in changes confirms the results in levels in total. Although, the coefficients on the liquidity measures show some inconsistencies across the two geographic regions. The macroeconomic indicators remain all highly significant in explaining the variation in CDS spread changes, even the measure for market volatility shows the expected sign.

In our robustness analysis, the empirical results of the fixed effect and random effect models confirm our previous findings, hence allowing to conclude that the results are robust to the use of different estimation frameworks.

Given the significance and robustness of our panel model results, we apply these findings in the following section 5.5 by establishing a trading strategy based on a predictive model which uses the significant explanatory variables of this analysis.

5.5 Signal Trading

5.5.1 Methodology

We find significant explanatory power of various parameters in our panel data model for predicting the level of CDS spreads (see section 5.4 on determinants of CDS spreads), which is expected to be even stronger on an individual firm level[23]. It naturally follows to investigate whether the simple, easily obtained, and frequently updated predictive variables can be used to predict CDS spreads for the purpose of setting up an investment strategy. For the trading strategies, eight companies are left out of the analysis. The eight excluded companies include four and three European investment grade and high yield companies, respectively, and one U.S. high yield company. These are companies which had enough data overall for conducting a cointegration analysis and a pooled OLS but are missing too much data in either the testing or the training period for correctly estimating or testing the trading models.

Importantly, to correctly approximate the returns of our trading strategy, we will switch from CDS spreads as our dependent variable to using the percentage upfront price[24]. As discussed in detail in 2.3.6 the lack of availability of transaction prices for CDS contracts comes along with severe challenges in correctly estimating CDS returns. We follow the proposed approximation by Augustin et al. (2020) as it is the most accurate pricing approach compared to a number of other methods. Based on empirical analysis by Augustin et al. (2020) it has a correlation of at least 99% with the real CDS return. To briefly recall, the conversion from quoted CDS spread to upfront price follows the below formulas

$$P_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left[1 - e^{-\left(r_t + \frac{s_t}{1-R}\right)(T-t)} \right] \tag{5.17}$$

using the directly observable values for the quoted CDS spread (s_t), the fixed coupon (c), the expected recovery rate (R) and the ($T-t$)-year risk-free rate (r_t). Depending on whether it is an investment grade or high yield company the fixed coupon (c) is set to either 100 or 500 basis points and the expected recovery rate (R) is either 30% or 40% based on the assumptions of the ISDA CDS Standard Model[25]. Further, we use 5-year USD or EUR swap rates as a proxy for the risk-free rate for U.S. and European companies, respectively.

We implement a predictive model by selecting statistically significant independent variables based on the findings from section 5.4. A price forecast is calculated based on the model, which is then compared to today's price level. A trading decision is made based on whether the model predicts the CDS upfront price to significantly change over the next trading period.

[23] Models on a firm level can be fitted specifically to the particular firms.

[24] Expressed as a percentage of the notional.

[25] 30% recovery rate is assumed for U.S. HY companies. 40% is assumed for U.S. IG companies and all European companies (ISDA and Markit Group Limited, 2021).

Depending on whether our model forecasts an increase or decrease in the CDS upfront price, we open either a long or short position in the CDS contract to participate in the anticipated future price move.

To avoid inflating the returns of our investment strategy as a result of in-sample bias, we split our sample into a training and testing period representing the first five (62.5%) and the remaining three years (37.5%) of our data set, respectively.

Predictive Model

As mentioned, we only use explanatory variables that have been found significant in section 5.4 to make our model as parsimonious and accurate as possible. Overall and across our different subsamples both of our liquidity measures ($BIDASK$ and $DEPTH$), the stock return ($\log RETURN$), the logarithm of the 90-day option implied volatility ($\log IMPVOL90$) and all three macroeconomic indicators ($RATE$, $SLOPE$ and VIX or $VSTOXX$) show significant power in explaining CDS spreads and are, therefore, included into our investment strategy.

While we have used weekly data for our panel model in section 5.4, the predictive model in our trading strategy uses daily data in order to more efficiently find and pursue investment opportunities as they arise. Consequently, we use data from the previous trading day to forecast the upfront price for the following day.

Therefore, our final predictive regression for the U.S. and European subsamples is given by Equation 5.18 and 5.19, respectively

$$\begin{aligned} UPFRONT_{i,t} = \beta_0 + \beta_1 \log RETURN_{i,t-1} + \beta_2 + \log IMPVOL90_{i,t-1} \\ + \beta_3 RATE_{i,t-1} + \beta_4 SLOPE_{i,t-1} + \beta_5 VIX_{i,t-1} \\ + \beta_6 BIDASK_{i,t-1} + \beta_7 DEPTH_{i,t-1} + \varepsilon_{i,t-1} \end{aligned} \tag{5.18}$$

$$\begin{aligned} UPFRONT_{i,t} = \beta_0 + \beta_1 \log RETURN_{i,t-1} + \beta_2 + \log IMPVOL90_{i,t-1} \\ + \beta_3 RATE_{i,t-1} + \beta_4 SLOPE_{i,t-1} + \beta_5 VSTOXX_{i,t-1} \\ + \beta_6 BIDASK_{i,t-1} + \beta_7 DEPTH_{i,t-1} + \varepsilon_{i,t-1} \end{aligned} \tag{5.19}$$

The above parameters are estimated for each company in our sample based on the training period.

Trading Signal

In this subsection, we explain how to create the trading signal to either go long, short, or stay neutral for our investment strategy.

Using equation 5.18 and 5.19 from above, we calculate the predicted upfront prices for each day of our training set. Next, we calculate the difference ($Model_{t+1} - Actual_t$) between the model-implied price for time $t+1$ using our time-t input variables and the actual upfront price at time t (converted from observed par spreads based on equation 5.17). This difference between the predicted and observed upfront prices we define as the spread.

The spread is used for calculating a standardized z-score for each day. Given the spread (ω_t) on a given day t, the mean (μ_ω) spread, and the standard deviation (σ_ω) of daily spreads, the z-score given by equation 5.20

$$z\text{-score}_t = \frac{\omega_t - \mu_\omega}{\sigma_\omega} \tag{5.20}$$

Spreads means and standard deviations are calculated based on the training period for each company. The normalization allows us to more easily introduce and apply the thresholds which provide the limits beyond which we open up a trade. In particular, a z-score of one equals a one standard deviation difference of day t's spread from the mean spread.

In combining these steps, we use the training period estimated coefficients from our regression model given by equation 5.18 and 5.19 to predict the one-day ahead upfront price on a daily frequency in our testing period. Then, we estimate the difference (ω_t) between today's actual value and the predicted one-day ahead value, calculate the z-score by using equation 5.20. The estimated z-scores are then compared to our thresholds for going long or short, and trades are opened if the z-scores breach either of the upper of lower boundaries. An open position is closed once the z-score has crossed zero, corresponding to the spread, ω_t, crossing its mean, μ_ω.

Performance

As in Junge and Trolle (2015), we assume that 100% of the notional is required in collateral on top of the upfront price when investing in the CDS. This is assumed to be the case for both sides of the contract. Since the upfront is denoted in percentage points of the notional, 1 is simply added to the upfront price for the CDS to cover the collateral. Returns are then calculated by the percentage change in the collateral and the CDS upfront price. A side effect of this is that it significantly reduces the volatility of the CDS return component. We assume that the interest rate on the posted collateral is 0%.

The returns are multiplied with the sign of our position (1 for being long, -1 for being short and 0 for staying neutral). Due to the low liquidity in large segments of the single-name CDS space (see ISDA, 2019) taking transaction costs into account is key to assessing true real-world performance and applicability of the strategy. Thus, we use the observed bid-ask spreads from Markit together with the quoted spreads to approximate the bid- and ask-price in upfront terms using equation 5.17 and then deduct half of the calculated upfront bid-ask spread every time we change our positioning in the CDS contract. Further, we investigate how different thresholds for going long or short affect performance, especially in the context of transaction costs since a lower threshold is associated with a higher trading frequency and consequently higher transaction costs. In particular, we select the optimal threshold for the out-of-sample period by running our strategy for different thresholds between 0.25 and 5 standard deviation moves in steps of 0.25 for the training period. Then, the performance net of transaction costs is compared across strategies and the threshold associated with the highest return is selected for the testing period analysis.

5.5.2 Empirical Results

Following the implementation of our signal trading strategy, as described in section 5.5.1, this section focuses on evaluating its performance.

We start out by assessing the in-sample performance of the strategy net of transaction costs for different thresholds ranging between 0.25 and 5 standard deviation moves. Table 14 summarizes the return performance and reports the number of companies for which trades are executed based on the different thresholds.

Across the entire sample, a threshold of 4.75 standard deviation moves results in the best performance. With this threshold, however, no trades are made for any companies in the sample. That is, for the full sample, the training period results suggest that the strategy should not be implemented. Following this, it makes sense to consider differences across subgroups of the sample.

The difference between observed net returns for the investment grade and the high yield sample is substantial. The optimal threshold of IG companies is 1.25 whereas it is significantly higher for the HY sample at 3.75. Further, at a threshold of 3.75, trades are only made for 2 companies in the HY sample, which clearly indicates that including these companies in the trading strategy is likely to be unprofitable. At a threshold of 1.25, trades are made for 133 out of 141 companies in the IG sample, and a positive annualized net return of 0.06% is estimated. The large difference between the IG and HY subsamples can be explained by the significantly higher transaction costs, as measured by the bid-ask spread, of the high yield companies.

As for the difference between EU and U.S. optimal thresholds, there is not as much value to gain from differentiation. Optimal thresholds for these subsamples are 3.75 and 4.75, corresponding to trades for close to no companies.

Table 14: Threshold assessment for the signal trading strategy.

Assessment of selecting the optimal threshold for creating the trading signal. The table compares the strategy's financial performance net of transaction costs during the training period for different thresholds between 0.25 and 5 standard deviation moves in steps of 0.25. In addition, the number of companies that would be actively traded given a selected threshold is reported.

Thresholds	**Total Return**					**Annualized Return**					**Companies traded**				
	All	EU	U.S.	IG	HY	All	EU	U.S.	IG	HY	All	EU	U.S.	IG	HY
0.25	-30.08%	-32.25%	-28.43%	-10.28%	-75.11%	-6.91%	-7.49%	-6.47%	-2.15%	-24.28%	203	88	115	141	62
0.50	-17.85%	-20.37%	-15.91%	-4.21%	-48.85%	-3.86%	-4.45%	-3.41%	-0.86%	-12.55%	203	88	115	141	62
0.75	-9.82%	-12.42%	-7.84%	-1.10%	-29.66%	-2.05%	-2.62%	-1.62%	-0.22%	-6.80%	203	88	115	141	62
1.00	-5.37%	-7.64%	-3.63%	0.03%	-17.64%	-1.10%	-1.58%	-0.74%	0.01%	-3.81%	200	88	112	138	62
1.25	-2.45%	-3.79%	-1.42%	**0.32%**	-8.74%	-0.49%	-0.77%	-0.29%	**0.06%**	-1.81%	190	86	104	133	57
1.50	-1.35%	-1.87%	-0.95%	0.28%	-5.05%	-0.27%	-0.38%	-0.19%	0.06%	-1.03%	169	81	88	120	49
1.75	-0.74%	-0.79%	-0.71%	0.11%	-2.67%	-0.15%	-0.16%	-0.14%	0.02%	-0.54%	143	74	69	103	40
2.00	-0.62%	-0.59%	-0.65%	0.05%	-2.14%	-0.12%	-0.12%	-0.13%	0.01%	-0.43%	117	64	53	87	30
2.25	-0.53%	-0.68%	-0.40%	-0.02%	-1.69%	-0.11%	-0.14%	-0.08%	0.00%	-0.34%	93	50	43	67	26
2.50	-0.41%	-0.58%	-0.29%	-0.06%	-1.23%	-0.08%	-0.12%	-0.06%	-0.01%	-0.25%	66	40	26	47	19
2.75	-0.32%	-0.39%	-0.26%	-0.08%	-0.86%	-0.06%	-0.08%	-0.05%	-0.02%	-0.17%	43	27	16	33	10
3.00	-0.24%	-0.19%	-0.28%	-0.05%	-0.67%	-0.05%	-0.04%	-0.06%	-0.01%	-0.13%	29	20	9	20	9
3.25	-0.19%	-0.17%	-0.22%	-0.04%	-0.54%	-0.04%	-0.03%	-0.04%	-0.01%	-0.11%	21	15	6	13	8
3.50	-0.14%	-0.03%	-0.22%	-0.04%	-0.36%	-0.03%	-0.01%	-0.04%	-0.01%	-0.07%	16	11	5	11	5
3.75	**-0.01%**	**0.00%**	-0.02%	-0.03%	**0.04%**	**0.00%**	**0.00%**	0.00%	-0.01%	**0.01%**	8	5	3	6	2
4.00	-0.04%	-0.07%	-0.01%	-0.02%	-0.08%	-0.01%	-0.01%	0.00%	0.00%	-0.02%	4	2	2	3	1
4.25	-0.04%	-0.07%	-0.01%	-0.02%	-0.08%	-0.01%	-0.01%	0.00%	0.00%	-0.02%	4	2	2	3	1
4.50	-0.04%	-0.07%	-0.01%	-0.01%	-0.08%	-0.01%	-0.01%	0.00%	0.00%	-0.02%	3	2	1	2	1
4.75	0.00%	0.00%	**0.00%**	0.00%	0.00%	0.00%	0.00%	**0.00%**	0.00%	0.00%	0	0	0	0	0
5.00	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0	0	0	0	0
Companies	203	88	115	141	62	203	88	115	141	62	203	88	115	141	62

Thus, given the significant divergence between optimal thresholds for the investment grade and the high yield sample, using different thresholds for these subgroups is appropriate. Hence, a threshold of 1.25 standard deviations is used for investment grade companies going forward, that is, we open a long position if the z-score exceeds 1.25 and go short when it falls below -1.25. As for the HY sample companies, the negative mean returns during the training period would, in practice, prevent the implementation of the strategy. For comparison, however, we proceed with a testing period analysis of the signal trading strategy for the HY companies as well. In particular, we chose a threshold of 2 for the high yield subsample as this allows us to trade for around 50% of our HY sample companies.

Based on the threshold assessment, the strategy is implemented. To visualize the results, we start by walking through the results for an example company. Figure 6 plots the z-score and the resulting trading signal from using the optimal threshold of 1.25 for this Belgian brewing company Anheuser-Busch InBev throughout the sample period. For the European investment grade company, we have found cointegration throughout the entire sample period and for both the pre-crisis and crisis periods separately.

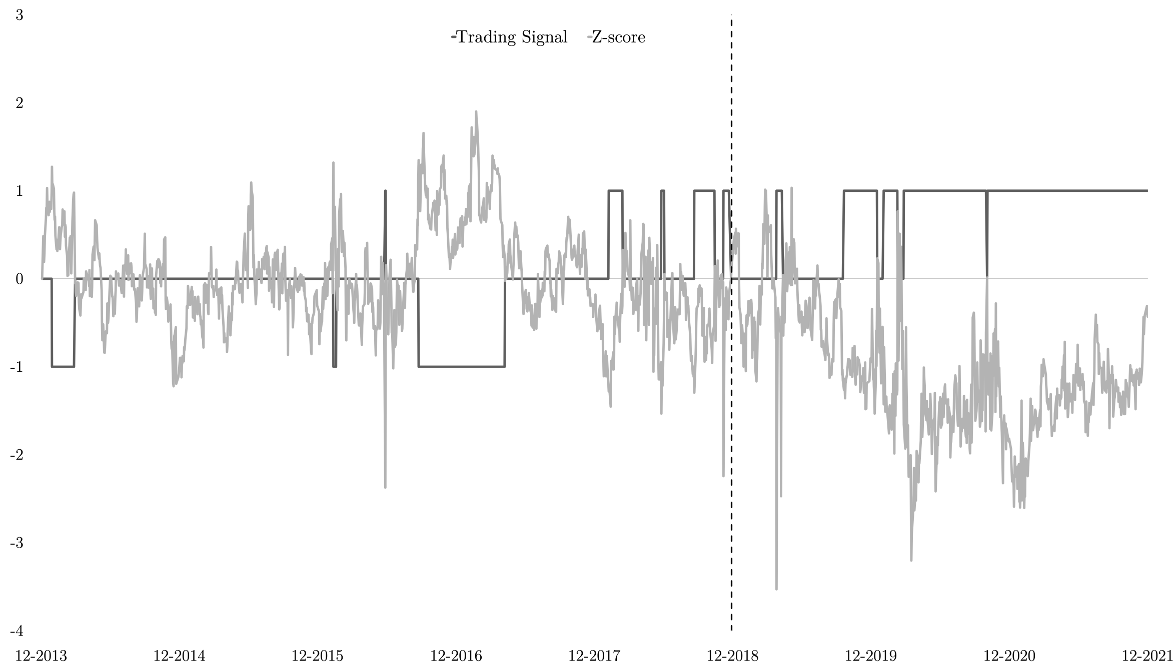


Figure 6: Z-score and trading signal for Anheuser-Busch InBev.

Z-score and trading signal, based on a threshold of 1.25, of the European investment grade company Anheuser-Busch InBev. Noteworthy, the company's stock and CDS are found to be cointegrated throughout the whole sample period and for both the pre-crisis and crisis periods separately. The dotted line denotes the end of the training period and the beginning of the testing period.

The dotted line denotes the end of the training period and the beginning of the testing period. A signal of 1 corresponds to a long position in the CDS contract whereas -1 indicates a short position in the CDS. This particular company follows our expectations quite well as the z-score has a clear mean-reverting tendency, indicating the profitability of our bet that CDS contracts revert back to their long-run trend after abnormal price movements. Figure 7 shows the return gross and net transaction costs for the company.

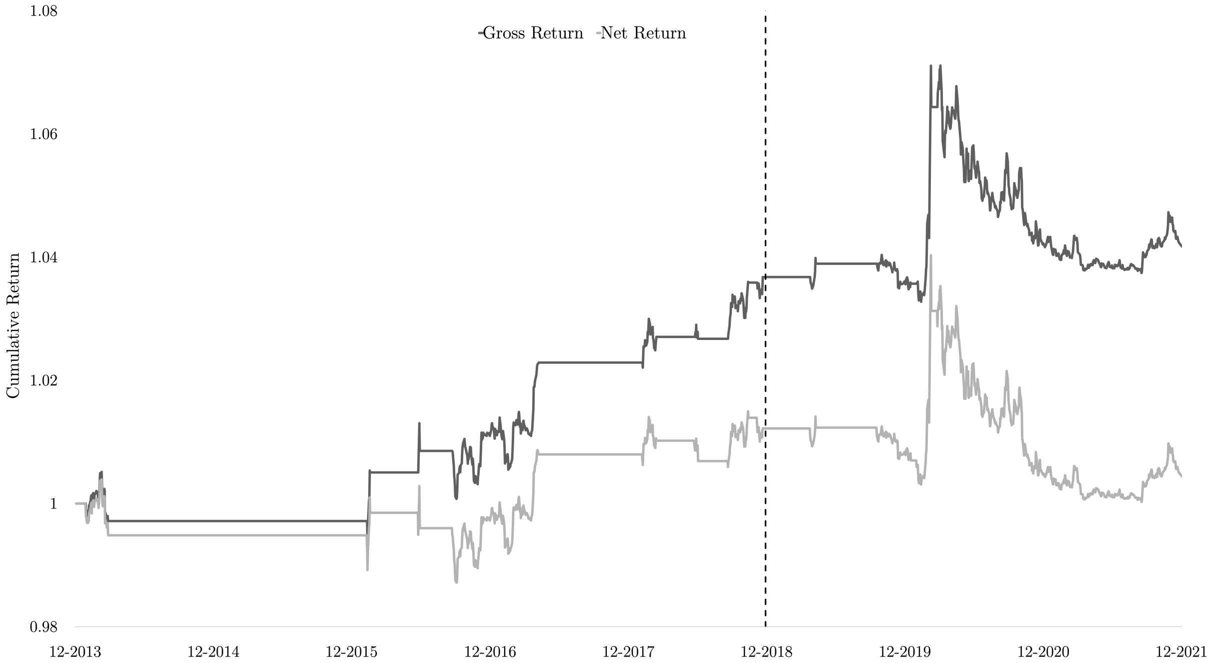


Figure 7: Signal trading performance gross and net transaction costs for Anheuser-Busch InBev.

Over the entire sample period, the signal trading strategy yields a gross return of 4.17% and a net return of 0.44%. During the testing period, the signal trading strategy yields a gross return of 0.48% and a net return of -0.77%.

For this company, the strategy is yielding positive returns in both the training and the testing period. However, when accounting for transaction costs, the return is still positive over the whole period but becomes negative during the testing period. The significant impact of costs on the profitability becomes visual. Over the entire sample period, the signal trading strategy yields a gross return of 4.17% and a net return of 0.44%. During the testing period, the signal trading strategy yields a gross return of 0.48% and a net return of -0.77%.

Moving on to the results for our entire sample, Table 15 summarizes the financial performance for different subgroups.

Table 15: Financial performance of the signal trading strategy.

The table summarizes the performance of the signal trading strategy for the entire sample and split by different subgroups based on geographic region, credit rating, and whether we have found a cointegration relationship during either the training or testing period. Performance is reported both in total returns and annualized. Further, the average number of position changes per firm, the average annualized volatility measured by the annualized standard deviation of returns and the maximum drawdown (DD) are reported.

		For the period				Annualized							
	Companies	Return		Net Return		Return		Net Return		Std. Dev.	Trades	Max DD	
		Full	Test	Full	Test	Full	Test	Full	Test	Test	Test	Full	Test
Full Sample	203	4.24%	2.07%	-2.29%	-1.92%	0.52%	0.69%	-0.29%	-0.64%	2.05%	5.4	6.27%	6.12%
European	88	5.62%	2.83%	-2.47%	-2.12%	0.69%	0.93%	-0.31%	-0.71%	1.61%	6.2	4.47%	4.28%
U.S.	115	3.19%	1.49%	-2.16%	-1.76%	0.39%	0.50%	-0.27%	-0.59%	1.62%	4.8	7.65%	7.52%
IG	141	3.54%	1.24%	0.12%	-0.20%	0.44%	0.41%	0.02%	-0.07%	1.59%	6.2	4.26%	4.13%
HY	62	5.83%	3.97%	-7.79%	-5.82%	0.71%	1.31%	-1.01%	-1.98%	3.49%	3.4	10.85%	10.65%
Cointegrated '14-'18	19	10.69%	6.26%	-1.46%	-1.70%	1.28%	2.05%	-0.18%	-0.57%	2.81%	3.8	7.87%	7.55%
EU cointegrated '14-'18	13	12.90%	6.54%	-1.41%	-2.32%	1.53%	2.13%	-0.18%	-0.78%	1.61%	4.5	6.46%	5.98%
U.S. cointegrated '14-'18	6	5.91%	5.67%	-1.55%	-0.34%	0.72%	1.85%	-0.20%	-0.11%	1.62%	2.5	10.94%	10.95%
IG cointegrated '14-'18	6	4.78%	1.09%	2.17%	0.34%	0.59%	0.36%	0.27%	0.11%	1.59%	4.5	3.05%	2.94%
HY cointegrated '14-'18	13	13.42%	8.65%	-3.13%	-2.64%	1.59%	2.80%	-0.40%	-0.89%	3.57%	3.5	10.10%	9.67%
Cointegrated '14-'21	76	5.96%	2.84%	-1.85%	-1.90%	0.73%	0.94%	-0.23%	-0.64%	2.00%	6.3	6.31%	6.07%
EU cointegrated '14-'21	43	7.26%	3.73%	-2.15%	-1.98%	0.88%	1.23%	-0.27%	-0.67%	1.61%	7.0	4.38%	4.17%
U.S. cointegrated '14-'21	33	4.26%	1.67%	-1.45%	-1.80%	0.52%	0.55%	-0.18%	-0.60%	1.62%	5.4	8.81%	8.55%
IG cointegrated '14-'21	55	4.17%	1.04%	0.41%	-0.33%	0.51%	0.34%	0.05%	-0.11%	1.45%	7.0	4.79%	4.57%
HY cointegrated '14-'21	21	10.64%	7.55%	-7.75%	-6.02%	1.27%	2.45%	-1.00%	-2.05%	1.59%	4.5	10.28%	9.99%
Not cointegrated '14-'21	127	3.22%	1.61%	-2.56%	-1.92%	0.40%	0.53%	-0.32%	-0.64%	1.62%	4.8	6.25%	6.15%
EU not cointegrated '14-'21	45	4.06%	1.96%	-2.76%	-2.24%	0.50%	0.65%	-0.35%	-0.75%	1.61%	5.4	4.56%	4.39%
U.S. not cointegrated '14-'21	82	2.75%	1.42%	-2.45%	-1.75%	0.34%	0.47%	-0.31%	-0.59%	2.32%	4.5	7.18%	7.11%
IG not cointegrated '14-'21	86	3.14%	1.36%	-0.06%	-0.11%	0.39%	0.45%	-0.01%	-0.04%	1.62%	5.7	3.92%	3.84%
HY not cointegrated '14-'21	41	3.37%	2.13%	-7.80%	-5.73%	0.42%	0.71%	-1.01%	-1.95%	1.59%	2.9	11.14%	10.98%

The table shows both cumulative and annualized returns for the entire sample period (2014-2021) and for only the testing period (2019-2021). Furthermore, the *Net Return* columns report returns net of transaction costs, calculated as described in section 5.5.1. Moreover, we split our sample into subgroups based on whether we have found a cointegrating relationship between a firm's CDS contracts and its stock price either in the training period or over the entire sample period. Next, the sample is split by geographic region (Europe vs. U.S.) and by credit rating group (investment grade vs. high yield). Lastly, we combine the cointegration relationship splits with geographic region and credit rating group. In addition, the average number of position changes per firm, the average annualized volatility throughout the testing period, measured by annualized standard deviation of returns, and the maximum drawdown (DD) is reported.

Before accounting for transaction costs the strategy generates positive average returns during each time period – full sample period and testing period – and across each subgroup. This indicates that our strategy is able to generate systemic positive returns. When considering the entire sample, the strategy generates an annualized return of 0.52% and 0.69% for full sample and testing period, respectively. Thus, the positive gross returns of the strategy are robust to out-of-sample testing.

Furthermore, a cointegrating relationship between CDS contracts and the reference entity's stock price appears to have a positive influence on our strategy. Compared to the not-cointegrated samples the mean annualized returns for subgroups showing cointegration either in the training period or during the entire sample period are remarkably higher. For companies that are cointegrated during the full sample period the strategy generates mean annualized returns that are around two times as high as the annualized returns in the not-cointegrated group. Thus, before transaction costs, cointegration seems to positively contribute to the accuracy of the linear prediction model and thereby also the returns generated from the strategy.

Across credit ratings, the high yield group significantly outperforms its investment grade equivalent as the mean annualized testing period return is approximate two to three times as high as the return of the investment grade subsample (full period: 0.71% vs. 0.44%; testing period: 1.31% vs. 0.41%). This, however, is not surprising considering that high yield volatility of CDS spreads across our sample period is almost seven times higher than volatility in the investment grade space (see section 4.2 for summary statistics). Further, mean annualized volatility of returns is more than twice as high for the high yield group compared to the investment grade subsample (2.28% vs. 0.94%). This suggests that the model exploits larger deviations more efficiently and thereby better capitalizes from the short-term divergences of the high yield companies.

Considering region, European companies perform significantly better than its U.S. pendant as average annualized returns are almost twice as high (full period: 0.69% vs. 0.39%; testing period: 0.93% vs. 0.50%). Interestingly, both European and U.S. companies perform even better out-of-sample than during the full sample period.

Lastly, the best performing subgroup consists of high yield companies with cointegrated relationships during the training period. This subgroup generates a mean annualized out-of sample return of 2.80%. On the contrary, investment grade companies that are cointegrated during the full sample period deliver the worst performance during the testing period by only returning 0.34% per year. Yet, the better performance comes at the cost of higher volatility, as the high yield subgroup has the highest mean annualized volatility whereas investment grade companies rank among the lowest.

Taking transaction costs into account, however, significantly changes the strategy's performance. Overall performance becomes negative leading to a mean annualized return of -0.29% and -0.69% for the full period and the out-of-sample period, respectively. Consequently, our strategy loses between 0.80% and 1.50% of performance per year when taking costs into consideration. Further, only one subgroup generates positive annualized returns on average, namely the investment grade companies cointegrated in the training period. In addition, these returns are only barely positive (full period: 0.27%; testing period: 0.11%). Noteworthy, this group only consists of 6 companies out of a sample of 203 companies.

When selecting the investment threshold for the IG group, the strategy creates a net annualized training period return of 0.06%. Yet, applying the strategy to the testing period, the strategy generates a negative annualized return of 0.07%. As this is the primary subsample for which following the trading strategy seems profitable going into the testing period, the strategy overall fails to generate positive returns net of trading costs.

While high yield companies have negative net returns in the training period, and should therefore not be implementing in a portfolio during the testing period, considering the effect of the large trading costs still bring interesting insight. Before trading costs, the high yield companies make up the best performing subgroup, while it is also the subgroup for which we find average transaction costs, measured as the average bid-ask spread, to be the highest we need to add average bid ask spreads to summary statistics. Further, even when selecting a significantly higher threshold for HY companies compared to the IG group, which comes along with a lower trading frequency, transaction costs still eradicate the high gross returns for high yield companies. These findings strongly underline the importance of accounting for transaction costs when assessing and backtesting trading strategies (Pedersen, 2015).

Additional considerations

In conclusion, while our proposed signal trading strategy appears attractive before trading costs it suffers from several drawbacks when being implemented in financial markets. Even an optimized strategy which adjusts the trading frequency by varying the thresholds to take the impact of transaction costs into account suffers from the magnitude of costs to be financially profitable, especially for the high yield subsample. In addition, as explained in section 2.3 a credit default swap is essentially a marketable insurance product often used by an institutional investor to hedge overall portfolio risks (Augustin et al., 2014) and, hence, is by default usually not used to be traded on a daily frequency. This is reflected in overall market liquidity and resulting costs. Further, as we either go long or short at a given point in time the strategy is neither market neutral nor self financing. As such, it requires outside capital to be able to trade in the market. Also, it is evident that the strategy is risky as it, at least on a firm-by-firm level, can lose money during the time a trade is open. This is illustrated by the average maximum drawdown[26] for both the full period and the testing period in table Table 15. In the most severe case, an average maximum drawdown of 10.95% is found for one sample group. Hence, if an investor using the strategy also implements a stop-loss criterion this can potentially lead to a substantial number of early position closings.

In relation to assessing the correctness of the results of the signal trading tests, a potential bias in our results stemming from the data selection process used is now discussed. As outlined in section 4.1, reference entities are selected based on their inclusion in the main CDS indices[27] over the entire sample period from 2014 to 2021. The reason for this is to only includes the most liquid single-name CDS contracts, which provides better conditions for assessing market integration in our cointegration analyses. Yet, a consequence of this sample selection process is that it categorically excludes CDS contracts on reference entities that have had a credit event, including bankruptcy. This data selection bias could significantly impact the aggregate return of our sample as a long or a short position in a CDS contract of a defaulting reference entity could lead to severe return outliers in both directions. In addressing this issue, we find 44 exclusions of reference entities across the entire sample during our testing period. Out of the 44 companies, seven companies filed for bankruptcy and consequentially have been removed from the indices. The impact of on the performance is limited as all seven companies were part of the U.S. high yield index before exclusion. Since our analysis of trading thresholds for the high yield segment shows negative return across almost all thresholds during the training period, the strategy would not be implemented in the testing period for these companies by a rational investor. Thus, the potential bias discussed above do not influence the returns made from implementing this strategy for our companies.

Another consideration is how the performance of our strategy can potentially be increased by moving from a static predictive model to a rolling or expanding model. With the setup

[26]Maximum drawdown is calculated using gross returns to better reflect how the strategy can involve losses even before considering transaction costs.

[27]CDS.NA.IG, CDS.NA.HY, iTraxx Europe, and iTraxx Crossover.

we have chosen, the model incorporates only information for the training period to estimate the model coefficients used for estimating ω_t as well as μ_ω and σ_ω. Thereby, as the model uses no information from the testing period to reestimate these variables, even as the strategy moves further into this period. In particular, a rolling window approach would consider only an certain number of the most recent trading days to be included to estimate the coefficients in the predictive model. By that, the model would more accurately calculate variables used for setting up the strategy, which consequently could likely lead to investment decisions that better reflect current market conditions. Another, slight variation of the rolling window approach would be to use an expanding window, i.e., including the information of each additional passed trading day to update the predictive model. A less strict alternative compared to the rolling window approach is to apply exponential smoothing. Hereby, each past observation is assigned a weight defined by an exponential decay factor. The approach assigns a higher weight to more recent observations motivated by their potentially higher relevance to reflect current market conditions. It is less drastic than the rolling window approach as the weights slowly fade out when going further back in time and are not dropping to zero as in the rolling window approach. The idea is similar to the approach by Meucci (2010) to adjust the empirical distribution of financial returns to better fit historical scenarios. To conclude, our static predictive model can be interpreted as a conservative approach to the trading strategy, as further additions to better reflect current market conditions likely lead to a superior strategy with improved financial performance.

5.6 Pairs Trading

5.6.1 Methodology

As discussed, cointegrated variables are characterized by a stationary equilibrium error process, such that a linear combination of the two variables is mean-reverting. Thus, for a company with cointegrated stock and CDS markets, we expect a linear combination of the company stock and a CDS contract to be mean-reverting. The linear cointegrated system between two securities is expected to towards its long-run mean, while short-term divergences in prices of either asset are possible. Equation 5.21 shows the linear combination between two arbitrary cointegrated assets y_1 and y_2

$$z_t = y_{1t} - \gamma y_{2t} = \mu + \varepsilon_t \tag{5.21}$$

whereas μ represents the long-run equilibrium and ε_t a white-noise error term. In case of a deviation from the long-run equilibrium, either one or both assets adjust to converge back to the long-run mean. As our results from assessing the error correction terms in section 5.3.2 indicate, most of the price discovery occurs in the stock market, leaving the CDS market to contribute most to adjust to the changed level. In pairs trading, the short-term divergences are tried to be exploited by using the relation between two assets, as given by equation 5.21. In a long-short portfolio, an investor bets on the convergence of both securities to their long-run equilibrium spread. Hence, pairs trading is considered statistical arbitrage, as it, at least in theory, should create risk-free positive returns.

Figuerola-Ferretti and Paraskevopoulos (2013) use a similar approach after finding cointegration between the VIX and the 5-year iTraxx index as well as the 50 most representative index constituents. Their investment strategy yields positive abnormal returns, which are robust to out-of-sample testing and transaction costs. We consider both of these factors in our performance assessment and calculation of returns as well.

The pairs trading analysis is conducted for all companies in our sample. Nevertheless, we discuss how results differ between cointegrated and non-cointegrated companies, as cointegration is considered necessary for pairs trading. For each company, we use the CDS spread, the stock price, and bid-ask spreads for both of these securities. Further, as in our signal trading strategy (see section 5.5), the analysis uses daily data to more efficiently exploit short-term differences from the long-run trend, and CDS spreads are converted into upfront prices by using

$$P_t = \frac{s_t - c}{r_t + \frac{s_t}{1-R}} \left[1 - e^{-\left(r_t + \frac{s_t}{1-R}\right)(T-t)}\right] \tag{5.22}$$

The inputs for the different variables are the same as those used for signal trading, described in section 5.5.1. To obtain the bid-ask spread for the upfront price, half of the CDS bid-ask spread is deducted and added to the CDS spread, allowing us to calculate bid and ask upfront prices, respectively. This assumes that the upfront price lies in the middle of the bid-ask spread. These are then converted into percentages.

The next step is to estimate the size of the position to be taken in each of the two securities. We estimate γ_1 using a simple linear regression

$$UPFRONT_t = \gamma_0 + \gamma_1 STOCK_t + \varepsilon_t \tag{5.23}$$

The stock weight is γ_1 while the weight of the CDS is standardized to 1. The weights of two assets are used to form a long-short portfolio in which the short and long positions to bet on long-run convergence depend on spread movements. Next, the portfolio weights are normalized such that our absolute positioning is scaled to one for each asset pair to ensure an equal investment amount across firm pairs that does not depend on the stock is γ_1. Noteworthy, the relative weights between the two securities remain the same. Hence our portfolio weights $\mathbf{w}$ are changed from

$$\mathbf{w}_1 = \begin{bmatrix} 1 \\ -\gamma_1 \end{bmatrix} \quad \text{to} \quad \mathbf{w}_2 = \begin{bmatrix} \frac{1}{1+\gamma_1} \\ \frac{-\gamma_1}{1+\gamma_1} \end{bmatrix} \quad \text{such that} \quad ||\mathbf{w}_2|| = 1 \tag{5.24}$$

The relative weighting between the two securities ensures a similar risk profile and further that the typical movements of the long and short legs are of the same magnitude. Moreover, it is assumed that we are able to access cash to finance the remainder of the higher-weighted leg. For simplicity, we assume a 0% borrowing and lending rate for the cash financing similar to Figuerola-Ferretti and Paraskevopoulos (2013). We calculate the weighted spread ω_t from the normalized weights $\mathbf{w}_2$ using

$$\omega_t = \begin{bmatrix} CDS_t & STOCK_t \end{bmatrix} \begin{bmatrix} \frac{1}{1+\gamma_1} \\ \frac{-\gamma_1}{1+\gamma_1} \end{bmatrix} \tag{5.25}$$

The spread is used for calculating a standardized z-score for each day. Given the spread ω_t on a given day t, the mean μ_ω spread, and the standard deviation σ_ω of daily spreads, the z-score given by

$$z\text{-score}_t = \frac{\omega_t - \mu_\omega}{\sigma_\omega} \tag{5.26}$$

The normalization allows us to more easily introduce and apply the thresholds which provide the limits beyond which we open up a trade. In particular, a z-score of one equals a one standard deviation difference of day t's spread from the mean spread. The trading decisions are based on setting a threshold for a z-score required to open a trade. Since we incorporate bid-ask spread-based trading costs, there is a trade-off between the additional returns gained from more frequent trading and the costs incurred from each position change. The exact threshold used for opening a trade is decided based on a test of after trading cost returns in the 2014-2018 training period. In particular, we select the optimal threshold for the out-of-sample period by running our strategy for different thresholds between 0.25 and 3 standard deviation moves in steps of 0.25 for the training period. Then, the performance net of transaction costs is compared across strategies, and the threshold associated with the highest return is selected for the testing period analysis. A position is closed once the z-score crosses 0, corresponding to the spread crossing the long-run mean.

The stock weight γ_1, the spreads means μ_ω, and standard deviations σ_ω are calculated based on the 2014-2018 training period for each company. Consequently, components of the trading rule use all available information from the years 2014-2018 but none of the information from the 2019-2021 testing period. Hence, we consider returns separately for the entire sample period and the testing period. Optimally, trading rules would update on a rolling basis based on newly available information, yet, this is outside the scope of this paper (see section 5.5.2 for a discussion of further enhancements to systematically incorporate more recent information in the trading decision process). In addition, we make a separate analysis for companies that are cointegrated during the 2014-2018 period. Also, this condition should optimally be re-estimated on a rolling basis. To conclude, our more conservative approach assumes that an investor would use all relevant information available at the end of the year 2018 to carry out the strategy for the years 2019 to 2021.

As outlined in the *Performance* part of section 5.5.1, we assume that 100% of the notional is required in collateral on top of the upfront price when investing in the CDS, following the suggestion by Junge and Trolle (2015). This is assumed to be the case for both sides of the contract. Since the upfront is denoted in percentage points of the notional, 1 is added to the upfront price for the CDS to cover the collateral. Returns are then calculated by the percentage change in the collateral and the CDS upfront price.

5.6.2 Empirical Results

This section provides and discusses the performance of our proposed pairs trading strategy described in section 5.6.1. Like for the signal trading strategy, eight companies are removed because of too many missing values in either the training or the testing period. First, the optimal threshold for opening a new position is determined by assessing the in-sample performance of the strategy net of transaction costs for different thresholds ranging between 0.25 and 3 standard deviation moves. Table 16 summarizes the return performance and reports the number of companies for which trades are executed based on the different thresholds.

As for the signal trading, we see a clear difference between the optimal trading thresholds for investment grade and high yield companies. Again, the higher suggested threshold for the high yield companies can be attributed to the higher trading costs associated with trading these CDS contracts. The optimal threshold for investment grade companies is 1.5 standard deviations, while it is 2.5 standard deviations for high yield companies. Notably, the suggested threshold for the investment grade companies is close to the optimal one of the signal trading strategy (1.25) in section 5.5.2. The results differ, however, in the number of companies traded for each threshold. For example, at a threshold of 3, only 29 companies would be actively traded in the signal trading strategy, whereas 98 pairs of securities would be traded in the pairs trading strategy. Certainly, this results from the remarkable difference between how the two strategies are set up. Given the large proportion of actively traded companies, we are able to proceed with the strategy using a threshold of 2.5 standard deviations for the high yield sample.

Table 16: Threshold assessment for the pairs trading strategy.

Assessment of selecting the optimal threshold for creating the pairs trading signal. The table compares the strategy's financial performance net of transaction costs during the training period for different thresholds between 0.25 and 3 standard deviation moves in steps of 0.25. In addition, the number of companies that would be actively traded given a selected threshold is reported.

Thresholds	**Total Return**					**Annualized Return**					**Companies traded**				
	All	EU	U.S.	IG	HY	All	EU	U.S.	IG	HY	All	EU	U.S.	IG	HY
0.25	-7.31%	-7.60%	-7.09%	-1.67%	-20.14%	-1.51%	-1.57%	-1.46%	-0.34%	-4.40%	203	88	115	141	62
0.50	-4.48%	-4.75%	-4.27%	-0.53%	-13.46%	-0.91%	-0.97%	-0.87%	-0.11%	-2.85%	203	88	115	141	62
0.75	-2.82%	-3.04%	-2.66%	0.10%	-9.47%	-0.57%	-0.62%	-0.54%	0.02%	-1.97%	203	88	115	141	62
1.00	-1.70%	-1.97%	-1.50%	0.46%	-6.61%	-0.34%	-0.40%	-0.30%	0.09%	-1.36%	203	88	115	141	62
1.25	-0.92%	-1.21%	-0.70%	0.67%	-4.54%	-0.18%	-0.24%	-0.14%	0.13%	-0.92%	203	88	115	141	62
1.50	-0.21%	-0.56%	0.06%	**0.85%**	-2.62%	-0.04%	-0.11%	0.01%	**0.17%**	-0.53%	203	88	115	141	62
1.75	0.06%	-0.15%	0.21%	0.83%	-1.70%	0.01%	-0.03%	0.04%	0.17%	-0.34%	202	88	114	141	61
2.00	0.36%	0.19%	0.50%	0.75%	-0.50%	0.07%	0.04%	0.10%	0.15%	-0.10%	198	87	111	140	58
2.25	0.43%	0.25%	0.56%	0.62%	0.00%	0.09%	0.05%	0.11%	0.12%	0.00%	183	79	104	130	53
2.50	**0.51%**	**0.42%**	0.58%	0.56%	**0.40%**	**0.10%**	**0.08%**	0.12%	0.11%	**0.08%**	153	66	87	111	42
2.75	0.50%	0.39%	**0.59%**	0.56%	0.38%	0.10%	0.08%	**0.12%**	0.11%	0.08%	130	55	75	95	35
3.00	0.34%	0.30%	0.36%	0.50%	-0.04%	0.07%	0.06%	0.07%	0.10%	-0.01%	98	41	57	76	22
Companies	203	88	115	141	62	203	88	115	141	62	203	88	115	141	62

As in section 5.5.2, we start by walking through the results for an example company. Figure 8 plots the z-score and the resulting trading signal from using the optimal threshold of 1.5 for the Belgian brewing company Anheuser-Busch InBev throughout the sample period. For this European investment grade company, we have found cointegration throughout the entire sample period and for both the pre-crisis and crisis periods separately.

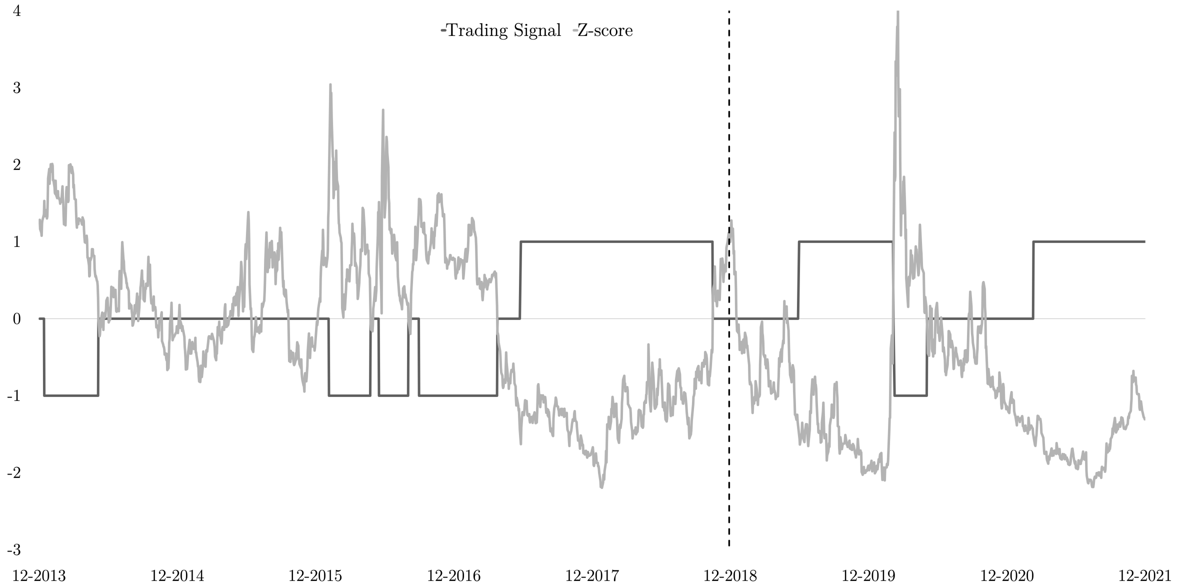


Figure 8: Z-score and trading signal for Anheuser-Busch InBev.

Z-score and trading signal, based on a threshold of 1.5, of the European investment grade company Anheuser-Busch InBev. Noteworthy, the company's stock and CDS are found to be cointegrated throughout the whole sample period and for both the pre-crisis and crisis periods separately. The dotted line denotes the end of the training period and the beginning of the testing period.

The dotted line denotes the end of the training period and the beginning of the testing period. A signal of 1 corresponds to a long position in the CDS contract and a short position in the stock and vice versa for a signal of -1. This particular company follows our expectations quite well as the z-score has a clear mean-reverting tendency, indicating the profitability of our convergence bet. Figure 9 shows the return gross and net transaction costs for the company.

For this company, the strategy is yielding positive returns in both the training and the testing period. When accounting for transaction costs, the return is still positive, although the significant impact of costs on the profitability becomes visual. Over the entire sample period, the pairs trading strategy yields a gross return of 5.83% and a net return of 3.51%. During the testing period, the pairs trading strategy yields a gross return of 1.92% and a net return of 1.03%.

Figure 9: Pairs trading performance gross and net transaction costs for Anheuser-Busch InBev. Over the entire sample period, the pairs trading strategy yields a gross return of 5.83% and a net return of 3.51%. During the testing period, the pairs trading strategy yields a gross return of 1.92% and a net return of 1.03%.

Moving from a company-specific example to the entire sample, Table 17 summarizes the financial performance for different subgroups by reporting the average return, cumulative and annualized.

The table shows both cumulative and annualized returns for the entire sample period (2014-2021) and the testing period (2019-2021). Furthermore, the *Net Return* columns report returns net of transaction costs, calculated as described in section 5.6.1. Moreover, we split our sample into subgroups based on whether we have found a cointegrating relationship between a firm's CDS contracts and its stock price either in the training period or over the entire sample period. Next, the sample is split by geographic region (Europe vs. U.S.) and credit rating group (investment grade vs. high yield). Lastly, we combine the cointegration relationship splits with geographic region and credit rating group. In addition, the average number of position changes per firm, the average annualized volatility throughout the testing period, measured by the annualized standard deviation of returns, and the maximum drawdown (DD) are reported.

Before accounting for transaction costs, the strategy generates positive average returns during each period – entire sample period and testing period – and across each subgroup. For the whole sample, the overall strategy yields an average annualized return of 0.67% before trading costs and -0.20% after trading costs during the testing period.

Table 17: Financial performance of the pairs trading strategy.

The table summarizes the performance of the signal trading strategy for the entire sample and split into different subgroups based on geographic region, credit rating, and whether we have found a cointegration relationship during either the training or testing period. Performance is reported both in total returns and annualized. Further, the average number of position changes per firm, the average annualized volatility measured by the annualized standard deviation of returns, and the maximum drawdown (DD) are reported.

		For the period				Annualized							
	Companies	Return		Net Return		Return		Net Return		Std. Dev.	Trades	Max DD	
		Full	Test	Full	Test	Full	Test	Full	Test	Test	Test	Full	Test
Full Sample	203	4.15%	2.03%	0.13%	-0.59%	0.51%	0.67%	0.02%	-0.20%	0.73%	3.3	2.44%	2.07%
European	88	3.76%	1.51%	0.77%	-0.02%	0.46%	0.50%	0.10%	-0.01%	0.72%	2.8	2.38%	2.07%
U.S.	115	4.45%	2.42%	-0.37%	-1.03%	0.55%	0.80%	-0.05%	-0.34%	0.74%	3.8	2.49%	2.07%
IG	141	3.42%	1.67%	1.44%	0.59%	0.42%	0.55%	0.18%	0.19%	0.54%	4.1	1.71%	1.42%
HY	62	5.80%	2.84%	-2.87%	-3.27%	0.71%	0.94%	-0.36%	-1.10%	1.17%	1.7	4.10%	3.54%
Cointegrated '14-'18	19	4.56%	2.06%	-1.96%	-2.45%	0.56%	0.68%	-0.25%	-0.82%	1.05%	2.5	3.75%	3.32%
EU cointegrated '14-'18	13	3.33%	1.35%	-1.11%	-1.62%	0.41%	0.45%	-0.14%	-0.54%	0.99%	2.4	3.58%	3.08%
U.S. cointegrated '14-'18	6	7.25%	3.62%	-3.79%	-4.24%	0.88%	1.19%	-0.48%	-1.43%	1.16%	2.8	4.13%	3.85%
IG cointegrated '14-'18	6	3.02%	1.29%	1.20%	0.21%	0.37%	0.43%	0.15%	0.07%	0.46%	4.2	1.05%	0.93%
HY cointegrated '14-'18	13	5.28%	2.42%	-3.41%	-3.68%	0.64%	0.80%	-0.43%	-1.24%	1.31%	1.8	5.00%	4.43%
Cointegrated '14-'21	76	4.04%	2.12%	0.11%	-0.40%	0.50%	0.70%	0.01%	-0.13%	0.70%	3.8	2.55%	2.35%
EU cointegrated '14-'21	43	3.23%	1.46%	0.55%	-0.01%	0.40%	0.49%	0.07%	0.00%	0.66%	3.0	2.40%	2.27%
U.S. cointegrated '14-'21	33	5.09%	2.97%	-0.48%	-0.90%	0.62%	0.98%	-0.06%	-0.30%	0.76%	4.8	2.74%	2.46%
IG cointegrated '14-'21	55	3.83%	1.96%	1.65%	0.75%	0.47%	0.65%	0.21%	0.25%	0.54%	4.6	1.66%	1.45%
HY cointegrated '14-'21	21	4.57%	2.53%	-3.95%	-3.41%	0.56%	0.84%	-0.50%	-1.15%	1.14%	1.6	4.86%	4.71%
Not cointegrated '14-'21	127	4.21%	1.97%	0.14%	-0.71%	0.52%	0.65%	0.02%	-0.24%	0.74%	3.1	2.38%	1.90%
EU not cointegrated '14-'21	45	4.26%	1.56%	0.98%	-0.02%	0.52%	0.52%	0.12%	-0.01%	0.78%	2.6	2.36%	1.88%
U.S. not cointegrated '14-'21	82	4.19%	2.20%	-0.32%	-1.08%	0.51%	0.73%	-0.04%	-0.36%	0.73%	3.4	2.38%	1.91%
IG not cointegrated '14-'21	86	3.15%	1.48%	1.31%	0.48%	0.39%	0.49%	0.16%	0.16%	0.53%	3.7	1.74%	1.41%
HY not cointegrated '14-'21	41	6.44%	3.00%	-2.31%	-3.20%	0.78%	0.99%	-0.29%	-1.08%	1.19%	1.8	3.71%	2.94%

Considering only the companies with cointegrated markets between 2014 and 2018, the gross and net returns are 0.68% and -0.82% for the testing period, respectively[28]. Compared to slightly higher returns of 0.70% and -0.13% for companies cointegrated throughout the entire ample period. When comparing gross returns, cointegration seems to yield slightly higher returns than the full sample group or the subgroup of not cointegrated companies. The effect, however, is relatively small and does not fulfill our expectations of higher returns based on a more pronounced convergence of cointegrated companies. Moreover, the sample of companies with cointegrated markets between 2014 and 2018 comprises only 19 companies which might make it less representative. Furthermore, from an investor's perspective, transaction costs should be considered in assessing whether or not an investment strategy should be set up. Given the lower net returns of the cointegrated subgroups, it becomes challenging to determine whether building a strategy on previously cointegrated markets companies is superior to including all companies. Based on our sample and analysis, it seems better to include all companies instead of only those with cointegrated relationships in the training period.

Comparing across credit ratings before trading costs, returns are higher for high yield companies than investment grade companies, with an annualized testing period return of 0.94% against 0.55%. However, as with the signal trading results, higher returns are also associated with higher volatility and higher risk. As can be seen in Table 17, the annualized volatility of the returns from the high yield firms is considerably higher than the investment grade pendant. When a company's assets are more volatile, the trading strategy can better capitalize from more frequent and more severe spread widening and its subsequent convergence to the long-run equilibrium, which specifically for the high yield companies translates into higher gross returns. This is the case even though only an average of 1.7 trades per company is made for the testing sample period, compared to 4.1 trades per company for investment grade firms. Noteworthy, the average number of trades is less comparable across different credit ratings due to the different thresholds used. Once trading costs are accounted for, the high yield returns become negative, while the investment grade returns drop slightly and remain positive. This is because bid-ask spreads for the high yield CDS are generally larger, so even with a significantly lower number of position changes, the absolute effect of the trading costs from the high yield group of companies is still more extensive than that of the investment grade companies. The effect of transaction costs on performance is also observed in the signal trading strategy results in section 5.5.2.

If we compare regions, the U.S. companies have higher annualized testing period returns than the European companies before accounting for trading costs but lower returns after trading costs. The returns switch from positive to negative for both regions when considering trading

[28]The significance level used as the threshold for cointegrated companies is 10%.

costs, although the European company's returns remain very close to 0 at -0.01%. The average number of position changes and the volatility of the trading strategies are similar across the two groups. Hence the more pronounced effect of transaction costs likely stems from wider bid-ask spreads.

Overall, given a respective trading threshold of 1.5 and 2.5 standard deviations for the investment grade and high yield companies, the pairs trading strategy has a positive gross return but a negative net return when accounting for trading costs associated with the bid-ask spreads. Interestingly, only including the investment grade companies yields a positive return net of trading costs, which, given the trading strategy's low volatility, is of a decent size. In addition, the estimate given here can be considered somewhat conservative since the testing period return does not consider any information after the cutoff between the training and testing period. An extended or rolling window estimate of the portfolio weights, spread mean, and spread variance can be used to improve this strategy (see section 5.5.2 for a further discussion of potential enhancements to better consider more recent information in the trading process).

Finally, it needs to be mentioned that even though it is a long-short strategy, it is not self-financing. The weights of the strategy are determined to achieve a similar risk of the long and short leg in the trade. Given the higher volatility of stock prices, the strategy, therefore, requires outside financing to achieve the correct position size.

6 Discussion

This section discusses the general findings of our thesis by briefly recalling the main results of each analysis, relating them to each other, and comparing them to the previous empirical literature. Overall, our findings throughout this paper confirm results from previous research on the topic of market integration between the CDS and equity markets and findings on the determinants of CDS spreads. Investigating the continuous correctness of previous results is highly relevant as the CDS market is still relatively new and has changed remarkably through regulatory reforms and overall market activity in recent years. Consequently, the amount of data on the behavior of this market is still limited. Furthermore, the market is still evolving, and the mentioned changes since the financial crisis are essential to assess. Specifically, the single-name market has been shrinking as funds are shifting into index markets instead, while investors prefer to move towards more aggregate solutions in hedging credit risk. Lastly, previous research finds differences in market integration between the pre-financial crisis period and the financial crisis. Given newly available data from the Covid crisis, an assessment of whether these differences are particular to the financial crisis or if they also hold during other crises, such as the Covid pandemic, is important.

In this paper, stationarity tests confirm the unit root in both markets, as also found by Figuerola-Ferretti and Paraskevopoulos (2013). These results are robust to splitting the sample into crisis and pre-crisis subsamples. As this is a necessary precondition for assessing cointegration, it is an important result. Following this, we proceed with an analysis of market integration and price discovery between CDS and equity markets.

We find clear evidence of a long-run equilibrium relationship between the two markets, thereby providing evidence of market integration. Similar to results from previous empirical analyses, we fail to detect cointegration in the markets for some companies (see Norden and Weber, 2009; Forte and Lovreta, 2015; Mateev and Marinova, 2017). If the CDS and equity markets efficiently incorporate the price implications of changes in credit risk over time, we would expect any market pair to be linearly cointegrated (Blanco et al., 2005).

As argued by Forte and Lovreta (2015), a lack of cointegration in the empirical analysis does not necessarily rule out a long-run relationship between two markets. The authors find a positive link between the length of the sample period and the success of empirically detecting cointegration.

Furthermore, there can be several reasons for the lack of cointegration between equity and CDS markets. First of all, when credit and equity markets are not fully integrated, at least one of the markets is not efficiently reflecting credit risk. Consequently, it implicates that the two markets systematically assign different credit spreads to the same company, causing arbitrage opportunities to arise (Blanco et al., 2005). If the markets align over time, we expect this will cause the lagging inefficient market to adjust.

Nevertheless, another potential reason for the lack of integration between the two market pairs exists. In particular, for some companies, we find cointegration throughout only some sub-periods, i.e., either the pre-crisis or crisis period. A potential explanation for this phenomenon is that changes in the degree of market integration depend on other market conditions. However, this reason is difficult to accurately detect, as cointegration is based on a long-run relationship. Thus, a certain time frame is required for the detection of cointegration. As argued by Mateev and Marinova (2017), markets can substantially diverge from their long-run equilibrium in the short-term, making the detection of cointegration time-dependent. In addition to using the linear Johansen test that we use in our analysis, Mateev and Marinova (2017) extend the model by allowing for a one-time structural break with unknown timing. The adjustment to the static base model allows them to detect cointegration for a higher number of companies. While we do not allow for unknown structural breaks in our cointegration tests, we specifically test for cointegration in a pre-crisis period and during the Covid crisis and find a higher number of market pairs to be cointegrated during the Covid crisis than during the entire sample period. As such, the integration between markets may vary depending on market conditions.

The credit risk mispricings and the potential market condition dependency of market integration have implications on the expectations of the price discovery analysis. First, if credit risk is systematically priced incorrectly in one market, we expect a leading role of the other market. Second, based on the result that the stock and the CDS market are more cointegrated in times of crisis, we expect to see a less clear lead-lag relationship during the crisis than the pre-crisis period.

In confirming the first of our expectations, all four of our price discovery measures show that the equity market is leading, as it accounts for approximately 75% of the price discovery between the two markets. Consequently, this result implies some degree of inefficiency in timely incorporating information in the CDS market, following the argumentation by Blanco et al. (2005). When this inefficiency becomes large, it can potentially lead to discrepancies between the two markets that prevent the detection of cointegration, which may be a reason behind the inability to find cointegration for a proportion of companies.

The second of our expectations is not as clearly confirmed in the price discovery analysis. While the Granger causality test and the VECM coefficient analysis live up to the expectation by indicating that the leading role of the stock market to some degree weakens during the crisis period, results from the Gonzalo-Granger and Hasbrouck measures indicate the opposite. Thus, the price discovery measures do not systematically confirm that crisis market conditions improve the efficiency of the CDS market, as otherwise indicated by the cointegration analysis.

Given the overall clear lagging role of the CDS market and the remaining uncertainty about what influences the efficiency of this market, we set up a pooled OLS model for a better understanding of what determines the variation in CDS levels and changes. The lagging role of the CDS market allows for creating a model that predicts CDS spreads ahead of time while we avoid a potential simultaneity bias arising from the use of contemporaneous data (Zhang et al., 2009). The analysis indicates that the level of the CDS can be significantly predicted one week ahead by firm-specific liquidity and equity components and overall market conditions, approximated by main macroeconomic indicators. Further, as we are also able to predict a portion of the changes in CDS spreads one week ahead, this underlines the inefficiency of the market. As stated in section 2.1.1 on market efficiency, in an efficient market, price movements cannot be predicted in the short-term given their perfect incorporation of all available information. In particular, the finding that market conditions are still highly significant after controlling for firm-specific liquidity factors is interesting in relation to our market integration analysis. More precisely, market conditions have a significant influence on the levels and changes of CDS spreads outside of what is incorporated in the company-specific equity markets and captured by liquidity measures. While this does not explain why we observe differences in the level of market integration between crisis and pre-crisis periods, it substantiates the finding that market conditions possibly affect the degree to which these markets are integrated.

Even though the pooled OLS model does not provide definitive answers on why we fail to detect cointegration for all market pairs, it specifies which variables to include in a predictive signal trading analysis. Along with a pairs trading analysis, the signal trading model helps investigate a previously mentioned point made by Blanco et al. (2005): If the inability to detect cointegration between some market pairs is caused by inefficient pricing of credit risk, arbitrage opportunities should arise.

Before trading costs, both strategies – signal trading and pairs trading – provide positive returns with relatively low volatility. This is especially true for the pairs trading strategy, as the volatility of this strategy is particularly low. While this may to some extent confirm the proposition made by Blanco et al. (2005), there are additional considerations to be made. When assessing the lack of integration between stock and CDS markets, Kapadia and Pu (2012) find that short-horizon pricing discrepancies between those markets are of economically and statistically significant size. Nevertheless, they find that the time-varying integration between the two markets is due to impediments to arbitrage, such as a lack of liquidity and idiosyncratic risk. In our assessment of arbitrage through trading strategies, we account for this issue by incorporating the market's transaction costs through bid-ask spreads. When incorporating the bid-ask spread, neither the signal nor the pairs trading strategy yields positive returns on average. This underlines the explanation put forward by Kapadia and Pu (2012), specifically that the lack of market integration between equity and credit markets arises from impediments to arbitrage. Hence, liquidity issues are likely to be causing the inefficiency of prices in the CDS market and, thereby, the lack of market integration.

Concluding that no exploitable arbitrage opportunities exist based on these results would involve omitting essential aspects. First, as discussed in section 5.5.2, our static approach to the trading strategy implementation can be considered a conservative estimate. In particular, higher returns may be obtainable by using a more dynamic implementation that incorporates more recent information. Consequently, this paper cannot definitively rule out that the lack of market integration creates exploitable arbitrage opportunities during specific periods. This warrants further research.

Second, while the trading strategies for our overall sample across credit ratings do not generate positive net returns, the investment grade subsample does. In addition, we find differences in our market integration results across rating group. Consequently, a separate discussion, which differentiates between credit ratings, follows below.

Credit rating differences

The results from the cointegration analysis show a clear difference between the two credit rating groups as we find a higher proportion of cointegrated companies in our investment grade sample than in the high yield counterpart. Following the above argumentation, we should expect the stock market to be a more dominant leader in the high yield sample. Since a majority of previous research find the equity market to be overall efficient[29], the more pronounced lead-lag relationship for high yield companies may result from a relatively more substantial inefficiency in this segment of the CDS market compared to the investment grade market.

In spite of the differences in market integration between high yield and investment grade companies, the results of the price discovery analysis shows no apparent differences in the leading role of the stock market between high yield and investment grade companies. As such, the price discovery results do not confirm that the more significant lack of price integration in the high yield sample can be attributed to the high yield CDS market being less efficient.

When considering the determinants of the CDS spread, the significant variables across high yield and investment grade groups are pretty similar. However, one crucial difference is the difference in the adjusted R^2 between the two credit rating groups, as this measure is considerably larger for the high yield group. This is the case for both the CDS levels and the CDS changes regression. Consequently, it indicates that the CDS spread level and its changes can be predicted to a larger degree for high yield companies than for investment grade companies. Further, it points toward a higher degree of inefficiency in the high yield CDS market than in the investment grade counterpart, which is in line with the finding that high yield market pairs are generally less cointegrated.

The higher degree of predictability for high yield companies materializes in the differences in returns seen in our trading analysis. Before costs, the returns of the high yield companies are much higher than for the investment grade companies. This is true for both the signal trading and the pairs trading analysis. We see two main reasons for this difference, the first one being the higher degree of predictability for high yield CDS spread changes. The second is the higher volatility in the CDS spreads, which inflates the return for a correctly predicted return direction. Combining the two effects makes the difference in profitability even more pronounced.

Net of trading costs, however, the results are inverted. More precisely, investment grade companies perform substantially better than high yield companies when accounting for transaction costs. This can be attributed to the much higher bid-ask spreads seen for high yield companies (see Table 1). The reasons behind the sizeable bid-ask spreads of high yield firms are essential for our conclusion about market integration and potential arbitrage opportunities in the CDS market. If the large bid-ask spreads are mainly due to a lack of liquidity in the high yield space, this could explain why the high yield CDS market is less efficient. If the bid-ask spreads are

[29]See section 2.1.1 for a discussion of market efficiency in the equity market.

wider because of the higher volatility of high yield CDS spreads, the magnitude of the spreads is not necessarily an indication of illiquidity and inefficiency in the market. No matter which of these reasons dominates, the large spreads serve as an important impediment to arbitrage. Thus, as argued by Blanco et al. (2005), the lack of market integration does result in what appears to be an arbitrage opportunity, although, as argued by Kapadia and Pu (2012), exploiting these is limited mainly by impediments to arbitrage. For the investment grade firms, the bid-ask spreads are lower in magnitude, although still large enough to make the returns of the strategies negative or very close to zero[30].

Therefore, our thesis confirms what is found in previous literature. That is, some degree of market integration exists, although it is limited due to inefficiencies in the CDS market (Norden and Weber, 2009; Forte and Lovreta, 2015; Mateev and Marinova, 2017). Further, while we do detect systematic mispricings in the CDS market, we are unable to set up a strategy that profitably exploits those due to impediments to arbitrage, confirming findings by Kapadia and Pu (2012). It is not unlikely that such strategies exist, although we leave that for future research.

6.1 Limitations

The approaches and findings in this paper have some limitations. These include choices in relation to cointegration detection methods, company characteristics, liquidity measures, and trading strategy approaches.

In relation to cointegration detection, we use a linear framework and do not allow for structural breaks with unknown timing. While we do split the sample into two sub periods, which enables us to detect a higher number of cointegrating relationships, applying a more flexible approach to structural changes could potentially increase this number even further. Although this is not the norm in the field, Mateev and Marinova (2017) finding an increasing number of cointegrated market pairs when allowing for a structural break with unknown timing. More accurately detecting cointegrating relationships potentially allows for a better assessment of what influences the degree of market integration.

When splitting the sample based on company characteristics, our analysis focuses on the influence on market integration of geography, credit ratings, and market conditions. Other company features such as industry or size may have influential effects as well.

In our use analysis on market integration influences, we assign a high importance to the influence of liquidity. Yet, it is relevant to note that these results are based on imperfect proxies of

[30] The returns of the signal trading strategy is negative net of trading costs, while the pairs trading strategy has an annualized positive net return of 0.19%. As this return is small and not entirely risk-less, it becomes rather unattractive to trade on.

liquidity. One of the proxies we use is the quotes depth, which is only indirectly linked to the number of transaction and the volume. Specifically, a high number of dealer quotes does not necessarily coincide with a high number of transactions in the market. As discussed by Qiu and Yu (2012), it can also be a measure of asymmetric information. The indirect link and the endogeneity increases risk of noise in the quotes depth measure. The second liquidity measure we use is the size of the bid-ask spreads. This measure is more directly linked to market transactions, given that a high trading volume directly puts pressure on the bid-ask spreads to narrow. Yet, other factors influence the spread as well, making the proxy somewhat noisy. In particular, an increase in volatility is often connected to a widening of spreads. The noise from volatility has implications for comparing liquidity of the more volatile high yield companies with the investment grade companies. Despite this noise, the general assumption in this paper is that a higher bid-ask spread is an indication of lower liquidity.

In relation to our trading analyses, this paper discusses whether the lack of market integration causes arbitrage opportunities to exist. If abnormal returns had been found net of trading costs, it would be important to consider whether these simply represent a liquidity premium in CDS returns, or if they could actually be considered arbitrage. This is outside the scope of this paper.

Another limitation in relation to our trading strategies relates to our time-wise data split. While the way we split our data into a crisis and pre-crisis period has certain advantages, it also has some drawbacks. The split allows us to directly compare market integration between a crisis and a non-crisis period. Yet, since the cointegration measure is a long-run measure, a certain time span is needed for correct cointegration detection (Forte and Lovreta, 2015). This means that we have chosen to include 2019 in the crisis period even though the market had no knowledge of the upcoming Covid-crisis at the time. Since a large number of cointegrating relationships are detected during the period, the influence of this limitation appears limited. A second consideration in relation to this split is its influence on the trading strategy. It is useful to use the same split, as this allows us to specifically test if companies that have been cointegrated in the training period provide different returns from our overall sample in the testing period. Yet, it creates a training and testing split with vastly different market conditions, potentially causing model predictions to be suboptimal.

Lastly, as discussed in detail in section 5.5.2, our static approach to trading implies that not all information is considered at the time where a trade is made. Specifically for our analysis, this means that the strategy is prevented from adjusting to the new market conditions arising during the Covid-crisis. Thus, our strategy can be considered to provide a conservative estimate of returns made from trading CDS in this period. Future research can consider more dynamic approaches.

6.2 Future Research

Our empirical analysis and its limitations form the foundation and allow for potential future research on the topic. We see three main areas where this is of particular interest.

First, it is relevant to analyze whether a different approach to cointegration detection causes the results to differ. Specifically, such an analysis can provide insights as to whether markets are, in fact, more significantly and more frequently cointegrated than our linear estimates as well as estimates from previous research suggests. Ngene et al. (2014) and Chan-Lau and Kim (2004) argue that a simple VECM approach followed by a linear cointegration test are insufficient for assessing the relation between asset markets thoroughly. Therefore, one could expand the linear analysis to a framework that detects non-linear links between markets by, for example, applying a threshold cointegration approach.

Second, we see noteworthy differences in market integration between European and U.S. companies as well as between high yield and investment grade companies. This raises a question of potential underlying influences such as firm size or industry. Therefore, future research is also relevant for analyzing whether other specific company characteristics increase market integration. Applying a sample split based on selected firm characteristics and a subsequent cointegration analysis or a quantile cointegration approach, as suggested by Gatfaoui (2017), could provide further insights.

Lastly, the performance of our trading strategies suggests that profits mostly cease to exist once transaction costs are accounted for, but, as discussed, these estimates are likely to be a lower bound of what can be achieved from a signal or pairs trading approach. Further, the pairs trading strategy for the investment grade segment still yields slight positive returns even net of trading costs. Thus, more research on the topic of arbitrage opportunities in relation to CDS is warranted. This is not only interesting from a trading perspective but also provides insights as to whether the CDS market is inefficient outside of what is due to liquidity issues. Furthermore, if a more dynamic approach delivers robust positive net returns it allows for a decomposition of the returns in relation to, for instance, the liquidity premium and market risk. This is also a relevant topic for future research.

Following this discussion of our results, limitations, and future research, we provide a final conclusion.

7 Conclusion

To sum up, our thesis seeks to answer the following research questions:

What influences the degree of market integration between the equity and CDS markets?

1. Using cointegration as a measure of market integration, how integrated are the two markets, and does the level of integration change depending on region, credit rating, and market conditions?

2. What characterizes the price discovery process between the two markets?

3. The CDS market is found to have a lagging role, although less so during crisis periods. What variables determine the levels and the changes of CDS spreads, and how can this help explain mentioned findings?

4. Given the systematic short-term market disconnections, can these inefficiencies be utilized to construct profitable trading strategies?

Starting with the first sub-question, we find that 37% of companies in our sample of 211 European and U.S. companies have cointegrated equity and CDS markets. This is in line with findings by Norden and Weber (2009), Forte and Lovreta (2015), and Mateev and Marinova (2017). Further, cointegration is more prevalent for European and investment grade companies. Moreover, markets become more integrated during the Covid crisis than in the pre-crisis period, confirming empirical results by Narayan et al. (2014), who find cointegration for a higher fraction of companies during the financial crisis than in the period before that.

In answering the second sub-question, we find that the price discovery process can be characterized by a dominant leading role of the stock market. Based on the Gonzalo-Granger and the Hasbrouck measure, the stock market contributes approximately 75% to the price discovery, which is in line with previous findings (Norden and Weber, 2009; Forte and Peña, 2009; Narayan et al., 2014). Hence, the degree of market integration may be lowered by the inefficiency in price adjustments to recent information in the CDS market. This interpretation follows arguments made by Blanco et al. (2005) when explaining the lack of market integration.

The third sub-question builds on the lead-lag relationship, which characterizes the price discovery process and the evidently lagging role of the CDS market. Our empirical results indicate that the levels and changes of CDS spreads can be predicted one week ahead by company-specific equity returns, option-implied volatility, and liquidity measures as well as overall macroeconomic conditions. These findings coincide with those by Da Fonseca and Gottschalk (2020). Furthermore, the findings further emphasize the inefficiency of the CDS market and confirm the influence of macroeconomic conditions on CDS spreads, even after controlling for stock returns or liquidity. In addition, it sustains the finding that the degree of market integration may depend on macroeconomic conditions, as exemplified in the difference between cointegration findings for the Covid crisis and the pre-crisis periods.

Two trading strategies are constructed based on our other findings in order to answer the fourth sub-question. A signal strategy utilizes the variables found to have significant predictive power in determining levels and changes of CDS spreads, while a pairs trading strategy attempts to exploit potential arbitrage opportunities that arise from short-term divergences in the cointegrating relationship between the two markets. Both of these strategies yield positive gross returns, which underlines the statement by Blanco et al. (2005) that a lack of market integration leads to potential arbitrage opportunities. Nevertheless, net of trading costs, these positive returns are eradicated. Empirical support is provided by Kapadia and Pu (2012), who find that impediments to arbitrage such as illiquidity may prevent arbitrage opportunities from being exploited. In our analysis, illiquidity is indicated by wide bid-ask spreads. Due to these high transaction costs, the apparent arbitrage opportunities cannot be exploited, and thus it is not surprising that the lagging role of the CDS market prevails.

Finally, in answering our main research question, we find the overall degree of market integration to be influenced by region, credit rating, and market conditions. Specifically, European and investment grade companies seem to have an overall higher degree of market integration. Further, the degree of market integration increases during crisis periods. In addition, our analysis provides an answer to why this may be the case. We find that the incomplete market integration follows from a lack of efficiency in the CDS market. Moreover, we find that for less cointegrated markets, in particular the U.S. and the high yield markets, CDS bid-ask spreads are higher than for their respective counterparts. This systematic difference indicates that liquidity is lower in these markets. In conclusion, illiquidity in the single-name CDS market seems to hinder CDS prices from moving efficiently, which prevents the market from being fully integrated with the equity market.

References

Abad, J., Aldasoro, I., Aymanns, C., D'Errico, M., Fache Rousová, L., Hoffmann, P., Langfield, S., Neychev, M., and Roukny, T. (2016). Shedding light on dark markets: First insights from the new EU-wide OTC derivatives dataset. Technical Report 11.

Acharya, V. V. and Johnson, T. C. (2007). Insider trading in credit derivatives. *Journal of Financial Economics*, 84(1):110–141.

Acharya, V. V. and Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, 77(2):375–410.

Aldasoro, I. and Ehlers, T. (2018). The credit default swap market: what a difference a decade makes. *BIS quarterly review, June.*

Augustin, P., Saleh, F., and Xu, H. (2020). CDS Returns. *Journal of Economic Dynamics and Control*, 118:103977.

Augustin, P., Subrahmanyam, M. G., Tang, D. Y., and Wang, S. Q. (2014). Credit default swaps: A survey. *Foundations and Trends in Finance*, 9(1-2):1–196.

Baillie, R. T., Booth, G. G., Tse, Y., and Zabotina, T. (2002). Price discovery and common factor models. *Journal of financial markets*, 5(3):309–321.

Bao, J. and Pan, J. (2013). Bond Illiquidity and Excess Volatility. *The Review of Financial Studies*, 26(12):3068–3103.

Berndt, A., Jarrow, R. A., and Kang, C. O. (2007). Restructuring risk in credit default swaps: An empirical analysis. *Stochastic Processes and their Applications*, 117(11):1724–1749.

Berndt, A. and Obreja, I. (2010). Decomposing European CDS Returns*. *Review of Finance*, 14(2):189–233.

Black, F. and Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *Journal of Political Economy*, 81(3):637–654.

Blanco, R., Brennan, S., and Marsh, I. W. (2005). An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. *The Journal of Finance*, 60(5):2255–2281.

Bongaerts, D., De Jong, F., and Driessen, J. (2011). Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market. *The Journal of Finance*, 66(1):203–240.

Borges, M. R. (2010). Efficient market hypothesis in European stock markets. *The European Journal of Finance*, 16(7):711–726.

Breitenfellner, B. and Wagner, N. (2012). Explaining aggregate credit default swap spreads. *International Review of Financial Analysis*, 22:18–29.

Bühler, W. and Trapp, M. (2009). Time-varying credit risk and liquidity premia in bond and CDS markets. Technical report.

Cao, C., Yu, F., and Zhong, Z. (2010). The information content of option-implied volatility for credit default swap valuation. *Journal of Financial Markets*, 13(3):321–343.

Chan-Lau, J. A. and Kim, Y. S. (2004). Equity prices, credit default swaps, and bond spreads in emerging markets.

Chaudhuri, K. and Wu, Y. (2003). Random walk versus breaking trend in stock prices: Evidence from emerging markets. *Journal of Banking & Finance*, 27(4):575–592.

Cochrane, J. H. (2009). *Asset pricing: Revised edition*. Princeton university press.

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

Collin-Dufresne, P., Junge, B., and Trolle, A. B. (2020). Market Structure and Transaction Costs of Index CDSs. *The Journal of finance (New York)*, 75(5):2719–2763.

Committee on the Global Financial System (2009). Credit risk transfer statistics. *CGFS Papers*, 35.

Cootner, P. H. (1962). Stock prices: Ramdom vs. systematic changes. *Industrial Management Review (pre-1986)*, 3(2):24.

Crouch, P. and Marsh, I. W. (2005). Arbitrage relationships and price discovery in the Autos sector of the credit market. *Cass Business School, Working Paper*, 34.

Da Fonseca, J. and Gottschalk, K. (2020). The Co-Movement of Credit Default Swap Spreads, Equity Returns and Volatility: Evidence from Asia-Pacific Markets. *International review of finance*, 20(3):551–579.

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a):427–431.

Dickey, D. A. and Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society*, pages 1057–1072.

Du, L., Masli, A., and Meschke, F. (2013). The effect of credit default swaps on the pricing of audit services. *Work. Pap., Sch. Bus., Univ. Kans.*

Duffie, D. (1999). Credit Swap Valuation. *Financial Analysts Journal*, 55(1):73–87.

Duffie, D. and Singleton, K. J. (1997). An econometric model of the term structure of interest-rate swap yields. *The Journal of Finance*, 52(4):1287–1321.

Enders, W. (2015). *Applied Econometric Time Series*. John Wiley & Sons, Inc., University of Alabama, 4 edition.

Ericsson, J., Jacobs, K., and Oviedo, R. (2009). The Determinants of Credit Default Swap Premia. *The Journal of Financial and Quantitative Analysis*, 44(1):109–132.

Eyssell, T., Fung, H.-G., and Zhang, G. (2013). Determinants and price discovery of China sovereign credit default swaps. *China Economic Review*, 24(C):1–15.

Fabozzi, F. J., Cheng, X., and Chen, R.-R. (2007). Exploring the components of credit risk in credit default swaps. *Finance Research Letters*, 4(1):10–18.

Fama, E. F. (1965). Random Walks in Stock Market Prices. *Financial Analysts Journal*, 21(5):55–59.

Fama, E. F. and French, K. R. (1988). Permanent and Temporary Components of Stock Prices. *The Journal of political economy*, 96(2):246–273.

Figuerola-Ferretti, I. and Paraskevopoulos, I. (2013). Pairing Market Risk and Credit Risk. *SSRN Electronic Journal*.

Filipović, D. and Trolle, A. B. (2013). The term structure of interbank risk. *Journal of Financial Economics*, 109(3):707–733.

Forte, S. (2011). Calibrating structural models: a new methodology based on stock and credit default swap data. *Quantitative Finance*, 11(12):1745–1759.

Forte, S. and Lovreta, L. (2015). Time-Varying Credit Risk Discovery in the Stock and CDS Markets: Evidence from Quiet and Crisis Times. *European financial management : the journal of the European Financial Management Association*, 21(3):430–461.

Forte, S. and Peña, J. I. (2009). Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS. *Journal of Banking & Finance*, 33(11):2013–2025.

Fung, H. G., Sierra, G. E., Yau, J., and Zhang, G. (2008). Are the U.S. stock market and credit default swap market related? Evidence from the CDX indices. *Journal of Alternative Investments*, 11(1):43–61.

Gala, T., Qiu, J., and Yu, F. (2010). Liquidity provision and informed trading in the credit derivatives market. *Unpublished working paper. Deutsche Bank, McMaster University, and Claremont McKenna College.*

Gatfaoui, H. (2017). Equity market information and credit risk signaling: A quantile cointegrating regression approach. *Economic Modelling*, 64:48–59.

Glosten, L. R. and Milgrom, P. R. (1985). Bid, ask and transaction prices in a specialist market with heterogeneously informed traders. *Journal of financial economics*, 14(1):71–100.

Gonzalo, J. and Granger, C. (1995). Estimation of Common Long-Memory Components in Cointegrated Systems. *Journal of Business & Economic Statistics*, 13(1):27.

Greatrex, C. A. (2008). The credit default swap market's determinants, efficiency, and relationship to the stock market.

Hasbrouck, J. (1995). One security, many markets: Determining the contributions to price discovery. *The journal of Finance*, 50(4):1175–1199.

Hausman, J. A. (1978). Specification Tests in Econometrics. *Econometrica*, 46(6):1251–1271.

He, Z., Kelly, B., and Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126(1):1–35.

Hilscher, J., Pollet, J. M., and Wilson, M. (2015). Are Credit Default Swaps a Sideshow? Evidence That Information Flows from Equity to CDS Markets. *Journal of Financial and Quantitative Analysis*, 50(3):543–567.

Hull, J. C. (2018). *Risk Management and Financial Institutions*. Wiley Finance. John Wiley & Sons, Incorporated, Newark.

IHS Markit (2021). CDS Indices Primer. Technical report, IHS Markit.

ISDA (2019). Global Credit Default Swaps Market Study. Technical report, International Swaps and Derivatives Association (ISDA).

ISDA and Markit Group Limited (2021). ISDA CDS Standard Model.

Jarrow, R. A. and Turnbull, S. M. (1995). Pricing derivatives on financial securities subject to credit risk. *The journal of finance*, 50(1):53–85.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, 12(2-3):231–254.

Junge, B. and Trolle, A. B. (2015). Liquidity risk in credit default swap markets. *Swiss Finance Institute Research Paper*, (13-65).

Juselius, K. (2006). *The cointegrated VAR model: methodology and applications*. Oxford university press.

Kapadia, N. and Pu, X. (2012). Limited arbitrage between equity and credit markets. *Journal of Financial Economics*, 105(3):542–564.

Kapar, B. and Olmo, J. (2011). The determinants of credit default swap spreads in the presence of structural breaks and counterparty risk. *Working Papers*.

Kelly, B. T., Manzo, G., and Palhares, D. (2019). Credit-implied volatility. *Available at SSRN 2576292*.

Kendall, M. G. and Hill, A. B. (1953). The analysis of economic time-series-part i: Prices. *Journal of the Royal Statistical Society. Series A (General)*, 116(1):11–34.

Kim, M. J., Nelson, C. R., and Startz, R. (1991). Mean reversion in stock prices? A reappraisal of the empirical evidence. *The Review of Economic Studies*, 58(3):515–528.

Kumar Narayan, P., Liu, R., and Westerlund, J. (2016). A GARCH model for testing market efficiency. *Int. Fin. Markets, Inst. and Money*, 41:121–138.

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica*, 53(6):1315.

Lee, K. H. (2011). The world price of liquidity risk. *Journal of Financial Economics*, 99(1):136–161.

Longstaff, F. A., Mithal, S., and Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *The journal of finance*, 60(5):2213–2253.

Longstaff, F. A. and Schwartz, E. S. (1995). A Simple Approach to Valuing Risky Fixed and Floating Rate Debt. *The Journal of Finance*, 50(3):789–819.

Longstaff, P. F., Longstaff, F. A., Mithal, S., and Neis, E. (2003). The credit-default swap market: is credit protection priced correctly? Working Paper.

Mateev, M. and Marinova, E. (2017). Relation between Credit Default Swap Spreads and Stock Prices: A Non-linear Perspective. *Journal of Economics and Finance 2017 43:1*, 43(1):1–26.

McQueen, G. (1992). Long-horizon mean-reverting stock prices revisited. *Journal of Financial and Quantitative Analysis*, 27(1):1–18.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, 29(2):449–470.

Meucci, A. (2010). Historical scenarios with fully flexible probabilities. *GARP Risk Professional*, pages 47–51.

Narayan, P. K., Sharma, S. S., and Thuraisamy, K. S. (2014). An analysis of price discovery from panel data models of CDS and equity returns. *Journal of Banking & Finance*, 41(1):167–177.

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703–708.

Ngene, G. M., Kabir Hassan, M., and Alam, N. (2014). Price discovery process in the emerging sovereign CDS and equity markets. *Emerging Markets Review*, 21:117–132.

Norden, L. (2017). Information in CDS spreads. *Journal of Banking & Finance*, 75:118–135.

Norden, L. and Weber, M. (2009). The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis. *European Financial Management*, 15(3):529–562.

Osterwald-Lenum, M. (1992). A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. *Oxford Bulletin of Economics and statistics*, 54(3):461–472.

Ötker-Robe, I. and Podpiera, J. (2010). The Fundamental Determinants of Credit Default Risk for European Large Complex Financial Institutions. Technical Report 2010/153.

Pástor, and Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political economy*, 111(3):642–685.

Pedersen, L. H. (2015). *How Smart Money Invests and Market Prices Are Determined*. Princeton University Press.

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, 22(1):435–480.

Poterba, J. M. and Summers, L. H. (1988). Mean reversion in stock prices: Evidence and Implications. *Journal of Financial Economics*, 22(1):27–59.

Qiu, J. and Yu, F. (2012). Endogenous liquidity in credit derivatives. *Journal of Financial Economics*, 103(3):611–631.

Richardson, M. (1993). Temporary components of stock prices: A skeptic's view. *Journal of Business & Economic Statistics*, 11(2):199–207.

Richardson, M. and Stock, J. H. (1989). Drawing inferences from statistics based on multiyear asset returns. *Journal of financial economics*, 25(2):323–348.

Scheicher, M. and Fontana, A. (2010). An analysis of euro area sovereign CDS and their relation with government bonds. Technical Report 1271.

Schneider, P., Sögner, L., and Veža, T. (2010). The Economic Role of Jumps and Recovery Rates in the Market for Corporate Default Risk. *Journal of Financial and Quantitative Analysis*, 45(6):1517–1547.

Shan, S. C., Tang, D. Y., and Yan, H. (2014). The effects of credit default swaps on bank capital, lending, risk and return. Technical report.

Tang, D. Y. and Yan, H. (2007). Liquidity and credit default swap spreads. *Available at SSRN 1008325*.

Trutwein, P., Ramchander, S., and Schiereck, D. (2010). Jumps in Credit Default Swap Spreads and Stock Returns. *The Journal of Fixed Income*, 20(3):56.

Wang, H., Zhou, H., and Zhou, Y. (2013). Credit default swap spreads and variance risk premia. *Journal of Banking & Finance*, 37(10):3733–3746.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Zhang, B. Y., Zhou, H., and Zhu, H. (2009). Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. *Review of Financial Studies*, 22(12):5099–5131.

Zhang, G. and Zhang, S. (2013). Information efficiency of the U.S. credit default swap market: Evidence from earnings surprises. *Journal of Financial Stability*, 9(4):720–730.

Zhu, H. (2006). An empirical comparison of credit spreads between the bond market and the credit default swap market. *Journal of Financial Services Research*, 29(3):211–235.

A Appendix

A.1 Correlation Matrices

Table A.1: Correlation matrix for European companies.

The table shows the correlation between each pair of variables used in our analyses for the European subgroup. Each correlation pair is first calculated on a company level and then averaged across the European sample. *CDS* refers to the 5-year single-name CDS spreads. *Stock* and *Return* to the stock price and the corresponding stock return. *Depth* is the quotes depth, defined as the number of contributors that submit quotes on a CDS contract for each trading day. *Bid-Ask* is the daily average bid-ask spread of a CDS contract. *Vol. (30D)* and *Vol. (90D)* represent the 30-day and 90-day option implied volatility. *OIS* is the 3-month EUR OIS swap rate and *Slope* represents the slope of the term structure (10-year OIS rate minus 3-month rate). *Mkt. Vol.* corresponds to the VSTOXX.

Variables	CDS	Stock	Return	Depth	Bid-Ask	Vol. (30D)	Vol. (90D)	OIS	Slope	Mkt. Vol.
CDS	1.00	-0.35	-0.01	0.00	0.38	-0.01	0.30	0.31	0.12	0.30
Stock	-0.35	1.00	0.04	0.00	-0.29	-0.14	-0.25	-0.09	0.13	-0.27
Return	-0.01	0.04	1.00	-0.01	0.00	-0.01	-0.02	0.00	0.00	-0.06
Depth	0.00	0.00	-0.01	1.00	0.00	-0.07	-0.03	-0.20	0.00	-0.17
Bid-Ask	0.38	-0.29	0.00	0.00	1.00	0.21	0.41	-0.02	-0.28	0.41
Vol. (30D)	-0.01	-0.14	-0.01	-0.07	0.21	1.00	0.43	-0.33	-0.44	0.37
Vol. (90D)	0.30	-0.25	-0.02	-0.03	0.41	0.43	1.00	-0.17	-0.42	0.62
OIS	0.31	-0.09	0.00	-0.20	-0.02	-0.33	-0.17	1.00	0.56	-0.01
Slope	0.12	0.13	0.00	0.00	-0.28	-0.44	-0.42	0.56	1.00	-0.39
Mkt. Vol.	0.30	-0.27	-0.06	-0.17	0.41	0.37	0.62	-0.01	-0.39	1.00

Table A.2: Correlation matrix for U.S. companies.

The table shows the correlation between each pair of variables used in our analyses for the U.S. subgroup. Each correlation pair is first calculated on a company level and then averaged across the European sample. *CDS* refers to the 5-year single-name CDS spreads. *Stock* and *Return* to the stock price and the corresponding stock return. *Depth* is the quotes depth, defined as the number of contributors that submit quotes on a CDS contract for each trading day. *Bid-Ask* is the daily average bid-ask spread of a CDS contract. *Vol. (30D)* and *Vol. (90D)* represent the 30-day and 90-day option implied volatility. *OIS* is the 3-month USD OIS swap rate and *Slope* represents the slope of the term structure (10-year OIS rate minus 3-month rate). *Mkt. Vol.* corresponds to the VIX.

Variables	CDS	Stock	Return	Depth	Bid-Ask	Vol. (30D)	Vol. (90D)	OIS	Slope	Mkt. Vol.
CDS	1.00	-0.46	-0.01	0.11	0.38	0.26	0.29	0.07	0.06	0.09
Stock	-0.46	1.00	0.04	0.07	-0.18	-0.12	-0.16	0.06	-0.22	0.01
Return	-0.01	0.04	1.00	0.00	0.01	-0.05	0.01	-0.01	0.00	-0.06
Depth	0.11	0.07	0.00	1.00	-0.02	-0.08	-0.09	0.33	-0.22	-0.20
Bid-Ask	0.38	-0.18	0.01	-0.02	1.00	0.50	0.52	-0.08	-0.33	0.41
Vol. (30D)	0.26	-0.12	-0.05	-0.08	0.50	1.00	0.74	-0.25	-0.23	0.66
Vol. (90D)	0.29	-0.16	0.01	-0.09	0.52	0.74	1.00	-0.21	-0.26	0.53
OIS	0.07	0.06	-0.01	0.33	-0.08	-0.25	-0.21	1.00	-0.52	-0.40
Slope	0.06	-0.22	0.00	-0.22	-0.33	-0.23	-0.26	-0.52	1.00	-0.15
Mkt. Vol.	0.09	0.01	-0.06	-0.20	0.41	0.66	0.53	-0.40	-0.15	1.00

B Appendix

B.1 Stationarity Results

Table B.1: The table summarizes the stationarity assessment based on the augmented Dickey-Fuller test for each company. Reported are the test statistics for the CDS spreads and the stock prices and corresponding critical values at the 5% level (τ). The results are reported for the entire sample, the pre-crisis period, and the crisis period.

Company	Region	Rating	τ	Entire period		Pre-crisis		Crisis	
				CDS	Stock	CDS	Stock	CDS	Stock
Aegon N.V.	EU	IG	-3.42	-2.59	-2.56	-2.82	-2.22	-2.78	-3.24
Aktiebolaget Volvo	EU	IG	-3.43	-3.31	-2.64	-1.73	-1.32	-2.91	-1.66
Akzo Nobel N.V.	EU	IG	-3.42	-1.12	-2.78	-0.37	-2.38	-0.07	-2.44
Allianz SE	EU	IG	-3.42	-2.11	-1.21	-3.06	-2.58	-3.39	-2.67
Assicurazioni Generali	EU	IG	-3.42	-3.30	-2.74	-2.62	-2.27	-3.04	-2.74
AVIVA PLC	EU	IG	-3.42	-0.25	-2.52	-2.65	-1.91	-2.95	-1.73
AXA	EU	IG	-3.42	-0.56	-3.12	-2.58	-2.08	-0.40	-1.57
BAE SYSTEMS PLC	EU	IG	-3.42	0.00	-2.83	-2.16	-0.82	-0.73	-2.03
BANCO BILBAO VIZCAYA	EU	IG	-3.43	-3.07	-2.16	-1.72	-1.18	-2.56	-2.85
BASF SE	EU	IG	-3.42	-1.25	-2.45	-1.80	-1.26	-2.15	-1.64
Bayer AG	EU	IG	-3.42	-3.22	-3.02	-1.25	-1.10	-0.71	-1.90
BMW AG	EU	IG	-3.42	-3.22	-2.62	-2.24	-2.85	-2.48	-3.02
BP P.L.C.	EU	IG	-3.42	-1.37	-2.08	-2.62	-2.30	-2.39	-2.10
British American Tobacco	EU	IG	-3.42	-3.30	-2.32	-2.07	0.55	-2.48	-1.68
Carrefour	EU	IG	-3.42	-3.28	-3.10	-2.44	-2.79	-3.20	-0.29
Centrica plc	EU	IG	-3.42	-2.97	-2.21	-2.44	-3.14	-2.33	-2.71
COMMERZBANK AG	EU	IG	-3.43	-3.08	-2.41	-1.83	-1.10	-2.68	-1.41
COMPAGNIE GOBAIN	EU	IG	-3.42	-2.29	-1.60	-2.09	-0.95	-2.65	-2.44
Continental AG	EU	IG	-3.43	-3.30	-2.43	-1.59	-0.35	-2.85	-1.86
CREDIT AGRICOLE SA	EU	IG	-3.43	-3.22	-2.62	-1.91	-1.36	-3.25	-2.25
Daimler AG	EU	IG	-3.42	-2.94	-1.95	-2.47	-1.75	-2.10	-2.09
DANONE	EU	IG	-3.43	-2.61	-1.90	-0.81	0.48	-3.21	-1.67
DANSKE BANK A/S	EU	IG	-3.42	-2.06	-2.60	-0.12	-3.15	-3.43	-2.57
Deutsche Telekom AG	EU	IG	-3.42	-2.43	-3.36	-3.16	-2.49	-2.92	-2.36
DIAGEO PLC	EU	IG	-3.42	-1.36	-2.97	-2.76	-3.18	-2.51	-2.61
E.ON SE	EU	IG	-3.42	-2.60	-2.10	-2.12	-1.89	-3.29	-0.98
Electricite de France	EU	IG	-3.42	-1.10	-2.17	-2.43	-0.70	-1.38	-2.48
ENEL S.P.A.	EU	IG	-3.42	-1.77	-2.63	-2.68	-2.97	-3.32	-2.92
ENGIE	EU	IG	-3.43	-2.97	-2.46	-2.38	-3.05	-2.82	-2.01
ENI S.P.A.	EU	IG	-3.42	-1.39	-2.67	-2.44	-2.79	-2.41	-2.68
Fortum Oyj	EU	IG	-3.43	-1.23	-2.14	-2.80	-1.55	-3.37	-1.34
Hannover Rueck SE	EU	IG	-3.42	-1.67	-3.40	-2.75	-2.24	-2.42	-2.18

Table B.1 continued from previous page

Heineken N.V.	EU	IG	-3.42	-1.85	-3.13	-2.82	-1.97	-2.17	-2.89
Iberdrola, S.A.	EU	IG	-3.42	-1.07	-2.75	-2.95	-2.80	-2.71	-2.51
IMPERIAL BRANDS PLC	EU	IG	-3.43	-3.11	-2.41	-1.49	-2.86	-0.65	-2.29
INTESA SANPAOLO SPA	EU	IG	-3.43	-2.71	-2.66	-1.93	-1.76	-3.07	-2.18
Kering	EU	IG	-3.42	-3.07	-2.34	-2.44	-1.69	-2.07	-2.47
Koninklijke KPN N.V.	EU	IG	-3.42	-2.65	-2.90	-3.08	-2.16	-2.52	-3.02
LafargeHolcim Ltd	EU	IG	-3.43	-2.63	-3.20	-2.38	-2.18	-2.93	-1.52
LVMH	EU	IG	-3.42	-3.19	-2.56	-2.58	-2.23	-2.80	-2.48
MEDIOBANCA SpA	EU	IG	-3.43	-2.99	-3.18	-1.56	-2.22	-3.32	-2.20
Muenchener Rueck AG	EU	IG	-3.42	-2.13	-1.10	-2.51	-1.32	-3.33	-2.14
NATIONAL GRID PLC	EU	IG	-3.42	-0.88	-2.72	-3.13	-1.99	-3.17	-3.31
Nestle S.A.	EU	IG	-3.43	-2.50	-2.80	-2.60	-1.51	-0.53	-2.68
Orange	EU	IG	-3.42	-1.25	-3.01	-3.32	-3.01	-1.63	-2.61
PEARSON plc	EU	IG	-3.42	-2.57	-2.63	-1.68	-1.89	-2.24	-2.22
PERNOD RICARD	EU	IG	-3.42	-2.34	-3.33	-2.88	-3.42	-3.03	-1.91
PUBLICIS GROUPE SA	EU	IG	-3.42	-2.77	-1.60	-2.05	-2.47	-1.98	-1.39
ROYAL DUTCH SHELL PLC	EU	IG	-3.42	-3.15	-2.34	-2.26	-2.13	-2.26	-1.54
SANOFI	EU	IG	-3.42	-0.71	-2.48	-3.01	-1.84	-3.01	-1.47
Siemens AG	EU	IG	-3.42	-3.38	-2.79	-2.51	-2.08	-2.95	-1.64
Swiss Reinsurance Ltd	EU	IG	-3.43	-1.17	-0.52	-3.37	-1.57	-2.70	-2.47
TELEFONICA, S.A.	EU	IG	-3.42	-3.12	-2.57	-2.77	-2.82	-2.61	-2.49
Telekom Austria AG	EU	IG	-3.43	-2.63	-2.19	-2.60	-1.58	-2.69	-1.27
TELENOR ASA	EU	IG	-3.42	-0.22	-2.51	-2.17	-2.18	-0.08	-1.99
TOTAL SA	EU	IG	-3.42	-2.97	-2.60	-2.68	-2.82	-2.14	-2.05
Unilever N.V.	EU	IG	-3.42	-3.35	-1.85	-2.77	-2.83	-2.76	-2.47
VEOLIA	EU	IG	-3.42	-2.76	-2.76	-2.70	-2.08	-2.21	-2.70
VINCI	EU	IG	-3.42	-0.05	-2.82	-3.15	-1.77	-3.07	-1.90
Vivendi	EU	IG	-3.42	-0.37	-3.14	-3.08	-2.73	-0.76	-2.47
VODAFONE GROUP Ltd	EU	IG	-3.42	-3.22	-2.91	-2.33	-2.37	-2.53	-1.61
VOLKSWAGEN AG	EU	IG	-3.42	-2.84	-2.77	-2.22	-2.27	-2.35	-2.55
WPP 2005 LIMITED	EU	IG	-3.42	-3.08	-1.62	-1.54	-0.34	-2.37	-2.12
Zurich Insurance Ltd	EU	IG	-3.43	-2.19	-3.21	-3.09	-2.09	-3.07	-3.36
ACCOR	EU	HY	-3.42	-2.64	-2.11	-2.17	-1.94	-2.09	-2.23
AIR FRANCE - KLM	EU	HY	-3.42	-2.99	-3.04	-2.68	-2.52	-2.41	-2.20
ArcelorMittal	EU	HY	-3.42	-2.39	-1.57	-2.24	-1.88	-2.40	-2.05
ATLANTIA SPA	EU	HY	-3.42	-2.24	-2.59	-1.77	-2.85	-0.31	-2.61
Casino Guichardperrachon	EU	HY	-3.42	-2.83	-3.39	-2.05	-2.77	-2.91	-2.69
Clariant AG	EU	HY	-3.42	-3.22	-2.90	-3.13	-2.76	-1.79	-1.42
CNH Indl NV	EU	HY	-3.42	-2.67	-2.19	-2.34	-1.87	-1.80	-1.46
Deutsche Lufthansa AG	EU	HY	-3.42	-2.06	-1.93	-2.10	-2.32	-1.07	-1.34
EDP SA	EU	HY	-3.42	-0.63	-2.60	-2.76	-1.61	-2.22	-2.69
Eli	EU	HY	-3.42	-2.91	-3.07	-2.01	-2.34	-3.40	-2.62
FAURECIA	EU	HY	-3.42	-3.29	-2.55	-2.61	-2.00	-3.26	-2.35
Galp Energia SGPS SA	EU	HY	-3.42	-2.60	-2.37	-0.78	0.23	-2.10	-2.71

Table B.1 continued from previous page

HeidelbergCement AG	EU	HY	-3.42	-3.24	-2.46	-1.79	-0.29	-2.90	-1.91
Hellenic Telecom Org SA	EU	HY	-3.42	-2.56	-2.50	-1.32	-1.91	-2.71	-1.99
Intl Game Tech PLC	EU	HY	-3.42	-1.93	-3.03	-1.27	-2.30	-2.35	-2.37
ITV Plc	EU	HY	-3.43	-3.07	-2.39	-3.23	-0.32	-2.04	-2.10
J Sainsbury PLC	EU	HY	-3.42	-3.04	-2.58	-1.90	-0.74	-2.59	-1.19
Marks & Spencer p l c	EU	HY	-3.42	-0.10	-2.24	-2.66	-2.20	-3.03	-2.22
Nokia Oyj	EU	HY	-3.43	-3.15	-1.57	-1.59	-0.62	-2.86	-1.87
Peugeot SA	EU	HY	-3.42	-2.63	-2.36	-0.88	-1.63	-2.51	-1.57
Pub Pwr Corp Fin PLC	EU	HY	-3.42	-3.15	-1.53	-2.39	-2.33	-1.93	-0.77
Renault	EU	HY	-3.43	-2.98	-2.30	-3.36	-2.21	-1.59	-2.44
REXEL	EU	HY	-3.42	-0.83	-2.94	-3.00	-1.90	-1.21	-3.34
ROLLSROYCE PLC	EU	HY	-3.42	-2.40	-1.83	-1.59	-1.73	-2.26	-1.73
Stora Enso CORP	EU	HY	-3.42	-2.59	-1.84	-1.72	-1.90	-2.27	-1.30
Telecom Italia SpA	EU	HY	-3.42	-3.33	-0.30	-2.22	-2.38	-2.48	-2.51
TelefonAB L M Ericsson	EU	HY	-3.42	-2.83	-2.85	-1.71	-1.69	-2.16	-2.00
Tesco PLC	EU	HY	-3.42	-1.79	-1.83	-2.49	-1.53	-2.75	-2.63
thyssenkrupp AG	EU	HY	-3.42	-2.83	-2.47	-2.18	-1.65	-3.28	-3.03
UPM Kymmene CORP	EU	HY	-3.42	-2.90	-2.11	-2.42	-2.49	-2.41	-3.14
Valeo	EU	HY	-3.42	-3.36	-2.73	-0.02	-2.81	-2.98	-1.72
Allstate Corp	U.S.	IG	-3.42	-3.10	-1.88	0.50	-0.58	-3.27	-2.14
Altria Gp Inc	U.S.	IG	-3.42	-3.20	-2.50	-2.30	-2.77	-2.87	-3.40
Amern Elec Pwr Co Inc	U.S.	IG	-3.42	-1.13	-2.16	-1.77	-1.50	-3.23	-1.60
Amern Express Co	U.S.	IG	-3.42	-2.62	-2.13	-3.23	-0.52	-2.96	-1.30
Amern Intl Gp Inc	U.S.	IG	-3.42	-3.28	-2.04	-1.73	-3.41	-2.87	-2.29
Amgen Inc.	U.S.	IG	-3.42	-1.81	-2.64	-2.55	-3.15	-2.90	-2.06
ARROW ELECTRS INC	U.S.	IG	-3.42	-2.93	-1.17	-1.99	-1.04	-2.37	-1.98
AT&T Inc	U.S.	IG	-3.42	-2.65	-1.22	-2.07	-1.88	-2.99	-1.75
Autozone Inc	U.S.	IG	-3.42	-1.38	-3.08	-2.93	-0.68	-0.68	-1.47
Avnet Inc	U.S.	IG	-3.42	-2.14	-2.46	-2.17	-1.85	-1.41	-1.67
Barrick Gold Corp	U.S.	IG	-3.42	-3.32	-2.00	-1.81	-2.06	-2.43	-0.32
Baxter Intl Inc	U.S.	IG	-3.42	-2.44	-2.74	-2.32	-2.36	-3.28	-1.82
Berkshire Hathaway Inc	U.S.	IG	-3.42	-3.15	-2.32	-1.76	-2.92	-2.15	-3.12
BOEING CO	U.S.	IG	-3.42	-2.97	-3.30	-1.87	-2.64	-2.33	-2.53
Boston Scientific Corp	U.S.	IG	-3.42	-2.04	-2.28	-0.71	-0.76	-2.06	-2.18
Bristol Myers Squibb Co	U.S.	IG	-3.42	-3.32	-2.14	-2.05	-1.97	-2.26	-1.49
CAMPBELL SOUP CO	U.S.	IG	-3.42	-1.85	-3.35	-1.67	-1.66	-2.09	-2.25
Cap One Bk USA	U.S.	IG	-3.42	-2.97	-2.08	-1.90	-1.38	-3.14	-2.23
Cardinal Health Inc	U.S.	IG	-3.43	-0.98	-2.47	-1.68	-1.26	-2.40	-1.85
Caterpillar Inc	U.S.	IG	-3.42	-1.98	-3.16	-3.07	-2.05	-2.78	-2.02
Chubb Ltd	U.S.	IG	-3.42	-2.82	-2.37	-1.69	-1.47	-1.70	-1.79
Comcast Corp	U.S.	IG	-3.42	-3.15	-2.32	-2.58	-1.63	-2.95	-2.46
ConocoPhillips	U.S.	IG	-3.43	-1.45	-1.73	-2.87	-1.69	-3.39	-2.33
CSX Corp	U.S.	IG	-3.42	-2.95	-2.62	-1.49	-2.99	-2.57	-1.80
CVS Health Corp	U.S.	IG	-3.42	-2.94	-2.28	-1.85	-1.98	-3.20	-1.83

Table B.1 continued from previous page

Darden Restaurants Inc	U.S.	IG	-3.42	-2.99	-1.95	-1.54	-1.97	-3.37	-1.30
Deere & Co	U.S.	IG	-3.42	-2.85	-3.16	-2.01	-2.37	-2.69	-3.01
Devon Engy Corp	U.S.	IG	-3.42	-2.72	-1.97	-2.23	-1.14	-3.10	-1.86
Duke Energy Carolinas LLC	U.S.	IG	-3.42	-0.42	-2.43	-1.71	-1.59	-1.93	-2.28
E I du Pont de Nemours	U.S.	IG	-3.42	-2.92	-3.17	-1.73	-2.17	-3.14	-2.37
Eastman Chem Co	U.S.	IG	-3.42	-1.82	-2.02	-2.49	-1.94	-3.05	-1.30
Enbridge Inc	U.S.	IG	-3.42	-2.85	-2.70	-1.68	-3.28	-2.53	-1.87
Exelon Corp	U.S.	IG	-3.42	-3.09	-1.51	-1.75	0.61	-2.70	-1.64
FirstEnergy Corp	U.S.	IG	-3.42	-2.42	-2.48	-1.37	-0.83	-2.25	-3.00
Gen Elec Co	U.S.	IG	-3.42	-3.42	-2.76	-1.91	-1.15	-2.83	-2.53
Gen Mls Inc	U.S.	IG	-3.42	-1.37	-2.95	-1.89	-2.24	-3.39	-2.28
Halliburton Co	U.S.	IG	-3.42	-2.83	-3.06	-2.54	-1.87	-1.11	-2.04
Hartford Finl Services	U.S.	IG	-3.43	-1.98	-1.78	-0.41	-1.72	-2.07	-1.59
Hess Corp	U.S.	IG	-3.42	-3.07	-2.89	-1.45	-1.41	-0.90	-2.97
Home Depot Inc	U.S.	IG	-3.42	-0.40	-2.02	-2.15	-1.29	-2.90	-1.63
Honeywell Intl Inc	U.S.	IG	-3.42	-2.56	-3.01	-2.28	-2.01	-1.71	-0.07
HP Inc	U.S.	IG	-3.42	-2.94	-2.00	-2.21	-1.73	-1.84	-1.39
Intl Business Machs Corp	U.S.	IG	-3.42	-3.21	-2.39	-1.56	-1.48	-2.90	-1.78
Intl Paper Co	U.S.	IG	-3.42	-3.19	-1.93	-1.99	-0.50	-2.97	-3.21
Johnson & Johnson	U.S.	IG	-3.42	-2.40	-2.32	-1.93	-2.41	-3.05	-1.31
Kohls Corp	U.S.	IG	-3.42	-3.34	-2.53	-1.72	-2.39	-2.89	-2.65
Lincoln Natl Corp	U.S.	IG	-3.42	-2.79	-2.40	-1.27	-1.51	-1.95	-1.64
Lockheed Martin Corp	U.S.	IG	-3.42	-2.95	-2.95	-1.38	-1.86	-3.37	-2.11
Loews Corp	U.S.	IG	-3.42	-3.30	-2.42	-2.55	-2.14	-0.53	-2.36
Lowes Cos Inc	U.S.	IG	-3.42	-2.01	-1.49	-2.52	-2.70	-2.78	-0.37
Marriott Intl Inc	U.S.	IG	-3.42	-2.80	-2.81	-1.82	-2.24	-1.89	-1.80
Marsh & Mclennan Inc	U.S.	IG	-3.42	-1.06	-1.05	-2.77	-2.85	-2.34	-3.27
McDONALDS Corp	U.S.	IG	-3.42	-3.20	-3.06	-1.94	-2.82	-3.08	-1.68
McKesson Corp	U.S.	IG	-3.42	-3.14	-2.75	-2.33	-1.77	-3.29	-2.50
MetLife Inc	U.S.	IG	-3.42	-3.15	-1.82	-1.88	0.40	-2.95	-2.57
Mondelez Intl Inc	U.S.	IG	-3.42	-3.28	-2.40	-2.03	-2.19	-3.13	-1.58
Motorola Solutions Inc	U.S.	IG	-3.42	-0.76	-2.15	-1.70	-1.33	-2.79	-1.96
Norfolk Sthn Corp	U.S.	IG	-3.42	-3.38	-2.49	-2.85	-2.89	-3.41	-1.39
Northrop Grumman Corp	U.S.	IG	-3.42	-0.18	-2.12	-1.82	-1.46	-2.39	-1.62
Omnicom Gp Inc	U.S.	IG	-3.42	-2.43	-2.78	0.57	-0.78	-2.40	-2.43
Packaging Corp Amer	U.S.	IG	-3.42	-2.53	-1.90	-0.69	-1.28	-2.57	-1.48
Pfizer Inc	U.S.	IG	-3.42	-3.30	-3.17	-2.61	-2.46	-2.06	-3.10
Procter & Gamble Co	U.S.	IG	-3.42	-2.47	-2.13	-2.63	-2.06	-1.39	-1.07
Prudential Finl Inc	U.S.	IG	-3.42	-3.17	-2.55	-2.60	-2.04	-2.14	-1.66
Quest Diagnostics Inc	U.S.	IG	-3.42	-2.70	-1.69	-2.00	-2.48	-3.06	-2.61
Ryder Sys Inc	U.S.	IG	-3.42	-3.32	-2.51	-2.12	-0.94	-3.05	-2.51
Sempra Engy	U.S.	IG	-3.42	-2.48	-1.34	-1.71	-1.95	-1.80	-1.89
Sherwin Williams Co	U.S.	IG	-3.42	-0.98	-2.28	-1.61	-1.25	-2.81	-1.42
Simon Ppty Gp L P	U.S.	IG	-3.42	-0.74	-3.42	-2.29	-2.01	-1.58	-3.05

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Southwest Airls Co	U.S.	IG	-3.42	-2.02	-2.20	-2.65	-2.34	-1.72	-2.98
Target Corp	U.S.	IG	-3.42	-3.25	-2.36	-2.19	-2.01	-3.37	-3.00
The Kroger Co.	U.S.	IG	-3.42	-2.43	-2.54	-2.31	-2.48	-2.71	-2.60
Tyson Foods Inc	U.S.	IG	-3.42	-3.36	-2.22	-1.48	-0.77	-3.09	-1.79
Un Pac Corp	U.S.	IG	-3.42	-1.21	-2.50	-2.45	-1.52	-3.15	-3.00
UnitedHealth Gp Inc	U.S.	IG	-3.42	-3.02	-2.29	-1.92	-2.95	-3.10	-1.91
Utd Parcel Svc Inc	U.S.	IG	-3.42	-2.36	-2.78	-1.92	-2.69	-1.25	-3.21
Valero Energy Corp	U.S.	IG	-3.42	-3.20	-1.99	-1.77	-1.86	-2.47	-1.95
Verizon Comms Inc	U.S.	IG	-3.42	-0.64	-2.37	-0.05	-0.62	-2.65	-2.97
WESTROCK MWV LLC	U.S.	IG	-3.43	-1.03	-1.70	-1.83	-0.22	-3.00	-2.03
Weyerhaeuser Co	U.S.	IG	-3.42	-3.23	-2.47	-2.07	-0.98	-2.77	-2.18
Whirlpool Corp	U.S.	IG	-3.42	-3.35	-2.41	-1.46	-1.31	-3.31	-2.24
AMD Inc	U.S.	HY	-3.42	-2.43	-2.89	-1.52	-2.10	-2.93	-2.93
AK Stl Corp	U.S.	HY	-3.42	-3.28	-2.23	-1.13	-1.91	-3.01	-2.02
Amern Axle & Mfg Inc	U.S.	HY	-3.42	-2.71	-2.11	-2.25	-1.67	-2.73	-1.69
Amkor Tech Inc	U.S.	HY	-3.42	-1.90	-2.22	-1.28	-1.77	-3.27	-2.86
Avon Prods Inc	U.S.	HY	-3.42	-3.41	-2.43	-1.70	-2.19	-1.38	-0.71
BEAZER HOMES USA INC	U.S.	HY	-3.42	0.07	-1.08	-2.18	-2.72	-2.67	-1.47
Boyd Gaming Corp	U.S.	HY	-3.42	-1.62	-2.41	-0.95	-2.08	-3.28	-1.44
CCO Hldgs LLC	U.S.	HY	-3.42	-1.84	-2.27	-2.53	-2.24	-2.50	-1.74
CIT Gp Inc	U.S.	HY	-3.42	-2.58	-2.24	-0.62	-1.18	-3.37	-2.83
Cmnty Health Sys Inc	U.S.	HY	-3.42	-3.15	-3.05	-2.21	-1.41	-0.27	-0.94
DISH DBS Corp	U.S.	HY	-3.42	0.42	-0.15	-0.41	-1.94	-1.88	-2.82
Genworth Hldgs Inc	U.S.	HY	-3.42	-0.88	-0.95	-2.77	-2.75	-1.96	-2.83
HCA Inc.	U.S.	HY	-3.42	-2.09	-2.32	-1.46	-1.38	-2.25	-2.09
HD SUPPLY INC	U.S.	HY	-3.43	-2.85	-1.80	-1.66	-2.27	-1.24	-3.25
iStar Inc	U.S.	HY	-3.42	-2.48	-2.45	-1.27	-2.10	-2.80	-2.01
K Hovnanian Entpers Inc	U.S.	HY	-3.42	-1.62	-2.52	-3.04	-2.05	-2.19	-0.87
KB HOME	U.S.	HY	-3.43	-2.97	-2.52	-0.34	-2.43	-2.45	-2.84
Lennar Corp	U.S.	HY	-3.42	-1.92	-1.34	-2.11	-1.93	-2.18	-1.40
MGIC Invt Corp	U.S.	HY	-3.42	-2.99	-2.34	-1.45	-1.89	-2.36	-1.78
MGM Resorts Intl	U.S.	HY	-3.42	-3.11	-2.48	-1.05	-1.96	-3.33	-2.94
Navient Corp	U.S.	HY	-3.42	-3.17	-2.26	-1.84	-1.81	-2.37	-2.52
NRG Energy Inc	U.S.	HY	-3.42	-2.55	-1.78	-1.42	-0.81	-2.89	-1.08
Olin Corp	U.S.	HY	-3.43	-3.33	-1.77	-1.53	-2.20	-2.22	-1.29
PulteGroup Inc	U.S.	HY	-3.42	-3.05	-0.95	-1.99	-1.50	-3.26	-2.74
R R Donnelley & Sons Co	U.S.	HY	-3.42	-2.49	-3.26	-1.97	-2.33	-2.03	-1.84
Radian Gp Inc	U.S.	HY	-3.42	-2.58	-2.68	-1.31	-2.13	-1.96	-3.09
Rite Aid Corp	U.S.	HY	-3.42	-2.17	-2.01	-1.73	-1.28	-1.91	-1.33
Sealed Air Corp US	U.S.	HY	-3.43	-2.12	-2.97	-1.96	-2.25	-3.16	-1.87
T Mobile USA Inc	U.S.	HY	-3.43	-2.90	-2.80	-1.67	-1.47	-2.96	-1.96
TEGNA Inc	U.S.	HY	-3.42	-3.11	-1.11	-2.08	-1.84	-3.10	-1.24
Tenet Healthcare Corp	U.S.	HY	-3.42	-3.35	-1.89	-1.69	-1.83	-2.95	-2.39
The AES Corp	U.S.	HY	-3.42	-0.53	-2.11	-1.49	-1.53	-1.32	-1.77

Table B.1 continued from previous page

Unvl Health Svcs Inc	U.S.	HY	-3.42	-1.76	-1.90	-1.61	-1.81	-3.06	-2.14
UTD RENTS Inc	U.S.	HY	-3.42	-2.79	-3.37	-2.99	-2.46	-2.71	-2.12
Utd Sts Stl Corp	U.S.	HY	-3.42	-2.86	-3.13	-2.39	-2.42	-1.92	-2.69

B.2 Cointegration Results

Table B.2: Cointegration results are reported using a 5% and a 10% significance level. The table summarizes results on a company level for the entire sample, the pre-crisis period, and the crisis period. **, and * indicate significance at the 5% and 10% levels, respectively.

Company	Region	Rating	Entire period	Pre-crisis	Crisis
Aegon N.V.	EU	IG	**		
Aktiebolaget Volvo	EU	IG			
Akzo Nobel N.V.	EU	IG	*		**
Allianz SE	EU	IG	**		**
Assicurazioni Generali	EU	IG			*
AVIVA PLC	EU	IG	**	**	**
AXA	EU	IG	**		
BAE SYSTEMS PLC	EU	IG			**
BANCO BILBAO VIZCAYA	EU	IG			
BASF SE	EU	IG	**		**
Bayer AG	EU	IG			**
BMW AG	EU	IG	**		
BP P.L.C.	EU	IG	**		*
British American Tobacco	EU	IG			
Carrefour	EU	IG	**		
Centrica plc	EU	IG			
COMMERZBANK AG	EU	IG			
COMPAGNIE GOBAIN	EU	IG			
Continental AG	EU	IG	**		**
CREDIT AGRICOLE SA	EU	IG			**
Daimler AG	EU	IG			
DANONE	EU	IG		*	**
DANSKE BANK A/S	EU	IG			**
Deutsche Telekom AG	EU	IG	**		**
DIAGEO PLC	EU	IG	**		**
E.ON SE	EU	IG			**
Electricite de France	EU	IG	*		**
ENEL S.P.A.	EU	IG			**
ENGIE	EU	IG	**		
ENI S.P.A.	EU	IG	*		
Fortum Oyj	EU	IG	**	*	**

Table B.2 continued from previous page

Hannover Rueck SE	EU	IG	**		*
Heineken N.V.	EU	IG	*		**
Iberdrola, S.A.	EU	IG			**
IMPERIAL BRANDS PLC	EU	IG			**
INTESA SANPAOLO SPA	EU	IG	**		
Kering	EU	IG	**		*
Koninklijke KPN N.V.	EU	IG	**		
LafargeHolcim Ltd	EU	IG			*
LVMH	EU	IG			
MEDIOBANCA SpA	EU	IG			
Muenchener Rueck AG	EU	IG	**	*	*
NATIONAL GRID PLC	EU	IG			
Nestle S.A.	EU	IG	*		**
Orange	EU	IG	**		**
PEARSON plc	EU	IG			**
PERNOD RICARD	EU	IG			
PUBLICIS GROUPE SA	EU	IG	*		
ROYAL DUTCH SHELL PLC	EU	IG	*		*
SANOFI	EU	IG	**		**
Siemens AG	EU	IG			*
Swiss Reinsurance Ltd	EU	IG	**		*
TELEFONICA, S.A.	EU	IG			
Telekom Austria AG	EU	IG			
TELENOR ASA	EU	IG	**		**
TOTAL SA	EU	IG	**		
Unilever N.V.	EU	IG			**
VEOLIA	EU	IG			
VINCI	EU	IG	**		*
Vivendi	EU	IG			**
VODAFONE GROUP Ltd	EU	IG			
VOLKSWAGEN AG	EU	IG			
WPP 2005 LIMITED	EU	IG	*		
Zurich Insurance Ltd	EU	IG	**	**	*
ACCOR	EU	HY	*		
AIR FRANCE - KLM	EU	HY	**	**	
ArcelorMittal	EU	HY			**
ATLANTIA SPA	EU	HY	*		
Casino Guichardperrachon	EU	HY			
Clariant AG	EU	HY	**	**	
CNH Indl NV	EU	HY			*
Deutsche Lufthansa AG	EU	HY		*	
EDP SA	EU	HY			
Eli	EU	HY		**	
FAURECIA	EU	HY			**

Table B.2 continued from previous page

Galp Energia SGPS SA	EU	HY			
HeidelbergCement AG	EU	HY			*
Hellenic Telecom Org SA	EU	HY		**	*
Intl Game Tech PLC	EU	HY	**	**	
ITV Plc	EU	HY	**		
J Sainsbury PLC	EU	HY	*		
Marks & Spencer p l c	EU	HY	**		
Nokia Oyj	EU	HY	**		**
Peugeot SA	EU	HY			
Pub Pwr Corp Fin PLC	EU	HY			
Renault	EU	HY			
REXEL	EU	HY	**		
ROLLSROYCE PLC	EU	HY	*	*	
Stora Enso CORP	EU	HY	**	**	*
Telecom Italia SpA	EU	HY			*
TelefonAB L M Ericsson	EU	HY			**
Tesco PLC	EU	HY			
thyssenkrupp AG	EU	HY			
UPM Kymmene CORP	EU	HY	**	**	**
Valeo	EU	HY			
Allstate Corp	U.S.	IG			
Altria Gp Inc	U.S.	IG			**
Amern Elec Pwr Co Inc	U.S.	IG			*
Amern Express Co	U.S.	IG	*		*
Amern Intl Gp Inc	U.S.	IG			
Amgen Inc.	U.S.	IG			*
ARROW ELECTRS INC	U.S.	IG	**		
AT&T Inc	U.S.	IG	*		
Autozone Inc	U.S.	IG			
Avnet Inc	U.S.	IG	**	**	**
Barrick Gold Corp	U.S.	IG			
Baxter Intl Inc	U.S.	IG			**
Berkshire Hathaway Inc	U.S.	IG			
BOEING CO	U.S.	IG			
Boston Scientific Corp	U.S.	IG	**		*
Bristol Myers Squibb Co	U.S.	IG			*
CAMPBELL SOUP CO	U.S.	IG			*
Cap One Bk USA	U.S.	IG			
Cardinal Health Inc	U.S.	IG			
Caterpillar Inc	U.S.	IG			
Chubb Ltd	U.S.	IG			
Comcast Corp	U.S.	IG	*		**
ConocoPhillips	U.S.	IG			**
CSX Corp	U.S.	IG			**

Table B.2 continued from previous page

CVS Health Corp	U.S.	IG			
Darden Restaurants Inc	U.S.	IG			
Deere & Co	U.S.	IG			**
Devon Engy Corp	U.S.	IG			*
Duke Energy Carolinas LLC	U.S.	IG			*
E I du Pont de Nemours	U.S.	IG			
Eastman Chem Co	U.S.	IG	**		**
Enbridge Inc	U.S.	IG	**		**
Exelon Corp	U.S.	IG			
FirstEnergy Corp	U.S.	IG	**	**	**
Gen Elec Co	U.S.	IG	*		
Gen Mls Inc	U.S.	IG			
Halliburton Co	U.S.	IG			
Hartford Finl Services	U.S.	IG			
Hess Corp	U.S.	IG	**		**
Home Depot Inc	U.S.	IG	**		
Honeywell Intl Inc	U.S.	IG	*		*
HP Inc	U.S.	IG			
Intl Business Machs Corp	U.S.	IG			**
Intl Paper Co	U.S.	IG			**
Johnson & Johnson	U.S.	IG	*		
Kohls Corp	U.S.	IG	*		**
Lincoln Natl Corp	U.S.	IG			**
Lockheed Martin Corp	U.S.	IG			
Loews Corp	U.S.	IG	*		*
Lowes Cos Inc	U.S.	IG			
Marriott Intl Inc	U.S.	IG			
Marsh & Mclennan Inc	U.S.	IG			
McDONALDS Corp	U.S.	IG	*		*
McKesson Corp	U.S.	IG			
MetLife Inc	U.S.	IG			**
Mondelez Intl Inc	U.S.	IG			
Motorola Solutions Inc	U.S.	IG			
Norfolk Sthn Corp	U.S.	IG			**
Northrop Grumman Corp	U.S.	IG			
Omnicom Gp Inc	U.S.	IG			
Packaging Corp Amer	U.S.	IG			
Pfizer Inc	U.S.	IG	*		**
Procter & Gamble Co	U.S.	IG	**		
Prudential Finl Inc	U.S.	IG			**
Quest Diagnostics Inc	U.S.	IG			
Ryder Sys Inc	U.S.	IG	**		**
Sempra Engy	U.S.	IG	*		**
Sherwin Williams Co	U.S.	IG			

Table B.2 continued from previous page

Simon Ppty Gp L P	U.S.	IG			
Southwest Airls Co	U.S.	IG	**	**	
Target Corp	U.S.	IG			
The Kroger Co.	U.S.	IG			
Tyson Foods Inc	U.S.	IG			
Un Pac Corp	U.S.	IG	*		**
UnitedHealth Gp Inc	U.S.	IG			
Utd Parcel Svc Inc	U.S.	IG			
Valero Energy Corp	U.S.	IG			**
Verizon Comms Inc	U.S.	IG	**		*
WESTROCK MWV LLC	U.S.	IG			**
Weyerhaeuser Co	U.S.	IG			*
Whirlpool Corp	U.S.	IG	*		
AMD Inc	U.S.	HY			
AK Stl Corp	U.S.	HY			
Amern Axle & Mfg Inc	U.S.	HY	**	**	
Amkor Tech Inc	U.S.	HY			
Avon Prods Inc	U.S.	HY			
BEAZER HOMES USA INC	U.S.	HY	*		
Boyd Gaming Corp	U.S.	HY			
CCO Hldgs LLC	U.S.	HY	**	**	**
CIT Gp Inc	U.S.	HY			
Cmnty Health Sys Inc	U.S.	HY			
DISH DBS Corp	U.S.	HY			
Genworth Hldgs Inc	U.S.	HY	**	*	
HCA Inc.	U.S.	HY	**	*	
HD SUPPLY INC	U.S.	HY			
iStar Inc	U.S.	HY			
K Hovnanian Entpers Inc	U.S.	HY			
KB HOME	U.S.	HY			
Lennar Corp	U.S.	HY			
MGIC Invt Corp	U.S.	HY			*
MGM Resorts Intl	U.S.	HY			**
Navient Corp	U.S.	HY			
NRG Energy Inc	U.S.	HY			
Olin Corp	U.S.	HY	*		**
PulteGroup Inc	U.S.	HY	*		
R R Donnelley & Sons Co	U.S.	HY			
Radian Gp Inc	U.S.	HY			
Rite Aid Corp	U.S.	HY		**	
Sealed Air Corp US	U.S.	HY	*		
T Mobile USA Inc	U.S.	HY		**	
TEGNA Inc	U.S.	HY			
Tenet Healthcare Corp	U.S.	HY	*		

Table B.2 continued from previous page

The AES Corp	U.S.	HY				
Unvl Health Svcs Inc	U.S.	HY				
UTD RENTS Inc	U.S.	HY			*	**
Utd Sts Stl Corp	U.S.	HY			**	

B.3 Price Discovery Results

Table B.3: The table summarizes the price discovery assessment based on the VECM coefficients for each company. The results are reported for the entire sample, the pre-crisis period, and the crisis period. Blank cells indicate too many missing values for the particular time period.

Company	Region	Rating	Entire period		Pre-crisis		Crisis	
			5%	10%	5%	10%	5%	10%
Aegon N.V.	EU	IG	Stock	None	Stock	Stock	Stock	Stock
Aktiebolaget Volvo	EU	IG	Stock	Stock	Stock	Stock	None	None
Akzo Nobel N.V.	EU	IG	Stock	Stock	Stock	Stock	Stock	None
Allianz SE	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
Assicurazioni Generali	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
AVIVA PLC	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
AXA	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
BAE SYSTEMS PLC	EU	IG	Stock	Stock	None	None	Stock	None
BANCO BILBAO VIZCAYA	EU	IG	Stock	None	Stock	Stock	Stock	Stock
BASF SE	EU	IG	Stock	None	Stock	Stock	Stock	Stock
Bayer AG	EU	IG	Stock	Stock	None	CDS	None	None
BMW AG	EU	IG	Stock	Stock	None	None	Stock	Stock
BP P.L.C.	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
British American Tobacco	EU	IG	Stock	Stock	None	None	Stock	None
Carrefour	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
Centrica plc	EU	IG	Stock	Stock	CDS	CDS	Stock	Stock
COMMERZBANK AG	EU	IG	None	None	Stock	Stock	Stock	Stock
COMPAGNIE GOBAIN	EU	IG	Stock	Stock	Stock	Stock	None	None
Continental AG	EU	IG	Stock	Stock	None	Stock	None	None
CREDIT AGRICOLE SA	EU	IG	CDS	CDS	None	Stock	Stock	Stock
Daimler AG	EU	IG	Stock	Stock	Stock	Stock	None	None
DANONE	EU	IG	CDS	CDS	Stock	Stock	None	None
DANSKE BANK A/S	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
Deutsche Telekom AG	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
DIAGEO PLC	EU	IG	Stock	None	Stock	Stock	None	None
E.ON SE	EU	IG	None	None	None	None	None	None
Electricite de France	EU	IG	Stock	Stock	CDS	None	Stock	Stock
ENEL S.P.A.	EU	IG	None	None	None	None	Stock	Stock

Table B.3 continued from previous page

ENGIE	EU	IG	CDS	CDS	CDS	CDS	Stock	Stock
ENI S.P.A.	EU	IG	None	None	Stock	None	Stock	Stock
Fortum Oyj	EU	IG	None	None	Stock	Stock	None	None
Hannover Rueck SE	EU	IG	Stock	Stock	Stock	Stock	None	None
Heineken N.V.	EU	IG	Stock	Stock	CDS	CDS	Stock	Stock
Iberdrola, S.A.	EU	IG	Stock	Stock	None	None	None	None
IMPERIAL BRANDS PLC	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
INTESA SANPAOLO SPA	EU	IG	CDS	CDS	None	CDS	CDS	CDS
Kering	EU	IG	Stock	None	Stock	Stock	None	None
Koninklijke KPN N.V.	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
LafargeHolcim Ltd	EU	IG	None	Stock	CDS	None	Stock	Stock
LVMH	EU	IG	Stock	Stock	Stock	Stock	CDS	None
MEDIOBANCA SpA	EU	IG	CDS	CDS	CDS	CDS	Stock	Stock
Muenchener Rueck AG	EU	IG	Stock	Stock	Stock	Stock	None	None
NATIONAL GRID PLC	EU	IG	Stock	Stock	CDS	CDS	Stock	None
Nestle S.A.	EU	IG	Stock	Stock	None	None	Stock	None
Orange	EU	IG	None	None	CDS	CDS	Stock	Stock
PEARSON plc	EU	IG	Stock	None	CDS	CDS	Stock	Stock
PERNOD RICARD	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
PUBLICIS GROUPE SA	EU	IG	Stock	Stock	None	None	Stock	Stock
ROYAL DUTCH SHELL PLC	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
SANOFI	EU	IG	None	None	None	None	CDS	None
Siemens AG	EU	IG	Stock	None	Stock	Stock	None	None
Swiss Reinsurance Ltd	EU	IG	Stock	Stock	Stock	Stock	None	Stock
TELEFONICA, S.A.	EU	IG	None	None	Stock	None	Stock	Stock
Telekom Austria AG	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
TELENOR ASA	EU	IG	None	None	CDS	CDS	Stock	Stock
TOTAL SA	EU	IG	Stock	Stock	None	Stock		
Unilever N.V.	EU	IG	Stock	Stock	CDS	CDS	Stock	Stock
VEOLIA	EU	IG	Stock	Stock	None	None	Stock	Stock
VINCI	EU	IG	Stock	Stock	Stock	None	None	None
Vivendi	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
VODAFONE GROUP Ltd	EU	IG	None	None	CDS	CDS	None	None
VOLKSWAGEN AG	EU	IG	Stock	Stock	CDS	None	Stock	Stock
WPP 2005 LIMITED	EU	IG	Stock	Stock	None	None	Stock	Stock
Zurich Insurance Ltd	EU	IG	Stock	Stock	Stock	Stock	Stock	Stock
ACCOR	EU	HY	None	None	CDS	CDS	None	None
AIR FRANCE - KLM	EU	HY	Stock	Stock	Stock	Stock	None	CDS
ArcelorMittal	EU	HY	Stock	Stock	CDS	CDS	Stock	Stock
ATLANTIA SPA	EU	HY	None	None	CDS	CDS	Stock	Stock
Casino Guichardperrachon	EU	HY	None	Stock	None	Stock	None	None
Clariant AG	EU	HY	None	None	Stock	Stock	Stock	None
CNH Indl NV	EU	HY	Stock	Stock	Stock	Stock	Stock	Stock
Deutsche Lufthansa AG	EU	HY	Stock	Stock	Stock	Stock	CDS	CDS

Table B.3 continued from previous page

EDP SA	EU	HY	Stock	Stock	None	None	None	None
Eli	EU	HY	Stock	Stock	Stock	None	None	None
FAURECIA	EU	HY	CDS	CDS	None	Stock	CDS	CDS
Galp Energia SGPS SA	EU	HY	None	Stock	None	CDS	Stock	Stock
HeidelbergCement AG	EU	HY	None	None	None	Stock	Stock	Stock
Hellenic Telecom Org SA	EU	HY	CDS	CDS	CDS	CDS	Stock	Stock
Intl Game Tech PLC	EU	HY	Stock	None	Stock	None	None	None
ITV Plc	EU	HY	None	None	Stock	Stock	Stock	Stock
J Sainsbury PLC	EU	HY	None	None	Stock	Stock	Stock	Stock
Marks & Spencer p l c	EU	HY	Stock	Stock	Stock	Stock	None	Stock
Nokia Oyj	EU	HY	None	None	None	None	None	None
Peugeot SA	EU	HY	None	Stock	CDS	CDS	Stock	None
Pub Pwr Corp Fin PLC	EU	HY	Stock	Stock	CDS	CDS	CDS	CDS
Renault	EU	HY	Stock	None	Stock	None	Stock	Stock
REXEL	EU	HY	None	None	None	Stock	Stock	None
ROLLSROYCE PLC	EU	HY	None	None	Stock	Stock	CDS	CDS
Stora Enso CORP	EU	HY	Stock	Stock	Stock	Stock	Stock	Stock
Telecom Italia SpA	EU	HY	Stock	None	Stock	Stock	Stock	None
TelefonAB L M Ericsson	EU	HY	Stock	Stock	None	None	None	None
Tesco PLC	EU	HY	CDS	CDS	CDS	CDS	None	None
thyssenkrupp AG	EU	HY	Stock	Stock	None	Stock	Stock	Stock
UPM Kymmene CORP	EU	HY	Stock	None	Stock	Stock	Stock	Stock
Valeo	EU	HY	Stock	Stock	None	None	Stock	Stock
Allstate Corp	U.S.	IG	Stock	None	None	None	None	None
Altria Gp Inc	U.S.	IG	CDS	CDS	CDS	CDS	None	None
Amern Elec Pwr Co Inc	U.S.	IG	None	None	CDS	CDS	CDS	CDS
Amern Express Co	U.S.	IG	Stock	Stock	None	Stock	Stock	Stock
Amern Intl Gp Inc	U.S.	IG	None	None	Stock	Stock	Stock	Stock
Amgen Inc.	U.S.	IG	Stock	Stock	CDS	CDS	Stock	Stock
ARROW ELECTRS INC	U.S.	IG	Stock	Stock	Stock	Stock	None	None
AT&T Inc	U.S.	IG	None	None	CDS	CDS	Stock	Stock
Autozone Inc	U.S.	IG	CDS	CDS	Stock	Stock	CDS	None
Avnet Inc	U.S.	IG	None	None	None	None	Stock	None
Barrick Gold Corp	U.S.	IG	None	None	None	None	None	CDS
Baxter Intl Inc	U.S.	IG	Stock	Stock	None	Stock	CDS	CDS
Berkshire Hathaway Inc	U.S.	IG	CDS	CDS	Stock	None	None	Stock
BOEING CO	U.S.	IG	Stock	Stock	None	CDS	None	Stock
Boston Scientific Corp	U.S.	IG	None	None	CDS	CDS	None	None
Bristol Myers Squibb Co	U.S.	IG	None	None	CDS	CDS	Stock	Stock
CAMPBELL SOUP CO	U.S.	IG	CDS	None	CDS	CDS	None	None
Cap One Bk USA	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Cardinal Health Inc	U.S.	IG	CDS	CDS	CDS	CDS	CDS	CDS
Caterpillar Inc	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Chubb Ltd	U.S.	IG	Stock	Stock	CDS	CDS	Stock	Stock

Table B.3 continued from previous page

Comcast Corp	U.S.	IG	Stock	Stock	None	None	Stock	Stock
ConocoPhillips	U.S.	IG	Stock	Stock	None	Stock	None	None
CSX Corp	U.S.	IG	Stock	Stock	Stock	None	Stock	Stock
CVS Health Corp	U.S.	IG	None	CDS	CDS	CDS	None	Stock
Darden Restaurants Inc	U.S.	IG	None	None	Stock	Stock	None	None
Deere & Co	U.S.	IG	Stock	Stock	None	Stock	Stock	Stock
Devon Engy Corp	U.S.	IG	None	None	None	CDS	None	None
Duke Energy Carolinas LLC	U.S.	IG	Stock	Stock	CDS	CDS	Stock	Stock
E I du Pont de Nemours	U.S.	IG	None	None	Stock	Stock	None	None
Eastman Chem Co	U.S.	IG	Stock	Stock	None	Stock	Stock	Stock
Enbridge Inc	U.S.	IG	CDS	CDS	Stock	Stock	Stock	Stock
Exelon Corp	U.S.	IG	Stock	Stock	Stock	Stock	None	None
FirstEnergy Corp	U.S.	IG	None	None	None	None	None	None
Gen Elec Co	U.S.	IG	Stock	Stock	Stock	Stock	None	Stock
Gen Mls Inc	U.S.	IG	Stock	Stock	CDS	CDS	CDS	CDS
Halliburton Co	U.S.	IG	None	None	Stock	Stock	None	None
Hartford Finl Services	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Hess Corp	U.S.	IG	Stock	None	Stock	None	None	None
Home Depot Inc	U.S.	IG	None	None	None	CDS	None	None
Honeywell Intl Inc	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
HP Inc	U.S.	IG	Stock	Stock	CDS	CDS	Stock	Stock
Intl Business Machs Corp	U.S.	IG	None	None	Stock	Stock	None	None
Intl Paper Co	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Johnson & Johnson	U.S.	IG	None	None	CDS	CDS	Stock	Stock
Kohls Corp	U.S.	IG	None	None	Stock	Stock	Stock	Stock
Lincoln Natl Corp	U.S.	IG	Stock	None	None	None	Stock	Stock
Lockheed Martin Corp	U.S.	IG	None	None	CDS	CDS	CDS	CDS
Loews Corp	U.S.	IG	Stock	Stock	None	None	Stock	Stock
Lowes Cos Inc	U.S.	IG	None	None	Stock	Stock	None	None
Marriott Intl Inc	U.S.	IG	Stock	Stock	CDS	CDS	None	None
Marsh & Mclennan Inc	U.S.	IG	None	None	CDS	CDS	Stock	None
McDONALDS Corp	U.S.	IG	Stock	Stock	CDS	CDS	Stock	Stock
McKesson Corp	U.S.	IG	Stock	Stock	Stock	Stock	None	None
MetLife Inc	U.S.	IG	Stock	Stock	None	CDS	Stock	Stock
Mondelez Intl Inc	U.S.	IG	Stock	Stock	Stock	Stock	None	None
Motorola Solutions Inc	U.S.	IG	CDS	CDS	None	Stock	Stock	Stock
Norfolk Sthn Corp	U.S.	IG	Stock	None	CDS	CDS	Stock	Stock
Northrop Grumman Corp	U.S.	IG	Stock	Stock	CDS	CDS	None	None
Omnicom Gp Inc	U.S.	IG	None	None	None	Stock	None	None
Packaging Corp Amer	U.S.	IG	None	Stock	Stock	Stock	Stock	Stock
Pfizer Inc	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Procter & Gamble Co	U.S.	IG	None	None	None	None	None	None
Prudential Finl Inc	U.S.	IG	None	None	Stock	None	Stock	Stock
Quest Diagnostics Inc	U.S.	IG	None	None	CDS	CDS	None	None

Table B.3 continued from previous page

Ryder Sys Inc	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Sempra Engy	U.S.	IG	None	None	Stock	Stock	None	None
Sherwin Williams Co	U.S.	IG	CDS	CDS	None	None	None	None
Simon Ppty Gp L P	U.S.	IG	Stock	Stock	None	None	Stock	Stock
Southwest Airls Co	U.S.	IG	CDS	CDS	Stock	Stock	CDS	CDS
Target Corp	U.S.	IG	Stock	Stock	CDS	CDS	Stock	Stock
The Kroger Co.	U.S.	IG	CDS	CDS	CDS	CDS	Stock	Stock
Tyson Foods Inc	U.S.	IG	Stock	Stock	CDS	CDS	None	None
Un Pac Corp	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
UnitedHealth Gp Inc	U.S.	IG	Stock	None	CDS	CDS	Stock	Stock
Utd Parcel Svc Inc	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Valero Energy Corp	U.S.	IG	Stock	Stock	None	None	None	None
Verizon Comms Inc	U.S.	IG	None	None	Stock	Stock	Stock	Stock
WESTROCK MWV LLC	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Weyerhaeuser Co	U.S.	IG	Stock	Stock	None	None	Stock	Stock
Whirlpool Corp	U.S.	IG	Stock	Stock	None	CDS	Stock	Stock
AMD Inc	U.S.	HY	None	None	None	None	Stock	Stock
AK Stl Corp	U.S.	HY	CDS	CDS			None	CDS
Amern Axle & Mfg Inc	U.S.	HY	None	None	None	None	Stock	Stock
Amkor Tech Inc	U.S.	HY	Stock	Stock	None	None	CDS	CDS
Avon Prods Inc	U.S.	HY	None	None	None	None	None	None
BEAZER HOMES USA INC	U.S.	HY	Stock	Stock	None	None	None	None
Boyd Gaming Corp	U.S.	HY	None	None	None	None	CDS	CDS
CCO Hldgs LLC	U.S.	HY	None	None	None	None	Stock	Stock
CIT Gp Inc	U.S.	HY	Stock	Stock	Stock	Stock	CDS	CDS
Cmnty Health Sys Inc	U.S.	HY	CDS	CDS	Stock	Stock	Stock	Stock
DISH DBS Corp	U.S.	HY	Stock	Stock	CDS	CDS	None	None
Genworth Hldgs Inc	U.S.	HY	CDS	CDS	CDS	CDS	CDS	CDS
HCA Inc.	U.S.	HY	None	None	None	None	None	Stock
HD SUPPLY INC	U.S.	HY	CDS	CDS	Stock	Stock	CDS	CDS
iStar Inc	U.S.	HY	Stock	Stock	Stock	None	CDS	CDS
K Hovnanian Entpers Inc	U.S.	HY	Stock	Stock	Stock	Stock	Stock	Stock
KB HOME	U.S.	HY	Stock	Stock	None	None	CDS	None
Lennar Corp	U.S.	HY	Stock	Stock	None	None	CDS	CDS
MGIC Invt Corp	U.S.	HY	None	None	None	None	None	None
MGM Resorts Intl	U.S.	HY	None	None	CDS	None	CDS	CDS
Navient Corp	U.S.	HY	None	None	None	None	CDS	CDS
NRG Energy Inc	U.S.	HY	None	None	None	None	CDS	CDS
Olin Corp	U.S.	HY	None	None	None	None	Stock	Stock
PulteGroup Inc	U.S.	HY	None	None	None	None	Stock	Stock
R R Donnelley & Sons Co	U.S.	HY	None	CDS	None	CDS	None	Stock
Radian Gp Inc	U.S.	HY	Stock	None	CDS	CDS	None	None
Rite Aid Corp	U.S.	HY	Stock	Stock	CDS	CDS	Stock	Stock
Sealed Air Corp US	U.S.	HY	None	None	None	None	CDS	CDS

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T Mobile USA Inc	U.S.	HY	Stock	Stock	None	None	None	Stock
TEGNA Inc	U.S.	HY	None	None	Stock	Stock	CDS	CDS
Tenet Healthcare Corp	U.S.	HY	Stock	Stock	None	None	None	None
The AES Corp	U.S.	HY	None	Stock	None	None	Stock	Stock
Unvl Health Svcs Inc	U.S.	HY	None	None	None	None	CDS	CDS
UTD RENTS Inc	U.S.	HY	Stock	Stock	None	None	CDS	CDS
Utd Sts Stl Corp	U.S.	HY	None	None	None	None	CDS	CDS

Table B.4: The table summarizes the price discovery assessment based on the Gonzalo-Granger (GG) measure for each company. Reported is the percentage of price discovery in the CDS market GG_{CDS}. The stock market's equivalent is obtained by $1 - GG_{CDS}$.The results are reported for the entire sample, the pre-crisis period, and the crisis period. Blank cells indicate too many missing values for the particular time period.

Company	Region	Rating	Entire period	Pre-crisis	Crisis
Aegon N.V.	EU	IG	22%	0%	17%
Aktiebolaget Volvo	EU	IG	15%	0%	25%
Akzo Nobel N.V.	EU	IG	14%	14%	17%
Allianz SE	EU	IG	6%	3%	9%
Assicurazioni Generali	EU	IG	9%	18%	15%
AVIVA PLC	EU	IG	0%	0%	0%
AXA	EU	IG	0%	0%	18%
BAE SYSTEMS PLC	EU	IG	17%	38%	0%
BANCO BILBAO VIZCAYA	EU	IG	25%	14%	0%
BASF SE	EU	IG	18%	3%	11%
Bayer AG	EU	IG	16%	0%	32%
BMW AG	EU	IG	7%	38%	17%
BP P.L.C.	EU	IG	11%	8%	1%
British American Tobacco	EU	IG	4%	0%	20%
Carrefour	EU	IG	12%	20%	0%
Centrica plc	EU	IG	28%	60%	33%
COMMERZBANK AG	EU	IG	40%	0%	0%
COMPAGNIE GOBAIN	EU	IG	17%	3%	28%
Continental AG	EU	IG	17%	0%	30%
CREDIT AGRICOLE SA	EU	IG	85%	0%	12%
Daimler AG	EU	IG	12%	0%	30%
DANONE	EU	IG	100%	14%	34%
DANSKE BANK A/S	EU	IG	24%	8%	0%
Deutsche Telekom AG	EU	IG	7%	14%	15%
DIAGEO PLC	EU	IG	13%	11%	15%
E.ON SE	EU	IG	0%	100%	25%
Electricite de France	EU	IG	0%	100%	1%

Table B.4 continued from previous page

ENEL S.P.A.	EU	IG	26%	41%	4%
ENGIE	EU	IG	74%	83%	0%
ENI S.P.A.	EU	IG	22%	26%	17%
Fortum Oyj	EU	IG	27%	10%	32%
Hannover Rueck SE	EU	IG	5%	0%	17%
Heineken N.V.	EU	IG	0%	51%	11%
Iberdrola, S.A.	EU	IG	0%	33%	28%
IMPERIAL BRANDS PLC	EU	IG	24%	25%	18%
INTESA SANPAOLO SPA	EU	IG	77%	0%	47%
Kering	EU	IG	20%	0%	25%
Koninklijke KPN N.V.	EU	IG	13%	19%	7%
LafargeHolcim Ltd	EU	IG	0%	0%	0%
LVMH	EU	IG	5%	3%	43%
MEDIOBANCA SpA	EU	IG	100%	70%	23%
Muenchener Rueck AG	EU	IG	3%	1%	20%
NATIONAL GRID PLC	EU	IG	4%	80%	18%
Nestle S.A.	EU	IG	8%	33%	10%
Orange	EU	IG	45%	58%	5%
PEARSON plc	EU	IG	40%	87%	5%
PERNOD RICARD	EU	IG	0%	0%	8%
PUBLICIS GROUPE SA	EU	IG	20%	43%	24%
ROYAL DUTCH SHELL PLC	EU	IG	0%	0%	4%
SANOFI	EU	IG	50%	39%	54%
Siemens AG	EU	IG	23%	9%	24%
Swiss Reinsurance Ltd	EU	IG	10%	1%	0%
TELEFONICA, S.A.	EU	IG	30%	24%	12%
Telekom Austria AG	EU	IG	0%	0%	9%
TELENOR ASA	EU	IG	0%	100%	2%
TOTAL SA	EU	IG	0%	0%	
Unilever N.V.	EU	IG	11%	49%	0%
VEOLIA	EU	IG	17%	43%	11%
VINCI	EU	IG	18%	23%	30%
Vivendi	EU	IG	0%	0%	5%
VODAFONE GROUP Ltd	EU	IG	28%	100%	34%
VOLKSWAGEN AG	EU	IG	20%	45%	0%
WPP 2005 LIMITED	EU	IG	15%	100%	23%
Zurich Insurance Ltd	EU	IG	0%	0%	11%
ACCOR	EU	HY	0%	61%	100%
AIR FRANCE - KLM	EU	HY	14%	11%	62%
ArcelorMittal	EU	HY	19%	91%	0%
ATLANTIA SPA	EU	HY	27%	40%	17%
Casino Guichardperrachon	EU	HY	28%	5%	41%
Clariant AG	EU	HY	18%	17%	20%
CNH Indl NV	EU	HY	2%	0%	9%

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Deutsche Lufthansa AG	EU	HY	1%	11%	100%
EDP SA	EU	HY	10%	43%	28%
Eli	EU	HY	23%	21%	0%
FAURECIA	EU	HY	51%	37%	100%
Galp Energia SGPS SA	EU	HY	32%	0%	23%
HeidelbergCement AG	EU	HY	28%	29%	13%
Hellenic Telecom Org SA	EU	HY	100%	100%	8%
Intl Game Tech PLC	EU	HY	24%	0%	34%
ITV Plc	EU	HY	24%	0%	21%
J Sainsbury PLC	EU	HY	35%	0%	12%
Marks & Spencer p l c	EU	HY	0%	0%	0%
Nokia Oyj	EU	HY	52%	51%	40%
Peugeot SA	EU	HY	0%	89%	25%
Pub Pwr Corp Fin PLC	EU	HY	6%	73%	96%
Renault	EU	HY	29%	24%	8%
REXEL	EU	HY	27%	0%	27%
ROLLSROYCE PLC	EU	HY	0%	0%	100%
Stora Enso CORP	EU	HY	0%	0%	13%
Telecom Italia SpA	EU	HY	24%	15%	27%
TelefonAB L M Ericsson	EU	HY	30%	0%	34%
Tesco PLC	EU	HY	96%	100%	42%
thyssenkrupp AG	EU	HY	30%	0%	29%
UPM Kymmene CORP	EU	HY	0%	0%	0%
Valeo	EU	HY	0%	100%	0%
Allstate Corp	U.S.	IG	15%	0%	18%
Altria Gp Inc	U.S.	IG	71%	100%	26%
Amern Elec Pwr Co Inc	U.S.	IG	28%	42%	46%
Amern Express Co	U.S.	IG	0%	0%	12%
Amern Intl Gp Inc	U.S.	IG	27%	0%	15%
Amgen Inc.	U.S.	IG	10%	91%	0%
ARROW ELECTRS INC	U.S.	IG	0%	25%	0%
AT&T Inc	U.S.	IG	25%	74%	9%
Autozone Inc	U.S.	IG	87%	21%	38%
Avnet Inc	U.S.	IG	25%	37%	16%
Barrick Gold Corp	U.S.	IG	0%	0%	0%
Baxter Intl Inc	U.S.	IG	10%	0%	48%
Berkshire Hathaway Inc	U.S.	IG	74%	24%	0%
BOEING CO	U.S.	IG	0%	0%	30%
Boston Scientific Corp	U.S.	IG	23%	86%	28%
Bristol Myers Squibb Co	U.S.	IG	25%	66%	5%
CAMPBELL SOUP CO	U.S.	IG	0%	100%	29%
Cap One Bk USA	U.S.	IG	8%	5%	12%
Cardinal Health Inc	U.S.	IG	64%	78%	67%
Caterpillar Inc	U.S.	IG	2%	13%	0%

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Chubb Ltd	U.S.	IG	15%	100%	15%
Comcast Corp	U.S.	IG	9%	31%	0%
ConocoPhillips	U.S.	IG	6%	0%	18%
CSX Corp	U.S.	IG	16%	35%	0%
CVS Health Corp	U.S.	IG	100%	69%	3%
Darden Restaurants Inc	U.S.	IG	35%	19%	37%
Deere & Co	U.S.	IG	0%	0%	0%
Devon Engy Corp	U.S.	IG	35%	41%	34%
Duke Energy Carolinas LLC	U.S.	IG	12%	33%	9%
E I du Pont de Nemours	U.S.	IG	36%	13%	32%
Eastman Chem Co	U.S.	IG	0%	0%	9%
Enbridge Inc	U.S.	IG	100%	0%	5%
Exelon Corp	U.S.	IG	21%	31%	25%
FirstEnergy Corp	U.S.	IG	22%	0%	22%
Gen Elec Co	U.S.	IG	14%	18%	0%
Gen Mls Inc	U.S.	IG	0%	100%	35%
Halliburton Co	U.S.	IG	40%	12%	27%
Hartford Finl Services	U.S.	IG	19%	22%	21%
Hess Corp	U.S.	IG	23%	33%	24%
Home Depot Inc	U.S.	IG	22%	0%	25%
Honeywell Intl Inc	U.S.	IG	1%	0%	8%
HP Inc	U.S.	IG	17%	100%	0%
Intl Business Machs Corp	U.S.	IG	22%	8%	24%
Intl Paper Co	U.S.	IG	0%	6%	0%
Johnson & Johnson	U.S.	IG	22%	38%	2%
Kohls Corp	U.S.	IG	36%	32%	21%
Lincoln Natl Corp	U.S.	IG	39%	0%	26%
Lockheed Martin Corp	U.S.	IG	33%	100%	51%
Loews Corp	U.S.	IG	6%	0%	11%
Lowes Cos Inc	U.S.	IG	26%	0%	34%
Marriott Intl Inc	U.S.	IG	0%	0%	32%
Marsh & Mclennan Inc	U.S.	IG	27%	95%	19%
McDONALDS Corp	U.S.	IG	5%	0%	8%
McKesson Corp	U.S.	IG	11%	0%	0%
MetLife Inc	U.S.	IG	19%	48%	11%
Mondelez Intl Inc	U.S.	IG	15%	24%	16%
Motorola Solutions Inc	U.S.	IG	69%	0%	8%
Norfolk Sthn Corp	U.S.	IG	19%	59%	0%
Northrop Grumman Corp	U.S.	IG	0%	100%	23%
Omnicom Gp Inc	U.S.	IG	26%	30%	25%
Packaging Corp Amer	U.S.	IG	0%	0%	2%
Pfizer Inc	U.S.	IG	10%	16%	12%
Procter & Gamble Co	U.S.	IG	30%	30%	21%
Prudential Finl Inc	U.S.	IG	28%	34%	16%

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Quest Diagnostics Inc	U.S.	IG	25%	78%	23%
Ryder Sys Inc	U.S.	IG	19%	0%	0%
Sempra Engy	U.S.	IG	27%	24%	33%
Sherwin Williams Co	U.S.	IG	100%	27%	34%
Simon Ppty Gp L P	U.S.	IG	19%	44%	6%
Southwest Airls Co	U.S.	IG	53%	0%	36%
Target Corp	U.S.	IG	0%	48%	0%
The Kroger Co.	U.S.	IG	100%	68%	0%
Tyson Foods Inc	U.S.	IG	16%	100%	33%
Un Pac Corp	U.S.	IG	7%	20%	0%
UnitedHealth Gp Inc	U.S.	IG	0%	100%	10%
Utd Parcel Svc Inc	U.S.	IG	12%	20%	0%
Valero Energy Corp	U.S.	IG	13%	0%	35%
Verizon Comms Inc	U.S.	IG	14%	18%	10%
WESTROCK MWV LLC	U.S.	IG	4%	4%	12%
Weyerhaeuser Co	U.S.	IG	10%	33%	4%
Whirlpool Corp	U.S.	IG	21%	96%	7%
AMD Inc	U.S.	HY	40%	30%	40%
AK Stl Corp	U.S.	HY	66%		100%
Amern Axle & Mfg Inc	U.S.	HY	45%	51%	0%
Amkor Tech Inc	U.S.	HY	26%	31%	86%
Avon Prods Inc	U.S.	HY	49%	60%	48%
BEAZER HOMES USA INC	U.S.	HY	29%	39%	60%
Boyd Gaming Corp	U.S.	HY	34%	39%	81%
CCO Hldgs LLC	U.S.	HY	46%	43%	27%
CIT Gp Inc	U.S.	HY	22%	10%	50%
Cmnty Health Sys Inc	U.S.	HY	100%	0%	0%
DISH DBS Corp	U.S.	HY	5%	82%	0%
Genworth Hldgs Inc	U.S.	HY	100%	91%	100%
HCA Inc.	U.S.	HY	21%	27%	0%
HD SUPPLY INC	U.S.	HY	100%	9%	59%
iStar Inc	U.S.	HY	27%	40%	100%
K Hovnanian Entpers Inc	U.S.	HY	0%	14%	24%
KB HOME	U.S.	HY	13%	36%	58%
Lennar Corp	U.S.	HY	10%	30%	57%
MGIC Invt Corp	U.S.	HY	28%	43%	42%
MGM Resorts Intl	U.S.	HY	42%	46%	90%
Navient Corp	U.S.	HY	44%	45%	63%
NRG Energy Inc	U.S.	HY	0%	38%	90%
Olin Corp	U.S.	HY	42%	45%	11%
PulteGroup Inc	U.S.	HY	22%	26%	15%
R R Donnelley & Sons Co	U.S.	HY	84%	100%	4%
Radian Gp Inc	U.S.	HY	29%	54%	41%
Rite Aid Corp	U.S.	HY	0%	100%	14%

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Sealed Air Corp US	U.S.	HY	46%	48%	91%
T Mobile USA Inc	U.S.	HY	5%	20%	0%
TEGNA Inc	U.S.	HY	30%	21%	100%
Tenet Healthcare Corp	U.S.	HY	23%	47%	0%
The AES Corp	U.S.	HY	0%	28%	15%
Unvl Health Svcs Inc	U.S.	HY	47%	39%	100%
UTD RENTS Inc	U.S.	HY	13%	26%	80%
Utd Sts Stl Corp	U.S.	HY	100%	35%	83%

Table B.5: The table summarizes the price discovery assessment based on the Hasbrouck (HAS) measure for each company. The results are reported for the entire sample, the pre-crisis period, and the crisis period. Blank cells indicate too many missing values for the particular time period.

Company	Region	Rating	Entire period	Pre-crisis	Crisis
Aegon N.V.	EU	IG	11%	14%	17%
Aktiebolaget Volvo	EU	IG	9%	14%	22%
Akzo Nobel N.V.	EU	IG	8%	5%	13%
Allianz SE	EU	IG	15%	10%	19%
Assicurazioni Generali	EU	IG	12%	17%	17%
AVIVA PLC	EU	IG	21%	15%	43%
AXA	EU	IG	22%	14%	13%
BAE SYSTEMS PLC	EU	IG	8%	58%	44%
BANCO BILBAO VIZCAYA	EU	IG	19%	9%	27%
BASF SE	EU	IG	10%	7%	11%
Bayer AG	EU	IG	8%	54%	41%
BMW AG	EU	IG	12%	74%	14%
BP P.L.C.	EU	IG	7%	3%	21%
British American Tobacco	EU	IG	1%	47%	18%
Carrefour	EU	IG	4%	8%	25%
Centrica plc	EU	IG	11%	87%	15%
COMMERZBANK AG	EU	IG	44%	20%	21%
COMPAGNIE GOBAIN	EU	IG	9%	15%	19%
Continental AG	EU	IG	11%	49%	20%
CREDIT AGRICOLE SA	EU	IG	85%	20%	18%
Daimler AG	EU	IG	10%	35%	21%
DANONE	EU	IG	89%	7%	81%
DANSKE BANK A/S	EU	IG	18%	7%	27%
Deutsche Telekom AG	EU	IG	5%	5%	8%
DIAGEO PLC	EU	IG	9%	5%	15%
E.ON SE	EU	IG	56%	84%	30%
Electricite de France	EU	IG	17%	59%	12%
ENEL S.P.A.	EU	IG	30%	79%	12%

Table B.5 continued from previous page

ENGIE	EU	IG	93%	93%	28%
ENI S.P.A.	EU	IG	19%	34%	15%
Fortum Oyj	EU	IG	17%	4%	29%
Hannover Rueck SE	EU	IG	11%	23%	15%
Heineken N.V.	EU	IG	19%	84%	6%
Iberdrola, S.A.	EU	IG	12%	65%	45%
IMPERIAL BRANDS PLC	EU	IG	16%	19%	7%
INTESA SANPAOLO SPA	EU	IG	83%	64%	82%
Kering	EU	IG	9%	13%	20%
Koninklijke KPN N.V.	EU	IG	8%	6%	5%
LafargeHolcim Ltd	EU	IG	20%	59%	13%
LVMH	EU	IG	10%	7%	84%
MEDIOBANCA SpA	EU	IG	69%	90%	17%
Muenchener Rueck AG	EU	IG	13%	10%	16%
NATIONAL GRID PLC	EU	IG	3%	99%	15%
Nestle S.A.	EU	IG	4%	71%	13%
Orange	EU	IG	78%	91%	4%
PEARSON plc	EU	IG	43%	94%	3%
PERNOD RICARD	EU	IG	15%	18%	9%
PUBLICIS GROUPE SA	EU	IG	8%	57%	10%
ROYAL DUTCH SHELL PLC	EU	IG	27%	30%	19%
SANOFI	EU	IG	75%	35%	85%
Siemens AG	EU	IG	17%	5%	24%
Swiss Reinsurance Ltd	EU	IG	9%	8%	25%
TELEFONICA, S.A.	EU	IG	30%	24%	7%
Telekom Austria AG	EU	IG	13%	9%	4%
TELENOR ASA	EU	IG	38%	73%	0%
TOTAL SA	EU	IG	30%	40%	
Unilever N.V.	EU	IG	7%	77%	29%
VEOLIA	EU	IG	7%	73%	7%
VINCI	EU	IG	10%	17%	37%
Vivendi	EU	IG	19%	14%	11%
VODAFONE GROUP Ltd	EU	IG	26%	98%	37%
VOLKSWAGEN AG	EU	IG	14%	80%	26%
WPP 2005 LIMITED	EU	IG	11%	75%	15%
Zurich Insurance Ltd	EU	IG	18%	10%	13%
ACCOR	EU	HY	50%	91%	60%
AIR FRANCE - KLM	EU	HY	5%	2%	85%
ArcelorMittal	EU	HY	12%	84%	26%
ATLANTIA SPA	EU	HY	26%	77%	14%
Casino Guichardperrachon	EU	HY	18%	17%	57%
Clariant AG	EU	HY	9%	6%	13%
CNH Indl NV	EU	HY	14%	16%	14%
Deutsche Lufthansa AG	EU	HY	12%	6%	75%

Table B.5 continued from previous page

EDP SA	EU	HY	5%	82%	24%
Eli	EU	HY	14%	14%	46%
FAURECIA	EU	HY	79%	36%	98%
Galp Energia SGPS SA	EU	HY	41%	54%	16%
HeidelbergCement AG	EU	HY	32%	45%	14%
Hellenic Telecom Org SA	EU	HY	75%	78%	2%
Intl Game Tech PLC	EU	HY	11%	12%	34%
ITV Plc	EU	HY	9%	6%	10%
J Sainsbury PLC	EU	HY	40%	10%	4%
Marks & Spencer p l c	EU	HY	16%	11%	37%
Nokia Oyj	EU	HY	80%	78%	46%
Peugeot SA	EU	HY	32%	85%	19%
Pub Pwr Corp Fin PLC	EU	HY	2%	96%	93%
Renault	EU	HY	17%	15%	22%
REXEL	EU	HY	15%	34%	14%
ROLLSROYCE PLC	EU	HY	49%	36%	79%
Stora Enso CORP	EU	HY	30%	36%	9%
Telecom Italia SpA	EU	HY	12%	6%	17%
TelefonAB L M Ericsson	EU	HY	16%	45%	40%
Tesco PLC	EU	HY	92%	75%	68%
thyssenkrupp AG	EU	HY	17%	39%	22%
UPM Kymmene CORP	EU	HY	35%	41%	30%
Valeo	EU	HY	24%	63%	27%
Allstate Corp	U.S.	IG	15%	54%	19%
Altria Gp Inc	U.S.	IG	95%	90%	44%
Amern Elec Pwr Co Inc	U.S.	IG	45%	73%	89%
Amern Express Co	U.S.	IG	17%	31%	12%
Amern Intl Gp Inc	U.S.	IG	22%	10%	8%
Amgen Inc.	U.S.	IG	4%	94%	16%
ARROW ELECTRS INC	U.S.	IG	19%	21%	46%
AT&T Inc	U.S.	IG	35%	98%	14%
Autozone Inc	U.S.	IG	97%	17%	71%
Avnet Inc	U.S.	IG	21%	52%	9%
Barrick Gold Corp	U.S.	IG	49%	47%	62%
Baxter Intl Inc	U.S.	IG	8%	48%	95%
Berkshire Hathaway Inc	U.S.	IG	91%	41%	28%
BOEING CO	U.S.	IG	31%	52%	19%
Boston Scientific Corp	U.S.	IG	21%	91%	40%
Bristol Myers Squibb Co	U.S.	IG	42%	97%	5%
CAMPBELL SOUP CO	U.S.	IG	52%	91%	60%
Cap One Bk USA	U.S.	IG	10%	10%	9%
Cardinal Health Inc	U.S.	IG	94%	92%	94%
Caterpillar Inc	U.S.	IG	13%	8%	19%
Chubb Ltd	U.S.	IG	14%	89%	10%

Table B.5 continued from previous page

Comcast Corp	U.S.	IG	5%	53%	15%
ConocoPhillips	U.S.	IG	13%	28%	14%
CSX Corp	U.S.	IG	10%	48%	15%
CVS Health Corp	U.S.	IG	82%	96%	13%
Darden Restaurants Inc	U.S.	IG	50%	12%	57%
Deere & Co	U.S.	IG	31%	30%	38%
Devon Engy Corp	U.S.	IG	37%	69%	29%
Duke Energy Carolinas LLC	U.S.	IG	12%	66%	6%
E I du Pont de Nemours	U.S.	IG	60%	4%	50%
Eastman Chem Co	U.S.	IG	22%	36%	22%
Enbridge Inc	U.S.	IG	76%	35%	16%
Exelon Corp	U.S.	IG	13%	16%	36%
FirstEnergy Corp	U.S.	IG	21%	43%	29%
Gen Elec Co	U.S.	IG	9%	14%	32%
Gen Mls Inc	U.S.	IG	4%	82%	85%
Halliburton Co	U.S.	IG	52%	7%	19%
Hartford Finl Services	U.S.	IG	11%	24%	12%
Hess Corp	U.S.	IG	14%	31%	19%
Home Depot Inc	U.S.	IG	27%	63%	35%
Honeywell Intl Inc	U.S.	IG	12%	24%	12%
HP Inc	U.S.	IG	8%	82%	24%
Intl Business Machs Corp	U.S.	IG	17%	8%	25%
Intl Paper Co	U.S.	IG	17%	9%	24%
Johnson & Johnson	U.S.	IG	44%	81%	5%
Kohls Corp	U.S.	IG	29%	33%	22%
Lincoln Natl Corp	U.S.	IG	31%	41%	11%
Lockheed Martin Corp	U.S.	IG	66%	86%	92%
Loews Corp	U.S.	IG	7%	50%	13%
Lowes Cos Inc	U.S.	IG	25%	21%	43%
Marriott Intl Inc	U.S.	IG	22%	65%	54%
Marsh & Mclennan Inc	U.S.	IG	65%	98%	30%
McDONALDS Corp	U.S.	IG	4%	78%	10%
McKesson Corp	U.S.	IG	9%	26%	27%
MetLife Inc	U.S.	IG	12%	80%	17%
Mondelez Intl Inc	U.S.	IG	9%	19%	18%
Motorola Solutions Inc	U.S.	IG	95%	29%	6%
Norfolk Sthn Corp	U.S.	IG	19%	95%	17%
Northrop Grumman Corp	U.S.	IG	19%	86%	49%
Omnicom Gp Inc	U.S.	IG	31%	48%	22%
Packaging Corp Amer	U.S.	IG	48%	34%	7%
Pfizer Inc	U.S.	IG	4%	17%	8%
Procter & Gamble Co	U.S.	IG	81%	62%	70%
Prudential Finl Inc	U.S.	IG	27%	44%	15%
Quest Diagnostics Inc	U.S.	IG	31%	95%	29%

Table B.5 continued from previous page

Ryder Sys Inc	U.S.	IG	8%	28%	17%
Sempra Engy	U.S.	IG	35%	33%	51%
Sherwin Williams Co	U.S.	IG	90%	55%	72%
Simon Ppty Gp L P	U.S.	IG	9%	75%	25%
Southwest Airls Co	U.S.	IG	91%	19%	77%
Target Corp	U.S.	IG	40%	80%	12%
The Kroger Co.	U.S.	IG	87%	93%	13%
Tyson Foods Inc	U.S.	IG	6%	70%	57%
Un Pac Corp	U.S.	IG	6%	18%	18%
UnitedHealth Gp Inc	U.S.	IG	38%	88%	6%
Utd Parcel Svc Inc	U.S.	IG	7%	17%	32%
Valero Energy Corp	U.S.	IG	11%	35%	47%
Verizon Comms Inc	U.S.	IG	13%	10%	12%
WESTROCK MWV LLC	U.S.	IG	9%	8%	7%
Weyerhaeuser Co	U.S.	IG	6%	45%	13%
Whirlpool Corp	U.S.	IG	10%	83%	12%
AMD Inc	U.S.	HY	32%	29%	19%
AK Stl Corp	U.S.	HY	85%		66%
Amern Axle & Mfg Inc	U.S.	HY	35%	49%	33%
Amkor Tech Inc	U.S.	HY	11%	25%	85%
Avon Prods Inc	U.S.	HY	39%	88%	29%
BEAZER HOMES USA INC	U.S.	HY	14%	20%	70%
Boyd Gaming Corp	U.S.	HY	40%	60%	96%
CCO Hldgs LLC	U.S.	HY	29%	18%	8%
CIT Gp Inc	U.S.	HY	15%	22%	89%
Cmnty Health Sys Inc	U.S.	HY	63%	26%	42%
DISH DBS Corp	U.S.	HY	16%	83%	52%
Genworth Hldgs Inc	U.S.	HY	66%	89%	73%
HCA Inc.	U.S.	HY	17%	35%	47%
HD SUPPLY INC	U.S.	HY	82%	10%	77%
iStar Inc	U.S.	HY	10%	31%	77%
K Hovnanian Entpers Inc	U.S.	HY	18%	6%	9%
KB HOME	U.S.	HY	21%	35%	81%
Lennar Corp	U.S.	HY	19%	40%	88%
MGIC Invt Corp	U.S.	HY	21%	69%	60%
MGM Resorts Intl	U.S.	HY	54%	71%	86%
Navient Corp	U.S.	HY	50%	52%	90%
NRG Energy Inc	U.S.	HY	35%	78%	86%
Olin Corp	U.S.	HY	53%	57%	6%
PulteGroup Inc	U.S.	HY	15%	24%	10%
R R Donnelley & Sons Co	U.S.	HY	91%	84%	17%
Radian Gp Inc	U.S.	HY	23%	86%	59%
Rite Aid Corp	U.S.	HY	15%	89%	6%
Sealed Air Corp US	U.S.	HY	79%	83%	91%

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T Mobile USA Inc	U.S.	HY	3%	29%	24%
TEGNA Inc	U.S.	HY	21%	10%	65%
Tenet Healthcare Corp	U.S.	HY	20%	44%	45%
The AES Corp	U.S.	HY	27%	37%	5%
Unvl Health Svcs Inc	U.S.	HY	75%	54%	80%
UTD RENTS Inc	U.S.	HY	20%	21%	77%
Utd Sts Stl Corp	U.S.	HY	66%	16%	77%

Table B.6: The table summarizes the price discovery assessment based on the Granger causality test for each company. The results are reported for the entire sample, the pre-crisis period, and the crisis period.

Company	Region	Rating	Entire period		Pre-crisis		Crisis	
			5%	10%	5%	10%	5%	10%
Aegon N.V.	EU	IG	None	None	None	None	None	None
Aktiebolaget Volvo	EU	IG	None	Stock	Stock	Stock	None	None
Akzo Nobel N.V.	EU	IG	None	CDS	None	None	CDS	CDS
Allianz SE	EU	IG	CDS	CDS	None	None	CDS	Both
Assicurazioni Generali	EU	IG	CDS	CDS	None	None	CDS	CDS
AVIVA PLC	EU	IG	CDS	CDS	None	None	CDS	CDS
AXA	EU	IG	None	None	None	None	None	None
BAE SYSTEMS PLC	EU	IG	None	None	None	None	CDS	CDS
BANCO BILBAO VIZCAYA	EU	IG	None	None	None	None	None	None
BASF SE	EU	IG	CDS	CDS	Stock	Stock	CDS	Both
Bayer AG	EU	IG	Stock	Both	None	None	None	CDS
BMW AG	EU	IG	None	None	None	None	CDS	CDS
BP P.L.C.	EU	IG	None	None	Stock	Both	None	None
British American Tobacco	EU	IG	Stock	Stock	Stock	Stock	None	None
Carrefour	EU	IG	Both	Both	Stock	Stock	CDS	CDS
Centrica plc	EU	IG	None	CDS	Stock	Stock	CDS	CDS
COMMERZBANK AG	EU	IG	None	None	None	None	None	None
COMPAGNIE GOBAIN	EU	IG	CDS	CDS	Stock	Stock	CDS	CDS
Continental AG	EU	IG	CDS	CDS	None	None	None	None
CREDIT AGRICOLE SA	EU	IG	None	None	None	None	None	None
Daimler AG	EU	IG	None	None	None	None	None	None
DANONE	EU	IG	Both	Both	None	None	Both	Both
DANSKE BANK A/S	EU	IG	None	None	None	None	None	None
Deutsche Telekom AG	EU	IG	Stock	Stock	None	None	Stock	Stock
DIAGEO PLC	EU	IG	None	CDS	None	Stock	CDS	CDS
E.ON SE	EU	IG	None	None	None	None	None	None
Electricite de France	EU	IG	None	None	None	None	None	CDS

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ENEL S.P.A.	EU	IG	CDS	CDS	None	None	CDS	CDS
ENGIE	EU	IG	None	None	None	None	None	Stock
ENI S.P.A.	EU	IG	Stock	Stock	Stock	Stock	Stock	Both
Fortum Oyj	EU	IG	Both	Both	Stock	Stock	Both	Both
Hannover Rueck SE	EU	IG	CDS	CDS	None	None	CDS	CDS
Heineken N.V.	EU	IG	None	None	None	Stock	CDS	CDS
Iberdrola, S.A.	EU	IG	None	Stock	None	None	None	Stock
IMPERIAL BRANDS PLC	EU	IG	Both	Both	None	None	None	CDS
INTESA SANPAOLO SPA	EU	IG	None	None	None	None	None	None
Kering	EU	IG	None	None	Stock	Stock	CDS	CDS
Koninklijke KPN N.V.	EU	IG	None	None	None	Stock	None	None
LafargeHolcim Ltd	EU	IG	None	Both	None	None	CDS	CDS
LVMH	EU	IG	None	None	None	CDS	None	None
MEDIOBANCA SpA	EU	IG	CDS	CDS	CDS	CDS	CDS	CDS
Muenchener Rueck AG	EU	IG	CDS	CDS	None	None	CDS	Both
NATIONAL GRID PLC	EU	IG	CDS	CDS	CDS	CDS	None	Stock
Nestle S.A.	EU	IG	Stock	Stock	None	None	Stock	Both
Orange	EU	IG	Stock	Both	None	CDS	Both	Both
PEARSON plc	EU	IG	Stock	Stock	None	Stock	Stock	Stock
PERNOD RICARD	EU	IG	Stock	Both	None	Stock	Both	Both
PUBLICIS GROUPE SA	EU	IG	CDS	CDS	None	None	CDS	CDS
ROYAL DUTCH SHELL PLC	EU	IG	None	CDS	None	None	None	None
SANOFI	EU	IG	Both	Both	None	None	None	CDS
Siemens AG	EU	IG	None	None	None	CDS	CDS	CDS
Swiss Reinsurance Ltd	EU	IG	CDS	CDS	None	None	CDS	CDS
TELEFONICA, S.A.	EU	IG	None	Stock	None	None	Stock	Stock
Telekom Austria AG	EU	IG	None	None	None	None	CDS	CDS
TELENOR ASA	EU	IG	None	CDS	Stock	Stock	CDS	CDS
TOTAL SA	EU	IG	None	Stock	None	Stock	None	None
Unilever N.V.	EU	IG	Stock	Stock	Both	Both	Stock	Stock
VEOLIA	EU	IG	CDS	CDS	None	None	None	None
VINCI	EU	IG	Both	Both	None	None	CDS	CDS
Vivendi	EU	IG	None	CDS	None	None	Both	Both
VODAFONE GROUP Ltd	EU	IG	None	None	None	None	None	Stock
VOLKSWAGEN AG	EU	IG	None	None	None	None	None	None
WPP 2005 LIMITED	EU	IG	None	None	Both	Both	None	None
Zurich Insurance Ltd	EU	IG	None	None	None	None	CDS	CDS
ACCOR	EU	HY	Both	Both	Both	Both	Both	Both
AIR FRANCE - KLM	EU	HY	None	Stock	Stock	Stock	CDS	Both
ArcelorMittal	EU	HY	Stock	Stock	Stock	Stock	None	None
ATLANTIA SPA	EU	HY	Stock	Stock	None	None	None	None
Casino Guichardperrachon	EU	HY	Stock	Stock	Stock	Stock	None	None
Clariant AG	EU	HY	None	None	Stock	Stock	CDS	CDS
CNH Indl NV	EU	HY	None	None	Both	Both	CDS	CDS

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Deutsche Lufthansa AG	EU	HY	CDS	CDS	Stock	Stock	None	None
EDP SA	EU	HY	None	None	None	None	None	None
Eli	EU	HY	Both	Both	None	None	Both	Both
FAURECIA	EU	HY	Stock	Stock	None	Stock	Stock	Stock
Galp Energia SGPS SA	EU	HY	None	Stock	Stock	Both	None	None
HeidelbergCement AG	EU	HY	Both	Both	Stock	Stock	CDS	CDS
Hellenic Telecom Org SA	EU	HY	Stock	Stock	None	None	Stock	Stock
Intl Game Tech PLC	EU	HY	CDS	Both	None	None	CDS	CDS
ITV Plc	EU	HY	None	None	None	None	None	None
J Sainsbury PLC	EU	HY	None	None	Stock	Stock	None	None
Marks & Spencer p l c	EU	HY	Stock	Stock	Stock	Stock	CDS	CDS
Nokia Oyj	EU	HY	Both	Both	None	None	Both	Both
Peugeot SA	EU	HY	Both	Both	Both	Both	CDS	Both
Pub Pwr Corp Fin PLC	EU	HY	None	None	None	None	None	None
Renault	EU	HY	Stock	Stock	Stock	Stock	CDS	Both
REXEL	EU	HY	None	None	None	None	Both	Both
ROLLSROYCE PLC	EU	HY	Stock	Both	None	Stock	CDS	CDS
Stora Enso CORP	EU	HY	Stock	Stock	None	None	Stock	Stock
Telecom Italia SpA	EU	HY	Stock	Stock	Stock	Stock	Stock	Stock
TelefonAB L M Ericsson	EU	HY	None	Stock	None	None	CDS	CDS
Tesco PLC	EU	HY	None	None	None	None	None	None
thyssenkrupp AG	EU	HY	Stock	Stock	Stock	Stock	Stock	Stock
UPM Kymmene CORP	EU	HY	None	None	None	None	None	None
Valeo	EU	HY	Both	Both	None	Stock	Stock	Both
Allstate Corp	U.S.	IG	Both	Both	None	None	Both	Both
Altria Gp Inc	U.S.	IG	None	None	None	Stock	None	None
Amern Elec Pwr Co Inc	U.S.	IG	None	CDS	None	None	None	None
Amern Express Co	U.S.	IG	Both	Both	None	None	Both	Both
Amern Intl Gp Inc	U.S.	IG	Both	Both	None	None	Both	Both
Amgen Inc.	U.S.	IG	Stock	Both	None	CDS	None	None
ARROW ELECTRS INC	U.S.	IG	None	None	Stock	Stock	CDS	CDS
AT&T Inc	U.S.	IG	None	CDS	None	CDS	Both	Both
Autozone Inc	U.S.	IG	Both	Both	Stock	Stock	Both	Both
Avnet Inc	U.S.	IG	None	None	None	None	CDS	CDS
Barrick Gold Corp	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
Baxter Intl Inc	U.S.	IG	None	None	None	None	None	Stock
Berkshire Hathaway Inc	U.S.	IG	Both	Both	None	None	Stock	Stock
BOEING CO	U.S.	IG	Both	Both	None	None	Both	Both
Boston Scientific Corp	U.S.	IG	Both	Both	None	None	Stock	Stock
Bristol Myers Squibb Co	U.S.	IG	None	None	None	None	None	None
CAMPBELL SOUP CO	U.S.	IG	Stock	Stock	Both	Both	Stock	Stock
Cap One Bk USA	U.S.	IG	Both	Both	None	None	Stock	Stock
Cardinal Health Inc	U.S.	IG	Both	Both	None	None	Both	Both
Caterpillar Inc	U.S.	IG	None	None	CDS	Both	None	None

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Chubb Ltd	U.S.	IG	CDS	CDS	None	None	Both	Both
Comcast Corp	U.S.	IG	Stock	Stock	None	None	Stock	Stock
ConocoPhillips	U.S.	IG	CDS	CDS	Stock	Stock	CDS	CDS
CSX Corp	U.S.	IG	CDS	CDS	None	CDS	None	None
CVS Health Corp	U.S.	IG	None	None	None	None	Stock	Stock
Darden Restaurants Inc	U.S.	IG	Both	Both	None	None	Both	Both
Deere & Co	U.S.	IG	None	None	None	None	None	None
Devon Engy Corp	U.S.	IG	Both	Both	Stock	Stock	CDS	CDS
Duke Energy Carolinas LLC	U.S.	IG	Stock	Stock	None	None	CDS	CDS
E I du Pont de Nemours	U.S.	IG	None	None	None	None	None	None
Eastman Chem Co	U.S.	IG	None	CDS	Stock	Stock	None	None
Enbridge Inc	U.S.	IG	CDS	CDS	None	None	CDS	Both
Exelon Corp	U.S.	IG	None	CDS	None	None	Both	Both
FirstEnergy Corp	U.S.	IG	None	None	None	None	None	None
Gen Elec Co	U.S.	IG	Stock	Stock	None	Stock	Stock	Stock
Gen Mls Inc	U.S.	IG	Stock	Stock	None	None	Stock	Stock
Halliburton Co	U.S.	IG	Stock	Both	Stock	Stock	Both	Both
Hartford Finl Services	U.S.	IG	Both	Both	None	None	Both	Both
Hess Corp	U.S.	IG	None	CDS	Stock	Stock	CDS	CDS
Home Depot Inc	U.S.	IG	CDS	CDS	None	None	CDS	CDS
Honeywell Intl Inc	U.S.	IG	Both	Both	None	None	Stock	Stock
HP Inc	U.S.	IG	None	CDS	None	None	CDS	Both
Intl Business Machs Corp	U.S.	IG	None	CDS	None	None	None	Both
Intl Paper Co	U.S.	IG	None	None	None	Stock	Stock	Stock
Johnson & Johnson	U.S.	IG	None	None	None	None	Stock	Stock
Kohls Corp	U.S.	IG	Stock	Stock	None	Stock	None	CDS
Lincoln Natl Corp	U.S.	IG	Both	Both	Stock	Stock	Both	Both
Lockheed Martin Corp	U.S.	IG	Stock	Both	None	None	CDS	CDS
Loews Corp	U.S.	IG	Stock	Stock	CDS	CDS	None	Stock
Lowes Cos Inc	U.S.	IG	Stock	Stock	CDS	CDS	Stock	Stock
Marriott Intl Inc	U.S.	IG	CDS	CDS	Stock	Stock	CDS	CDS
Marsh & Mclennan Inc	U.S.	IG	CDS	Both	None	None	CDS	CDS
McDONALDS Corp	U.S.	IG	None	None	CDS	CDS	None	None
McKesson Corp	U.S.	IG	Both	Both	Stock	Stock	None	None
MetLife Inc	U.S.	IG	Both	Both	None	CDS	Both	Both
Mondelez Intl Inc	U.S.	IG	None	CDS	None	None	Stock	Stock
Motorola Solutions Inc	U.S.	IG	None	Stock	None	None	Stock	Both
Norfolk Sthn Corp	U.S.	IG	CDS	CDS	Stock	Stock	Both	Both
Northrop Grumman Corp	U.S.	IG	None	CDS	None	None	None	None
Omnicom Gp Inc	U.S.	IG	Stock	Stock	None	None	Stock	Stock
Packaging Corp Amer	U.S.	IG	None	None	Stock	Stock	Both	Both
Pfizer Inc	U.S.	IG	None	None	None	None	None	None
Procter & Gamble Co	U.S.	IG	None	CDS	None	None	Both	Both
Prudential Finl Inc	U.S.	IG	Both	Both	None	None	Both	Both

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Quest Diagnostics Inc	U.S.	IG	Both	Both	None	Stock	Stock	Stock
Ryder Sys Inc	U.S.	IG	Both	Both	None	None	CDS	CDS
Sempra Engy	U.S.	IG	CDS	Both	None	None	Both	Both
Sherwin Williams Co	U.S.	IG	None	None	None	None	CDS	CDS
Simon Ppty Gp L P	U.S.	IG	Both	Both	None	Stock	CDS	CDS
Southwest Airls Co	U.S.	IG	Both	Both	Stock	Stock	Both	Both
Target Corp	U.S.	IG	Stock	Stock	Stock	Stock	Stock	Stock
The Kroger Co.	U.S.	IG	Stock	Stock	None	None	Stock	Stock
Tyson Foods Inc	U.S.	IG	None	CDS	Stock	Stock	Both	Both
Un Pac Corp	U.S.	IG	None	None	Stock	Stock	Stock	Stock
UnitedHealth Gp Inc	U.S.	IG	None	None	None	None	None	None
Utd Parcel Svc Inc	U.S.	IG	CDS	CDS	None	None	CDS	CDS
Valero Energy Corp	U.S.	IG	Both	Both	Stock	Stock	Both	Both
Verizon Comms Inc	U.S.	IG	None	Stock	None	None	None	None
WESTROCK MWV LLC	U.S.	IG	Both	Both	None	Stock	Both	Both
Weyerhaeuser Co	U.S.	IG	Both	Both	Stock	Stock	None	CDS
Whirlpool Corp	U.S.	IG	CDS	CDS	Stock	Stock	Both	Both
AMD Inc	U.S.	HY	None	Stock	None	None	None	Stock
AK Stl Corp	U.S.	HY	None	None	None	None	Stock	Stock
Amern Axle & Mfg Inc	U.S.	HY	Stock	Both	Both	Both	Stock	Stock
Amkor Tech Inc	U.S.	HY	Stock	Stock	None	None	Stock	Stock
Avon Prods Inc	U.S.	HY	None	None	None	None	None	Stock
BEAZER HOMES USA INC	U.S.	HY	CDS	CDS	CDS	CDS	Stock	Stock
Boyd Gaming Corp	U.S.	HY	Both	Both	CDS	CDS	Stock	Stock
CCO Hldgs LLC	U.S.	HY	Both	Both	None	CDS	CDS	Both
CIT Gp Inc	U.S.	HY	Both	Both	CDS	Both	None	CDS
Cmnty Health Sys Inc	U.S.	HY	None	Stock	None	None	None	None
DISH DBS Corp	U.S.	HY	Both	Both	Both	Both	None	None
Genworth Hldgs Inc	U.S.	HY	None	None	None	None	None	None
HCA Inc.	U.S.	HY	None	None	None	None	Stock	Stock
HD SUPPLY INC	U.S.	HY	CDS	CDS	CDS	CDS	None	Stock
iStar Inc	U.S.	HY	CDS	CDS	CDS	CDS	Stock	Stock
K Hovnanian Entpers Inc	U.S.	HY	None	None	None	None	None	None
KB HOME	U.S.	HY	Both	Both	CDS	CDS	Stock	Both
Lennar Corp	U.S.	HY	Stock	Stock	None	None	Stock	Stock
MGIC Invt Corp	U.S.	HY	CDS	CDS	CDS	CDS	None	CDS
MGM Resorts Intl	U.S.	HY	CDS	CDS	CDS	CDS	Stock	Stock
Navient Corp	U.S.	HY	None	None	CDS	CDS	Stock	Stock
NRG Energy Inc	U.S.	HY	None	Stock	None	None	Stock	Stock
Olin Corp	U.S.	HY	Stock	Stock	Both	Both	Stock	Stock
PulteGroup Inc	U.S.	HY	CDS	CDS	CDS	CDS	Stock	Stock
R R Donnelley & Sons Co	U.S.	HY	Stock	Stock	None	Stock	None	CDS
Radian Gp Inc	U.S.	HY	CDS	CDS	CDS	CDS	CDS	CDS
Rite Aid Corp	U.S.	HY	Stock	Stock	None	Stock	Stock	Stock

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Sealed Air Corp US	U.S.	HY	Stock	Both	None	None	Stock	Stock
T Mobile USA Inc	U.S.	HY	None	None	None	CDS	None	None
TEGNA Inc	U.S.	HY	Stock	Stock	Stock	Stock	CDS	Both
Tenet Healthcare Corp	U.S.	HY	None	CDS	CDS	CDS	Stock	Stock
The AES Corp	U.S.	HY	CDS	CDS	None	CDS	Stock	Stock
Unvl Health Svcs Inc	U.S.	HY	None	None	None	CDS	Stock	Stock
UTD RENTS Inc	U.S.	HY	None	None	None	None	Stock	Stock
Utd Sts Stl Corp	U.S.	HY	None	Stock	Stock	Stock	None	None