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THE EFFECTS OF THE COMPONENTS OF LEVERAGE RATIO ON CDS SPREADS

Mehmet Çağlar KAYA
107664014

Prof. Dr. Cenktan ÖZYILDIRIM

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The Effects of the Components of Leverage Ratio on CDS Spreads

Finansal Kaldıraç Oranı Bileşenlerinin Kredi Temerrüt Takası Farklarına Etkisi

Mehmet Çağlar Kaya

107664014

Tez Danışmanı: Prof. Dr. Cenktan Özyıldırım
İstanbul Bilgi Üniversitesi

Jüri Üyesi: Dr. Öğr. Üyesi Barış Soybilgen
İstanbul Bilgi Üniversitesi

Jüri Üyesi: Prof. Dr. Ömür Süer Baklacı
Galatasaray Üniversitesi

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3) Credit Spread
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ABSTRACT

This thesis aims to analyze in detail the most common determinant of credit risk, the leverage ratio, proposed both by theoretical structural risk models relying on market information and credit risk models depending on accounting data. Distinct from previous works, this study is the first one which investigates how different types of debt affect corporate CDS spreads. We decompose leverage ratio into its components: market debt, bank debt, trade credit leverage ratios by account type classification. The results suggest that debt to financial markets (commercial papers, bonds, etc.) influences positively the next period's CDS spread more than other debt types. CDS spread also reacts positively to bank debt leverage, whereas not to trade credit leverage. Furthermore, we find that CDS spread is statistically responsive to trade receivables.

Key Words: Credit Default Swaps, Leverage, Credit Spread, Credit Risk, Accounting

ÖZET

Bu tez, kredi riskinin en genel belirleyici faktörü olan, gerek piyasa verilerine dayanan teorik yapısal modeller tarafından gerekse muhasebe verilerine dayanan kredi risk modelleri tarafından ortaklaşa önerilen finansal kaldıraç oranını kapsamlıca incelemektedir. Geçmişteki diğer çalışmalardan farklı olarak bu tez, ilk defa şirketlerin sahip oldukları değişik borç türlerinin kredi temerrüt takası farkını nasıl etkilediklerini araştırmaktadır. Bu çalışma finansal kaldıraç oranını borç türlerine göre bileşenlerine ayırmaktadır. Bu bileşenler, finansal piyasa borç kaldıracı, banka borcu kaldıracı ve ticari borç kaldıracıdır. Elde eldilen sonuçlara göre, finansal piyasa borç oranı bir sonraki çeyrekteki kredi temerrüt takası farkını pozitif şekilde ve diğer kaldıraç bileşenlerine kıyasla en çok etkilemektedir. Öte yandan, kredi temerrüt takası farkı, banka borç kaldıracına pozitif tepki verirken, ticari borç kaldıraç oranına istatistiki olarak tepki vermemektedir. Bu sonuçlara ek olarak, kredi temerrüt takası farkının ticari alacaklardan istatistiki ve ekonomik açıdan önemli şekilde etkinlendiği de tespit edilmektedir.

Anahtar Kelimeler: Kredi Temerrüt Takası, Finansal Kaldıraç Oranı, Kredi Farkı, Kredi Riski, Muhasebe

1 INTRODUCTION

The determinants of credit risk, particularly credit spread, have been an active research field in recent decades. However, the number of empirical studies studying credit risk or credit spread is still limited. Among these studies, most have focused on corporate bond spread while examining the determinants of credit risk, whereas there are few studies relying on credit derivatives which are much younger financial instruments compared to bonds. Although there are some influential publications (e.g. Ericsson et al. 2009; Hull et al., 2004; Longstaff et al., 2005), credit derivatives deserve much more attention of research. There are many reasons to study them. First of all, they make up an important part of financial markets as a volume. The total notional amount of CDS contracts is 8 trillion dollars as of June 2018.[1] Second, they are considered either as useful financial derivatives facilitating credit markets or accused of triggering or deepening a financial crisis (Stulz, 2010). Third, they are traded more frequently than corporate bonds, and their spreads are thought to be an improved measure to measure credit risk (Elton et al., 2001; Blanco et al., 2003). Many credit derivatives have become an actively traded financial instrument rapidly from an exotic niche instrument in the last 20 years.

In general, a credit derivative can be defined as a contingent claim which enables investors to trade credit risk independently of other causes of uncertainty. Thereby, these financial products allow market players to transfer credit risk by allowing risk-sharing as well as risk-taking. Among credit derivatives, one of them has emerged as the most impactful and controversial financial innovation in recent times: credit default swaps (CDS). Since its inception (beginning of 1990s), the CDS market had grown rapidly until the financial crisis that occurred in 2007-2009. However, since the financial crisis, the CDS market has shrunk in size and undergone a series of structural changes. In the report of the Bank for International Settlements, Aldasoro and Ehlers (2018) classify these changes as the standardisation and compression of contracts, new reporting requirements, elimination of redundant contracts, mandatory central clearing, and increased margin requirements. The outstanding notional amounts of CDS contracts decreased from USD 61.2 trillion in 2007 to USD 9.4 trillion in 2017 (Aldasoro and Ehlers, 2018). Although, there is a decline in its size, the CDS market has important implications for companies' capital cost, choices of financing and risk of credit (Ashcraft et al., 2009; Subrahmanyam et al., 2014; and Norden, 2017). Moreover,

[1]Source: Bank for International Settlements, Statistical release report of OTC derivatives statistics as of 30 June 2018, 31 October 2018.

CDSs are used actively as instruments in hedging by investors, funds and corporations.

As we have understood above, the CDS market still matters a lot for the financial world and corporations. However, there is still little empirical work on the CDS market itself. The studies focusing on explaining the determinant of CDS spread are few and limited, although some studies point out the importance of CDS by arguing that changes in credit risk may be quantified better by CDS spreads rather than the yield spreads of bonds (Blanco et al., 2003; Ericsson et al., 2009). The literature explains changes in CDS spread by employing two main types of factors: First group of factors consists of theoretical determinants proposed by structural credit risk models (e.g., Merton Model (1974)). These variables can be either market-based or accounting based. The second group includes solely accounting-based determinants proposed by credit risk models relying on accounting metrics (e.g., Altman's Z-score (1968) and Ohlson O-score Models (1980)). These two main branches of credit risk modelling propose one variable mutually. This is leverage ratio. Both structural and accounting credit risk models argue that the greater the leverage ratio, the higher the credit risk and so the greater the CDS spread. Studies analyzing CDS spread provide only evidence of the effect of the total leverage ratio, but not its components. Therefore, there are no studies to the best of our knowledge which separate leverage ratio into different components and analyze the effect of each component on credit risk and so CDS spread. Our study is the first research study which delves deeper research into leverage ratio. It contributes to literature on determining the causes of credit risk and CDS spread. We aim to analyze which leverage ratio component is more closely related with CDS spread and which one of them is relatively more important. By conducting this research, we will have a clearer understanding of both how the CDS market reacts different debt types according to who lends to the firms.

This paper examines the relative importance of the leverage ratio components in explaining CDS spread. We divide leverage ratio into its components according to the account types. We compute market debt leverage ratio, bank debt leverage ratio, trade credit leverage ratio. By market debt leverage ratio, we measure leverage stemming from firm debt to the financial markets consisting of commercial papers, bonds, capital & finance lease obligations. Bank debt leverage ratio gives us leverage originating from firm's indebtedness to banks, whereas trade credit leverage ratio provides us how much firm is leveraged based on its debt to its trade partners such as suppliers. We hypothesize that the higher any of these leverage ratio components, the greater a firm's CDS spread and so the higher its credit riskiness in the next financial period.

While focusing on leverage ratio and its components, we follow the existing literature and also evaluate the descriptive power of other market- and accounting-based measures as control variables on CDS spread. We use stock return, market capitalization, and stock return volatility which are all proposed by Merton-type structural models. Then, we also add income/asset ratio as an accounting-based variable suggested for firm profitability by credit risk models using accounting metrics.

Our results show that changes in all leverage ratio components except trade credit leverage influence the next period's CDS spread statistically and economically at significant levels. As predicted by our hypothesis, we find that the higher one of these statistically significant ratios, the higher the CDS spread in the next period. Market debt leverage ratio seems to be the most influential one in terms of economic magnitude on CDS spread among all components. Bank debt leverage ratio ranks the second most influential ratio among all components. Trade-credit leverage ratio has no statistically significant effect on CDS spread both in its individual analysis with control variables and when we regress CDS spread on it together with other leverage ratio components. While we do not find any statistically significant relationship between trade payable and CDS spread, we contemplate to evaluate the effects of trade relation on CDS spread from receivable side rather than payable side. We obtain a negative and significant relationship between trade receivables and next quarter's CDS spread.

The rest of this thesis is structured as follows. Section 2 summarizes relevant studies. Section 3 discusses the dependent variable, CDS spread, and its characteristics as well as the independent variables and their predicted relationship to CDS spread. The following section, Section 4, first describes the data and then provides details about the calculation of variables as well as their descriptive statistics. Section 5 explains the frameworks of the empirical models. Section 6 provides main empirical results. Section 7 extends our endeavour in analyzing determinants of CDS spread with another factor. Finally, Section 8 concludes the study.

2 RELEVANT LITERATURE

This study relates to research on credit risk in general, and the empirical determinants of CDS spreads in particular. Empirical research on CDS determinants is scarce and relatively recent compared to research on other financial instruments such as stocks and bonds. Academic studies on credit risk have developed some substantial empirical works focusing on corporate bonds as credit-sensitive instruments. Some of these empirical studies employ so called models of reduced-form to value credit-risky bonds. These models theorize the patterns of default probabilities exogenously and apply market data (e.g., bond yields) to estimate the parameters required to calculate credit-sensitive claims' values (Duffee, 1999; Duffie, Pedersen and Singleton, 2003). The literature judges these reduced-form models successful in practical applications, but poor in explaining the theoretical factors of the prices of these credit-risky securities.

In turn, a different set of empirical research (e.g., Collins-Dufresne et al., 2001; Campbell and Taksler, 2003) relies on an alternative and older approach called structural approach. In measuring credit risk, this approach uses the founding theoretical models of Black & Scholes (1973) and Merton (1974). Based on these models, a firm's default risk is calculated based on the variation in the firm's asset value which can be modelled by a process of geometric Brownian motion. In his model, Merton (1974) measures credit risk by relying on information provided by the market price of a stock. He considers a company's debt and equity as options written on the firm's asset value and determine the prices of these derivatives by using option pricing theory of Black & Scholes (1973). A firm goes bankrupt when the market value of its assets is lower than that of its debt. The Merton Model (1974) proposes financial leverage, the volatility of the firm's asset and the risk-free rate as the major determinants of financial stress and default (credit) risk. Although these models are considered to be effective in explaining the qualitatively essential characteristics of pricing default risk, they have been less effective regarding practical applications compared to models of reduced-form (Duffee, 1999; Duffie and Singleton, 1999). The literature notes that few studies attempt to price any particular instrument by implementing a Merton-type structural model solely.

Instead of implementing Merton-type structural models in practice, the literature mostly uses structural approach as a benchmark to identify theoretical predictors of credit risk and then employs them as explanatory variables in their regressions rather than inputs to a specific structural model. (Collins-Dufresne et al., 2001; Campbell and Taksler, 2003). Collin-Dufresne and co-authors (2001) argue that these variables based on the structural approach have modest predictive power to explain credit spread changes but they find a single common factor that drives a significant part of the residuals and the theoretical variables cannot explain this common systematic factor. Campbell and Taksler (2003) investigate the effects of equity volatility -one of the main determinants of credit risk in the Merton Model (1974)- on corporate bond yields. They claim that idiosyncratic firm-level volatility is an important determinant in explaining the cross sectional variation in the corporate bond spreads. Using corporate bond yields, Avramov et al. (2007) argue that the variables proposed by a Merton-type structural model explain over 54 % (67 %) of the variance in changes of credit spread for medium grade (low grade) bonds. Another study that considers corporate bond yields as a measure of credit risk and explains what factors can explain the changes in credit spreads is the work of Cremers and colleagues, 2008). They use option-based volatility and jump risk as market based measures for the theoretical determinants of credit spreads. Cremers et al. (2008) argue that individual options contain forward looking information regarding the volatility risk of the firm value, one of the main determinants of credit risk in Merton Model (1974). They conclude that implied option volatilities include valuable information about credit spreads and perform better than historical volatility measures when analyzing variations both in the cross sectional and temporal dimensions in a panel data of corporations' bonds.

The studies focusing on credit default swap spreads as a metric of credit risk are even more scarce than the studies focusing on corporate bond spreads. There are few studies analyzing both corporate bonds and default swaps (Blanco et al., 2003; Longstaff et al., 2005). For instance, Blanco et al. (2003) find that both CDS and bond markets seem to price credit risk same on average. They also argue that structural model inspired firm-specific variables are more significant statistically and have higher economic relevance for CDS prices than do for corporate bond spreads.

The most related literature to this study consists of the papers either analyzing determinants of CDS spreads with new and broader data set or searching for new determinants that can explain cross-sectional variability in CDS spreads more. Employing a data set of CDS's bid and offer quotes, Ericsson et al. (2009) search for the linkage between theoretical determinants of default risk and actual CDS spreads. This study shows that leverage, volatility, and the riskless interest rate are both statistically significant and economically important factors of CDS spreads. Nevertheless, the same authors conclude that a substantial portion of the variation in spread differences still stays unexplored. Zhang et al. (2009) enrich a Merton-type structural model by adding stochastic volatility and its jumps as additional determinants. They show that a large portion of variation in CDS spreads may be understood from intraday refined metrics of historical volatility and jump risk. By employing quantile regressions, Pires et al. (2015) document that CDS illiquidity costs estimated by absolute bid-ask spread determine CDS premiums strongly, while controlling for traditional variables such historical stock return, volatility, leverage and profitability. Management earnings forecast and announcement are other factors analyzed by the literature for their effects on CDS spreads. Shivakamur and his co-authors (2011) document that the credit market responds to forecasts of management earnings via changes in CDS spreads. They conclude that the responses to forecast news of earnings are even more pronounced than to actual earnings news.

The literature also analyzes and emphasizes the importance of accounting variables in measuring credit risk besides market-based variables proposed by structural models. There are studies relying exclusively on accounting data in credit risk analysis. Some pioneering studies from the accounting literature investigates the power of accounting ratios to predict firm default (Beaver, 1968; Deakin, 1972). Beaver (1968) concludes that default firms and non-default firms differ substantially in terms of the leverage ratio and cash flow metric. By using a discriminant analysis, Deakin (1972) finds that financial ratios predict firm default closely as soon as three years in advance. In parallel to these studies, in the finance literature, Altman (1968) develops his pioneering model called Z-score model that employs a multiple discriminant analysis of accounting ratios to measure financial distress and to predict default. [2] However, some criticism arises about discriminant analysis since this analysis requires limiting econometrical assumptions such as the normality requirement and the variables' independence (Demirovic et al., 2015). Then, the literature utilizes binary choice models. By employing a logit analysis, Ohlson (1980) develops his O-score model and concludes that firm size, liquidity, leverage, and profitability are significant variables affecting credit risk.

[2] In his work, Altman (1968) includes five accounting variables out of his initial list of twentytwo variables in the final discriminant function in his Z-score model. These five variables include: Working capital, shareholders' equity, retained earnings, EBIT, and sales. He scales all of them by total assets. Altman's Z-score model claims that only sales/total assets ratio is insignificant.

As it is expected, the literature examines whether accounting metrics or market-based determinants of credit risk are more informative (Demirovic & Thomas, 2007; Demirovic et al., 2015). Hillegeist et al. (2004) document that Merton Model's (1974) distance-to-default (DD) metric calculated from market information outperforms Altman's Z-score (1968) and Ohlson's O-score models (1980) that rely on accounting variables. Supporting the earlier study, Demirovic and Thomas (2007) find that Merton's distance-to-default metric is the most important variable in measuring credit risk by using UK data where credit ratings estimate credit risk. Noteworthy, they add that accounting variables add incremental information once they are included in the model of distance-to-default. In a following study where they use US data and proxy credit risk via bond credit spread, Demirovic et al. (2015) provide additional empirical evidence that market-based measures of credit risk (e.g., equity volatility and Merton's DD measure) perform better than variables obtained from financial statements in assessing variations in bond credit spread. In contrast, Agarwal and Taffler (2008) claim that DD measure and a composite accounting metric based on Altman's model capture different aspects of bankruptcy risk and neither stands alone as a sufficient metric in measuring credit risk. Das et al. (2009) document that these sources of information are complementary in pricing of CDS contracts.

Some studies focus on some so called macro factors and compare their effects on CDS spread with firm-specific, structural model variables. Galil et al. (2014) investigates the effects on CDS spread of common factors (market risk factors) such as spot interest rate, VIX index as market volatility as well as firm-specific variables inspired by structural models including stock return, stock volatility and leverage by using multivariate regressions for each category of variables separately. They conclude that the common market variables still have predictive power even when controlling for firm-specific variables. Das and Hanouna (2009) provide a theoretical relationship between stock market liquidity and CDS spreads via mechanism of hedging. They document that stock market liquidity still stands significant in describing the changes in CDS spreads while controlling for distance to default as a credit variable and three month treasury rate.

3 DESCRIPTION OF VARIABLES

3.1 Dependent Variable: CDS spread

We use credit default swap (CDS) spread as a measure for credit risk. A CDS spread is termed as the periodic rate that a protection buyer spends on the notional amount to a protection seller for exchanging credit event risk related to the firm or financial instrument (i.e. bond) that the CDS contract is written on. It is a swap contract which shields the buyer against the default risk of the reference firm or instrument. Since CDS contracts are generated by market players, CDS spreads informs us about market perceptions in regards to the financial standing of the reference firm (Annaert et al., 2013). Market regulatory authorities, institutional traders and investors interpret changes in CDS spread as signals regarding financial stability of a firm. (Annaert et al., 2013, Norden, 2017). Furthermore, corporate CDS trading is mostly driven by news and information about credit risk of the reference firm (Norden, 2017).

Using CDS spreads, instead of corporate bond yield spreads to measure credit risk provides important advantages. First, credit default swap contracts are traded more frequently than corporate bonds. Since the introduction of CDS as a new financial instrument, trading in default swap markets has increased substantially although there has been some decline after financial crisis of 2007-2009. The CDS market has become more liquid market throughout the time. It is a known fact that several corporate bonds are rarely traded. In this study, CDS data is collected daily. On the other hand, most research that measures credit risk via corporate bond yield spreads utilizes monthly data. Second, CDS spreads convey how the market perceives default risk in contrast to those of a rating agency (Norden, 2017). Blanco et al. (2003) comment that CDS spreads may mirror the variation in credit quality of the underlying name in the contract more closely and swiftly than corporate bond yield spreads. Third, CDS spreads are already spreads: When measuring credit or default risk by CDS spreads, we do not have to determine a riskless yield curve as a benchmark specification to calculate the spread as we would do in calculating bond yield spreads. Studying bond yield spreads requires a framework choice to eliminate coupon effects as well as the choice of a reference riskless asset that may be problem prone (Ericsson et al., 2009). As a final advantage, CDS spreads reflect aspects of both default and recovery risk of firm in distress while being less exposed to tax effects and liquidity than yield spreads of corporate bonds (Elton et al., 2001; Das et al., 2009).

3.2 Variables of Interest: Leverage Ratio Components

Financial ratios have been in widespread use in credit risk analysis. Academic studies identify us one of them as an essential measure of firm solvency, leverage ratio. Both accounting and economics literatures emphasize leverage ratio as one of the important determinants of credit risk. On the one hand, cash flow and leverage ratio of non-default companies diverge substantially from ratios of defaulting companies at least five years before their bankruptcy (Beaver, 1966). On the other hand, in the economics literature, Merton (1974) explicitly accounts for leverage in his forward-looking credit risk model and shows that firm leverage is one of the principal determinants of default probability. After the Merton Model (1974), all following academic works use leverage ratio as one of the determinants of credit risk in their theoretical or empirical frameworks (e.g., Collin-Dufresne et al., 2001, Campbell et al., 2008).

This work examines this important determinant, leverage ratio, by analyzing its components according to two types of classification. First, we classify leverage according to financial account type. We calculate the leverage ratio components according the classification of the main financial accounts that might exist in every industrial company's balance sheet on the liabilities side. To the extent of data that we obtain from CapitalIQ, we compute the leverage ratio components from these main financial accounts: Trade credits (account payable), financial debt to banks (bank debt), financial debt to markets (commercial papers, bonds, capital & finance lease obligations, federal loans, etc.) and remaining debt that consists of the liabilities that we do not classify in the first three groups. After calculating the balances of these accounts, we divide each of these balances by the all liabilities' book value plus the market value of equity to compute the respective leverage ratios. We scale all these leverage ratios by equity's market value rather than the book value of equity as per Campbell et al. (2008) and Frank & Goyal (2009) do. We name these leverage ratio components respectively as follows: Market debt leverage, bank debt leverage, trade credit leverage, and other leverage. Furthermore, we also calculate the overall leverage ratio which is simply the ratio of all liabilities over the summation of total liabilities' book value and equity's market value. Frank & Goyal (2009) name this ratio as "market leverage" and we call it "total leverage".

The Merton Model (1974) argues theoretically that greater leverage implies a smaller distance to the default point and higher default probability. Moreover, the empirical studies following Merton's structural model find that a positive interaction exists between leverage ratio and credit risk and specifically CDS spread (Campbell et al., 2008, Galil et al., 2014).

Therefore, we expect a positive relationship between each of the mentioned leverage ratio components and the dependent variable, CDS spread.

The summary about how we calculate total leverage ratio and its components is presented in Table I. We also calculate so called "counter leverage ratio" for every component. We use each counter ratio in the individual analysis of each leverage ratio component. For instance, for market debt leverage ratio, we compute non-market debt leverage ratio that is the ratio of all debt of a firm other than its market debt (i.e. commercial papers, bonds, capital and lease obligation, etc.) to the summation of book values of liabilities (BVL) and market value of equity (MVE). For other two components, we name their counter ratios respectively as follows: non-bank debt leverage ratio, non-trade credit leverage ratio. Furthermore, in Table I, other leverage ratio is the ratio of all liabilities that cannot be classified under three component to the sum of BVL and MVE. We use other leverage ratio when we perform a combined analysis of all three leverage ratio components.

Table I
Leverage Ratio Components

Measure	*Definition*
Total leverage	BVL /(BVL + MVE)
Components:	
Market debt leverage	Non-bank financial debt /(BVL + MVE)
Bank debt leverage	Bank Loans / (BVL + MVE)
Trade credit leverage	Account payable / (BVL + MVE)
Other leverage	Remaining Liabilities / (BVL + MVE)

Notes: BVL stands for book value of liabilities, MVE market value of equity. Market debt is the non-bank financial debt that consists of commercial papers, bonds, capital & finance lease obligations, federal loans, and other short-term & long-term borrowing derivatives.

3.3 Control Variables

Here we describe the control variables that we use in every regression model as well as their theoretical relationships to CDS spread. In the literature, the variables assessed as determinants of CDS spread are grouped under two groups: Market measures and accounting measures. The first group relies theoretically on the Merton Model (1974) and considers all information embedded in the market price of firms' securities. They are forward-looking metrics of credit risk. In turn, the second group, the group of accounting-based measures, depends on the firms' financial statements and these accounting statements are backward-looking. Although accounting measures depend on historical data of financial statements, accounting literature shows that accounting variables have power to predict firm default in advance (Beaver, 1968; Beaver et al., 2005).

The market-based measures that we use as control variables in this study are stock return, equity value (market capitalization), and equity volatility (stock return volatility). Besides the market-based measures, we use one accounting-based measure as a control variable: income/asset ratio. We review each of these control variables in detail in the following sub-sections:

Stock Return:

A firm's stock market price is the first key information that investors and bankers refer to while assessing the credit worthiness of the public firms. In his seminal work, Merton (1974) suggests that there is an inverse relationship between a firm's equity value in the market and the probability of its default. Higher stock return increases a firm's equity value. Therefore, higher stock return leads to lower probability of default and lower credit risk. Theoretically, we should expect a lower CDS spread implying a lower credit risk after a rise in the stock return of a firm. In short, a negative relationship is forecasted between stock return and CDS spreads. In this study, we use logarithmic returns calculated based on daily prices.

Equity Value:

Firm value is another major explanatory variable on credit risk that takes its grants from the Merton model (1974). The model deducts the face value of the company's debt from an estimation of the company's market value and then takes the ratio of this difference over an estimation of the volatility of the company's value. Based on this calculation, the model generates a score termed distance to default and calculates the bankruptcy probability based on this score within the framework of the Black-Scholes option pricing formula (Bharath and Shumway, 2008). In Merton's seminal model (1974), the market value of the corporation is the total market value of its assets. However, total asset value of a firm is not readily observable. According to the basic accounting principle that total assets' value is equal to the values of total liabilities plus equity value, one can simply calculate the market value of a firm as a sum of the market values of the firm's liabilities (debt) and the value of its equity. At this point, while equity's market value is obtained from the equity market, reliable data on the debt's market value are mostly unavailable (Bharath and Shumway, 2008). Since the asset value of a company and market value of debt can not be observed, Merton (1974) suggests using the equity value as a proxy for the firm value. Theoretically, higher equity value leads to lower default probability and thus lower credit risk. We expect an inverse relationship between equity value of a firm and its CDS spread. We use daily market capitalization to measure the equity value of a firm in this study. What is also noteworthy about equity value is that it also serves as a variable controlling for the size effect cross-sectionally in the regression analysis. In fact, firm size, itself, is an important accounting-based determinant in measuring credit risk (Altman, 1968; Ohlson, 1980).

Equity Volatility:

The third variable we use as a market-based control variable is the equity volatility in the Merton Model (1974) proxied by stock return volatility. The model estimates the equity of the company as a call option on the underlying company's value with a strike price the same as the face value of the company's debt and a time-to-maturity of T, whereas debt as the value of a riskless discount bond, less the value of a put option contracted on the company with a strike price the same as the debt's face value and a time left to maturity of T (Bharath and Shumway, 2008). The volatility of the underlying asset can be a critical factor of the default sensitive security's value (Ericsson et al., 2009). Both options' values depend on the volatility of corporation value that is measured by equity volatility by the Merton Model (1974). Furthermore, by finding a strong positive relationship between equity volatility and corporate bond yield spreads, Campbell and Taksler (2003) even argue that the effect of equity volatility on the borrowing cost of corporations seems to be much greater than what the standard structural models can explain. We expect that higher stock volatility will raise the firm's probability of default, and therefore its credit risk. A larger credit risk will lead to higher CDS spread.

Income/asset Ratio:

As an accounting-based measure, we employ one control variable indicating firms' profitability. Firms strengthen their equity base by retaining their net income as retained earnings in their balance sheet unless they distribute all their net income. Higher profitability leads to higher equity value and puts a firm far away from the default point in the Merton Model (1974). In fact, investors often rely on accounting ratios to assess the solvency of firms. One of the main ratios to which the accounting literature refers is the ratio of net income to total assets. In his empirical study of 79 failed firms and the same number of non-failed firms, Beaver (1968) argues that the cash flow stream and net profit have the same highest predictive power to forecast the bankruptcy of a firm. He ranks the debt-asset ratio as third and the working capital ratio as the poorest predictor of these four financial ratios. Moreover, by testing a sample of nearly 400 bankrupt firms, Barth et al. (1998) document that net profit decreases as financial health decreases. They add that net profit and book value of equity as the main measures of the financial statements have explanatory power to predict the firms' default in the five years prior to bankruptcy. By using US firm data and measuring credit risk via corporate bond spread, Demirovic et al. (2015) find that profitability is the most informative metric among accounting variables in describing cross sectional variability in the credit spread. Therefore, we expect that higher net income to total assets ratio should decrease credit risk of a firm, thereby its CDS spread theoretically.

4 EMPIRICAL METHODOLOGY

In this section, we first give general information about the data and the sample of the study. Then, we explain how we calculate variables from the data. Finally, we provide descriptive statistics of the variables employed in the analyses.

4.1 Data

The data for this study come from the CapitalIQ dataset. In setting up the initial sample, we select US and Canadian firms that operate in industrial sectors and have single name credit default swaps that refer to five-year contracts and senior unsecured debt. We exclude financial institutions from the sample since they are subject to different financial reporting standards and their financial statement analyses are distinct from the analyses of industrial firms. In addition, these two groups, industrial firms and financial institutions have distinct business risks. This screening generates 474 firms to us. Furthermore, we also exclude utility firms since their businesses and the legal and accounting standards that they are subject to make them exceptional cases compared to the other industry firms. After these initial screenings, we choose the firms publicly quoted in a stock market from these 474 firms. This leaves us with 355 firms. We use credit default swaps referring to 5 year maturity contract and senior unsecured debt, because they have come forth as the benchmark for CDS trading and the most actively traded CDS contracts (Meng and Gwilym, 2008; Zhang et al., 2009). The data includes mostly US dollar nominated and fewer Canadian dollar dominated CDS names. We only use US Dollar as a currency while downloading the financial statements data from CapitalIQ.

We establish our work on a sample of 355 firms that are frequently traded in CDS market. All these firms are also publicly quoted in the stock markets. The sample consists of 18,438 firm-quarter observations, spanning the period from January 2003 to December 2017. 93% (331) of the firms in the sample are US firms whereas 7% (24) of them are Canadian corporations. In the sample, almost half of the firms operates in the manufacturing industry (46%). The transportation industry follows the manufacturing industry with 17%, mining industry with 12% and trade (wholesale and retail) with 12%. The more information about the sample in Table II as follows:

Table II
Sample information

Industry	No. of Firms	*By Industry* Perc.	No. of Obs.	Perc.
Production Sectors				
Mining	42	12%	2118	11%
Construction	11	3%	626	3%
Manufacturing	162	45%	8570	47%
Sub-total:	214	60%	11314	61%
Service Sectors				
Transportation	59	17%	2956	16%
Wholesale Trade	11	3%	621	3%
Retail Trade	32	9%	1688	9%
Other Services	38	11%	1859	11%
Sub-total:	140	40%	7124	39%
Total	355	100%	18438	100%

Notes: Financial institutions (banks & insurance companies) as well as utility companies are excluded from the sample. The sample consists of 355 companies and 18,438 firm-quarter observations between January 2003 and December 2017.

4.2 Methods in Calculating Variables

We obtain CDS data on a daily basis from CapitalIQ. CapitalIQ depicts the CDS spread prices in basis points. We use "CDS spread mid price" from the data and in the analyses, we convert it into percentage terms since other variables are also used in percentage terms. Although, some research in the literature use daily frequency of CDS spread in their main analyses, we prefer to use quarterly frequency for CDS spread by averaging daily CDS spread mid prices for each quarter (Ericsson et al, 2009) in the regressions. Quarterly frequency is the more appropriate choice for the analyses in this study, since majority of main explanatory variables comes from financial statements and financial data's frequency is quarterly.

We obtain data for the main explanatory variables (the leverage ratio components) from quarterly financial statements downloaded from CapitalIQ. We multiple all these ratios by 100 to depict them in percentage terms.

In regards to the market-based control variables which come from stock market such as stock return and market capitalization, we use daily closing stock prices data and the number of outstanding shares daily data from CapitalIQ to calculate these variables respectively.

To compute the variable of stock return, we first calculate daily logarithmic returns. Then, we compute the quarter average of these daily returns. As a final step, we multiply these quarter daily averages with 252 to make them yearly return figures and with 100 to depict them in percentage terms before utilizing them in the regressions. For market capitalization as a measure for equity value, we first multiple daily stock prices with the number of outstanding shares for each day. Second, we take the averages of these daily market capitalization values for each quarter. Then, we deflate quarter averages of market capitalization to 2015 dollars using quarterly consumer price index sourced from Federal Reserve Bank of St. Louis. Finally, we take natural logarithm of these market capitalization values before using them in the regressions since they are large numbers compared to other explanatory variables.

In calculating equity volatility which is the volatility stock return, we compute the standard deviation of daily stock returns for each firm in each quarter. We convert these volatility numbers into annual terms by multiplying the squared root of 252 and depict them in percentage terms by multiplying by 100. When it comes to accounting-based control variable, profitability ratio (net income/total asset), its frequency is quarterly due to the frequency of each company's financial statements. We also multiply this ratio by 100 to represent it in percentage terms.

4.3 Descriptive Statistics

First, we trim all the variables at the upper and the lower 0.05-percentiles in order to remove effects of outliers before we start our data analysis. Table III depicts summary statistics regarding the dependent variable, CDS spreads (in percentage points), and independent variables (in percentage points for the ratios). The analysis is based on firm-quarter observations. The sample contains circa 14,700 firm-quarter observations for the dependent variable CDS spread and circa 17,700 firm-quarter observations. On average, corporations in the sample have a positive CDS spread of 1.75% as well as positive stock return of 6.5% in annual terms.

As we see from Table III, market debt leverage (18.7%) generates the largest part of total market leverage (42.4%). The category of other leverage (15.8%) follows it. In turn, trade credit leverage (5.7%) and bank debt leverage (2.1%) constitute smaller parts of total market leverage ratio. Moreover, we can see that some firms do not have bank debt as bank debt leverage ratios for first quartile and second quartile of the sample are zero.

Table IV consists of the correlation matrix of all the variables included in the main analyses. Since we have a panel data that has both time series and cross section dimensions, we first calculate the correlation coefficients amongst the variables for each firm in each quarter. Thereby, we obtain a correlation matrix for each quarter. As a final step, we simply take the average of these matrices across time. In short, the correlation matrix in Table IV is the time series mean of the quarterly cross sectional correlation matrices. In regards to the analysis of the matrix, all leverage ratio components are positively correlated with CDS spread. The total leverage ratio, called total market leverage, has a correlation coefficient of +0.63 with CDS spread. Market debt leverage has the highest positive correlation with CDS spread compared to other leverage ratio components which are bank debt leverage, trade credit leverage and other (remaining) leverage.

Table III
Summary Statistics

This table shows summary statistics of the variables in the analysis. The data extends from January 2003 to December 2017. All variables in this panel data are measured at the quarterly frequency. They are trimmed at the lower and upper 0.05-percentiles.

	mean	sd	p25	p50	p75	count
CDS Spread	1.746	2.480	0.434	0.816	1.867	14656
Total leverage	42.358	18.768	28.292	40.508	54.082	17709
Leverage ratio components:						
Market debt lev.	18.685	12.532	9.603	15.948	24.882	17709
Bank debt leverage	2.051	4.921	0.000	0.000	1.179	17709
Trade credit leverage	5.708	5.789	1.975	3.950	7.186	17572
Other leverage	15.776	11.477	8.529	13.841	21.080	17572
Control variables:						
Stock return	6.473	67.229	-25.485	11.153	44.769	17758
Equity volatility	31.698	18.730	19.622	26.614	37.188	17758
Market cap	9.391	1.380	8.432	9.404	10.288	17750
Income/asset	5.344	8.472	2.227	5.387	9.163	17883

Notes: Market capitalization is in million figures. All ratios and rates are depicted in percentage in annual terms.

Table IV
Correlation Matrix

The table shows the correlations amongst quarterly observations of CDS spread (cds), total leverage (lev), the components of this total leverage ratio and market & accounting-based measures. All variables are calculated based on quarterly measured values. The variable that measures credit risk (cds) is the average value of daily CDS spreads in a quarter. The leverage ratio (lev) components are: Market debt leverage (mrktlev), leverage due to bank debt (banklev), trade credit leverage (tclev), and leverage stemming from other liabilities other than first three categories, shortly called as “other leverage” (rlev). On the other hand, the market- and accounting-based measures as control variables are: stock return (r), stock return volatility (vol), logarithm of the market capitalization as equity value (mcap), and net income/total assets ratio (inc_at). Data covers the period between January 2003 and December 2017. We note that CDS has the expected positive correlation with all leverage ratios. In regards to the control variables, CDS spread has negative correlation with stock return (r), market capitalization (mcap), and net income/total asset ratio (inc_at), but positive correlation with stock return volatility (vol) as expected from theoretical knowledge. It is apparent that since total leverage ratio (lev) includes all debt types, it is highly correlated with its component ratios. As an alternative source of financing to others, trade credit leverage (tclev) is negatively correlated with market debt leverage (mrktlev) and bank leverage (banklev) ratios.

Variables	cds	r	vol	mcap	lev	mrktlev	banklev	rlev	tclev	inc_at
cds	1.000									
r	-0.081	1.000								
vol	0.618	-0.130	1.000							
mcap	-0.556	0.051	-0.528	1.000						
lev	0.629	-0.143	0.496	-0.593	1.000					
mrktlev	0.556	-0.118	0.405	-0.579	0.689	1.000				
banklev	0.319	-0.048	0.238	-0.275	0.333	0.407	1.000			
rlev	0.190	-0.058	0.170	-0.081	0.498	-0.111	-0.312	1.000		
tclev	0.104	-0.033	0.117	-0.212	0.332	-0.048	-0.003	0.022	1.000	
inc_at	-0.327	0.092	-0.286	0.297	-0.444	-0.353	-0.146	-0.198	-0.111	1.000

In this part, we also investigate the time series trend of dependent variable CDS spread against total leverage ratio and its components by plotting their time series in bivariate figures between first quarter of 2004 and the last quarter 2017. We take the cross sectional averages of each variable in their quarterly observations to create these time series.

In Figure 1, both CDS spread and total leverage ratio series follow the same trends. The positive relationship between each other is apparent. In Figure 2, the same is pattern is valid for the relationship between time series of CDS spread and the first leverage ratio component, market debt leverage ratio. Again, both series follow each other closely. Their spikes and troughs coincide with each other. In regards to the relationship between the time series of bank debt leverage ratio and CDS spread, Figure 3 shows that bank debt leverage has similar trend with CDS spread but we can argue that its correlation is not as strong as the market debt leverage's or the total leverage's correlation with CDS spread. On the other hand, as seen in Figure 4, trade credit leverage ratio's time series does not depict same trend as CDS spread does. In all figures, we observe the highest spike during 2007-2009 financial crises when both CDS market and corporations were exposed to the most significant financial and economic upheaval since the Great Depression.

We also plot time series of each control variable against CDS spread in the figures from Figure 5 to Figure 8 in Appendix, Section 10.1. Their time series trends provide us with an overall picture supporting the theoretical expectations about the sign of the relationship between CDS spread and each control variable respectively. Furthermore, as mentioned in earlier sections, we group the liabilities that we cannot classify under three categories of market debt, bank debt and trade credit. Then, we make a fourth group from these remaining liabilities and name its leverage as other leverage. The plot of CDS spread against other leverage ratio is presented in Figure 9 in Section 10.1 of Appendix. It shows the positive but relatively weaker correlation between the time series of CDS spread and other leverage ratio.

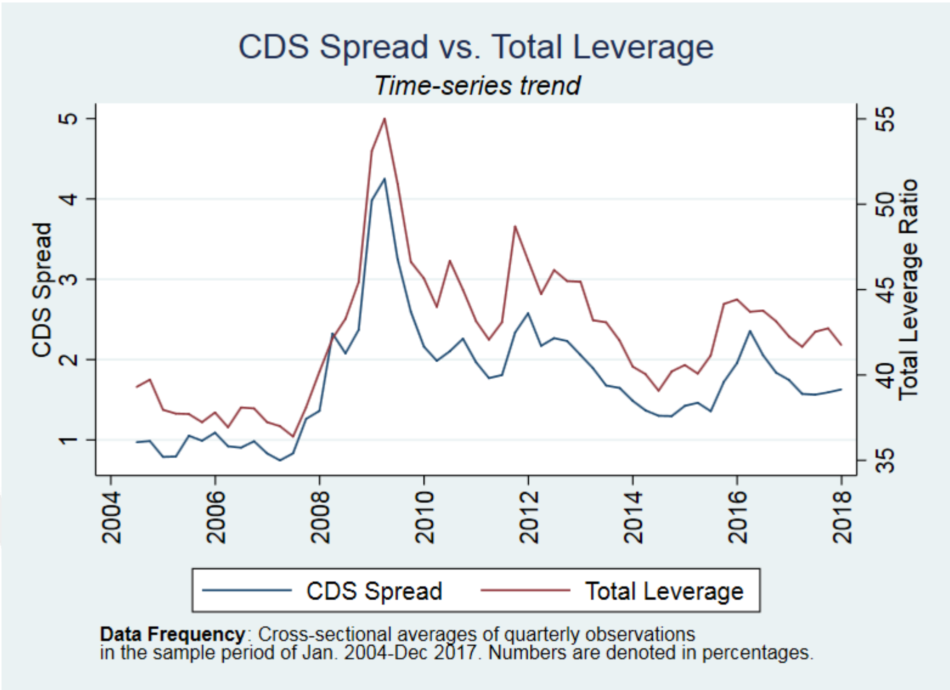

Figure 1: A Time Series Analysis of CDS Spread and Total Leverage Ratio

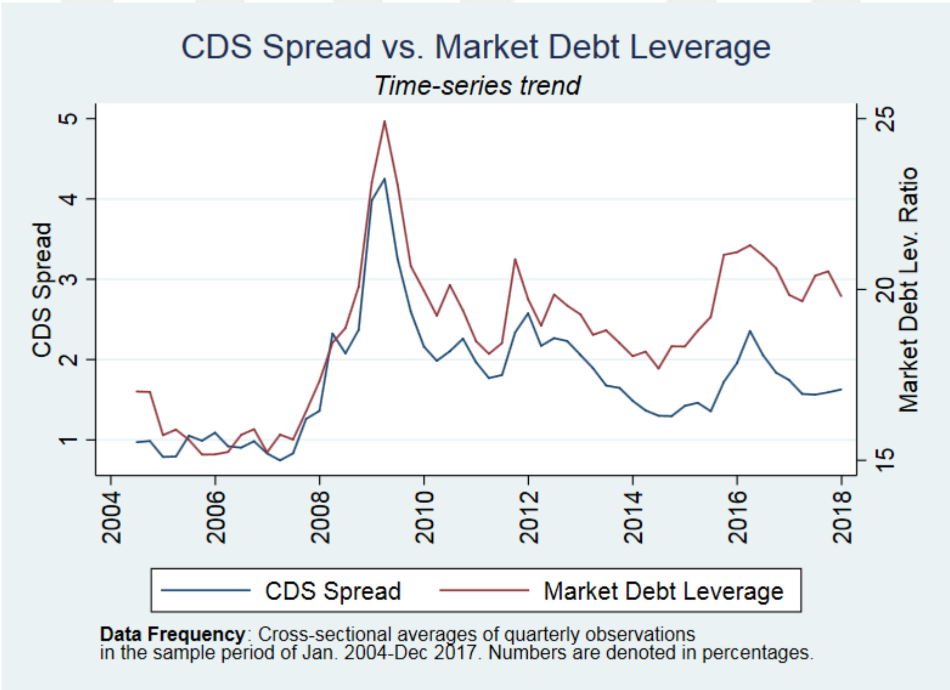

Figure 2: A Time Series Analysis of CDS Spread and Market Debt Leverage Ratio

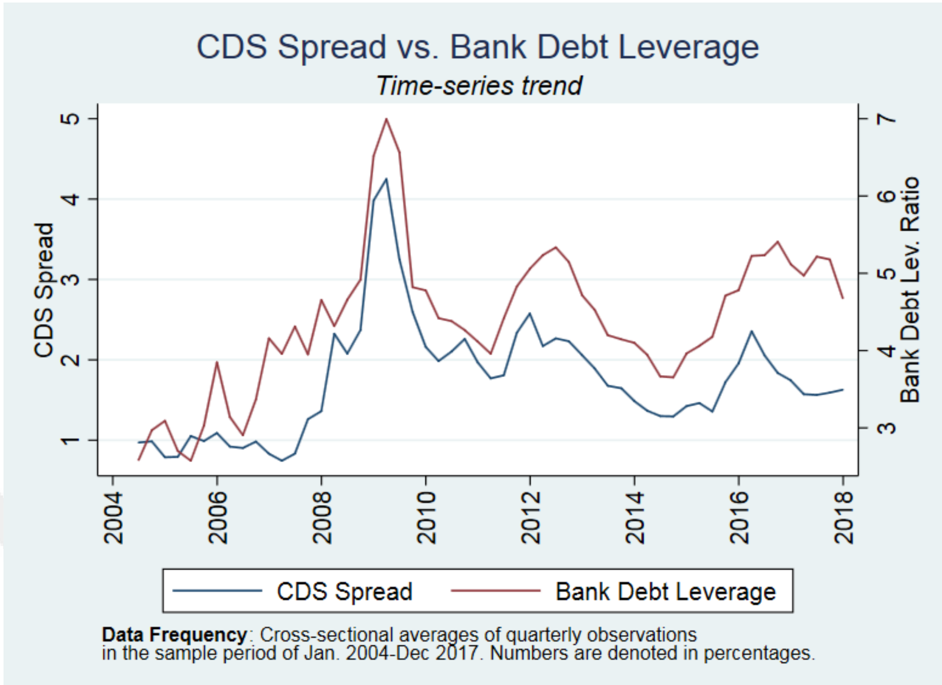

Figure 3: A Time Series Analysis of CDS Spread and Bank Debt Leverage Ratio

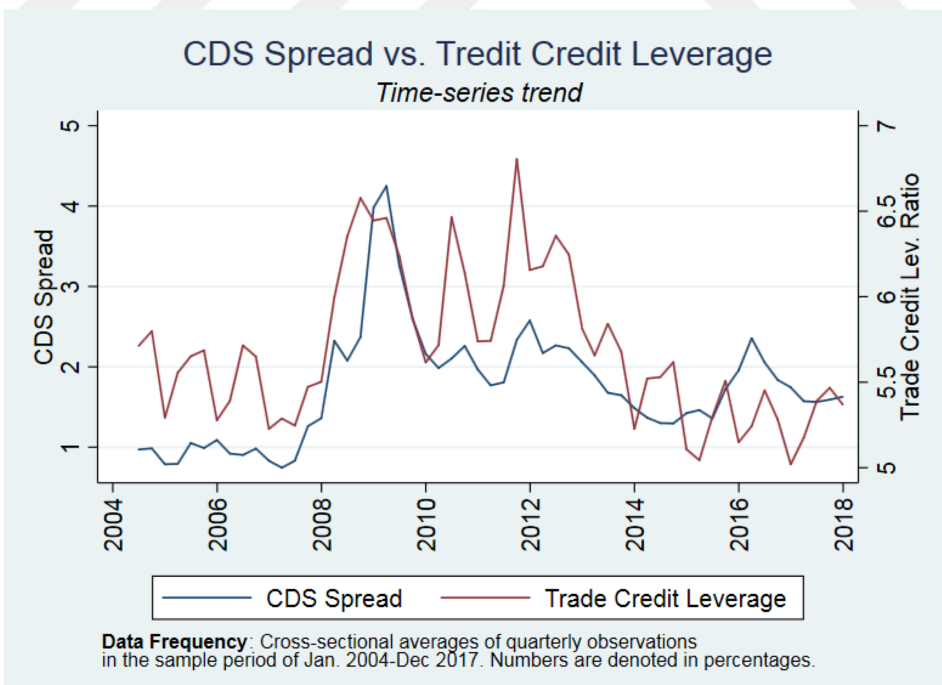

Figure 4: A Time Series Analysis of CDS Spread and Trade Credit Leverage Ratio

5 EMPIRICAL STRATEGY AND MODELS

We employ panel data regression methodology to estimate the effects of different components of the leverage ratio, such as market debt leverage ratio or bank debt leverage ratio, on CDS spread. We use five different regression model specifications in every analysis where we estimate the effect of the specific leverage ratio component or the combined effects of them on CDS spread. In line with our theoretical expectation that the effect goes from our independent variables to the dependent variable, CDS spread always has a lead of one financial quarter with respect to all regressors in all models. This strategy helps us to address the endogeneity concern. Moreover, in all models, we compute t-statistics using robust standard errors that are clustered at firm and quarter levels.

In the first model, we regress CDS spread only on the variable of interest, the specific leverage ratio component, and the leverage ratio stemming from the rest of the debt in the firm's liability in its balance sheet. For instance, if the variable of interest is bank debt leverage, we regress CDS spread on it and non-bank debt leverage. The second leverage ratio is simply the leverage from all liabilities other than bank debt. The first basic model's specification is as follows:

$$\text{CDS}_{i,t} = \beta^{c}\text{lev}^{c}_{i,t-1} + \beta^{nc}\text{lev}^{nc}_{i,t-1} + \epsilon_{i,t} \quad (1)$$

where average CDS spread of a firm i in quarter t is depicted by "$CDS_{i,t}$"; the specific leverage ratio component of firm i in quarter $t-1$ by "$lev^{c}_{i,t-1}$", the main coefficient of interest by "β^{c}"; the leverage ratio of firm i from other remaining debt other than this component in quarter $t-1$ by "$lev^{nc}_{i,t-1}$" and its coefficient of "β^{nc}"; and the residual of firm i in quarter t by "$\epsilon_{i,t}$".

In this model specification as well as in the following ones, the leverage ratio, "$lev^{c}_{i,t-1}$", is one of these specific leverage ratio components through which we quantify a specific component of a company's leverage. For instance, "$mrktlev_{i,t-1}$" indicates market debt leverage ratio, "$banklev_{i,t-1}$" bank debt leverage ratio, and "$tclev_{i,t-1}$" trade credit leverage ratio where i denotes each firm and $t-1$ denotes each previous financial quarter with respect to the financial quarter of CDS spread. In every regression, we also use the counter leverage ratio for each of these leverage ratio component, for instance, namely non-market debt leverage ratio or non-bank debt leverage ratio, which are denoted by "$non-mrktlev_{i,t-1}$"

or “$non - banklev_{i,t-1}$” respectively.

We add the control variables to the specification in the second model specification. We use at least four main control variables in all specifications where we use control variables. Three of them are what we refer as market-based control variables obtained from the stock market data. These are quarterly average of the daily stock returns indicated by “$r_{i,t-1}$”, equity volatility which is the volatility of stock returns in a quarter by “$vol_{i,t-1}$” and equity value that is the average market capitalization of a firm in each quarter denoted by “$mcap_{i,t-1}$”. The fourth control variable, the ratio of net income to total asset, is an accounting-based measure calculated from quarterly financial statements. We show it as “$inc/at_{i,t-1}$” in the regression specifications. The regression specification for the second model is as follows:

$$\begin{aligned} \text{CDS}_{i,t} =& \beta^c \text{lev}^c_{i,t-1} + \beta^{nc} \text{lev}^{nc}_{i,t-1} + \\ & \gamma^r \text{r}_{i,t-1} + \gamma^{vol} \text{vol}_{i,t-1} + \gamma^{mcap} \text{mcap}_{i,t-1} + \gamma^{inc/at} (\text{inc/at})_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{2}$$

In all model specifications, the explanatory variables are always used with a lag that is one financial quarter $(t-1)$ before the CDS spread’s financial quarter (t) according to the theoretical expectation mentioned above. In order to clarify the reasoning for it more, investors in the CDS market, bankers or other stakeholders collect information about the firms from the financial statements and their stock performance in the equity market. Therefore, we assume that both leverage ratio components and control variables influence CDS spread of each firm with a time lag. This is a way to address the endogeneity concern at our best effort based on our theoretical assumption.

One of the benefits that panel data methodology provides is its assumption that firms are heterogeneous. Panel data supply more informative data, greater variation and less collinearity between explanatory variables, more degrees of freedom and greater efficiency (Baltagi, 2001). On the other hand, we still need to check for whether there is a correlation between the unobservable heterogeneity, $\epsilon_{i,t}$ of each firm, and the models’ explanatory variables. If there is a correlation, we need to utilize fixed effects rather than random effects model. We use the Hausman (1978) test under the null hypothesis $E(\epsilon_{i,t} \mid x_{i,t}) = 0$ where $x_{i,t}$ denotes any explanatory variable in Model 1 or Model 2. The Hausman test generates a statistically significant p-value and makes us reject the null hypothesis that the preferred model includes random effects. In other words, we opt out of using random effects model since the effects are considered fixed in Model 1 and Model 2. Therefore, we utilize a specification with only firm fixed effects in Model 3 below:

$$\text{CDS}_{i,t} = \beta^c \text{lev}^c_{i,t-1} + \beta^{nc} \text{lev}^{nc}_{i,t-1} + \gamma^{control} \text{X}_{i,t-1} + \lambda_i + \epsilon_{i,t} \tag{3}$$

where $\text{X}_{i,t-1}$ depicts all the control variables and λ_i is the dummy variable used to control for any firm specific effects. Adding in firm-fixed effects enables us to control for unobserved individual heterogeneity among corporations. In fact, in a study of the determinants of firm leverage, Lemmon et al. (2008) find that leverage includes an essential unobserved firm-specific component and the well-known determinants of leverage suggested by the literature (e.g. firm size, asset tangibility, profitability, cash flow volatility) are not be able to capture this component of leverage fully. Therefore, we consider that the characteristics of our main explanatory variable, leverage, give us additional reasoning to control for unobserved firm-specific characteristics. The other variables are the same as mentioned earlier.

We assess the effects of the explanatory variables on CDS spread with adding time (quarter) fixed effects to firm fixed effects in Model 4:

$$\text{CDS}_{i,t} = \beta^c \text{lev}^c_{i,t-1} + \beta^{nc} \text{lev}^{nc}_{i,t-1} + \gamma^{control} \text{X}_{i,t-1} + \lambda_i + \eta_t + \epsilon_{i,t}, \tag{4}$$

where η_t is the dummy variable that captures time (quarter) fixed effects. The other variables are as explained previously.

In this last model, model 5, we use industry-by-quarter fixed effects to control for the fact that some industry specific characteristics or shocks in a certain time period might interfere with the effects of explanatory variables on CDS spread. By using industry-by-quarter fixed effects, we assure that the effect is driven only by variation within a given industry-quarter. The model's specification as follow:

$$\text{CDS}_{i,j,t} = \beta^c \text{lev}^c_{i,j,t-1} + \beta^{nc} \text{lev}^{nc}_{i,j,t-1} + \gamma^{control} \text{X}_{i,j,t-1} + \lambda_i + \eta_t + \nu_{j,t} + \epsilon_{i,j,t}, \tag{5}$$

where i and t index the firm and the quarter respectively as before, j indexes a specific industry to which the firm belongs. $\nu_{j,t}$ is the dummy variable that controls for industry-by-time fixed effects.

6 EMPIRICAL RESULTS

In this section, we present the estimates for the effect of each leverage ratio component on CDS spread starting with the analysis of market debt leverage that emerges relatively as the most important leverage ratio component explaining CDS spread economically. Then, we provide the empirical results about the analyses of other leverage ratio components: Bank debt leverage and trade-credit leverage. Finally, we provide a combined analysis where we use all leverage ratio components in the same regression specification.

Market Debt Leverage Ratio:

Table V provides us with the results of panel regression models when we examine the effect of market debt leverage ratio on CDS spread. In the table, each column presents the estimates in each model specification from equation 1 to equation 5 in Section 5. In column [1], the regressors are the explanatory variable of interest, market debt leverage ratio, and its so called counter leverage ratio, non-market debt leverage ratio, that measures the leverage stemming from other liabilities other than market debt. We do not employ any fixed effects in this specification, nor any other control variables. Market debt leverage ratio has an estimated coefficient of 0.105, whereas non-market debt leverage ratio has an estimated coefficient of 0.061. Both coefficients are statistically significant at 1 percent confidence level. The signs of both coefficients are positive as we expect theoretically: the higher leverage, the higher CDS spread. Economically, a 1 percentage point increase in market debt leverage of a firm in a quarter leads to a 0.11 percentage point increase in CDS spread in the next quarter. Regarding the comparison of coefficients in terms of economic magnitude, we interpret that market debt matters more for CDS spread than other types of debt in a firm's balance sheet in this basic model, model 1, since the coefficient of market debt leverage ratio is almost twice of the coefficient of non-market debt leverage. The adjusted R-square of this regression is 41%.

In column [2], we add the control variables to the regression specification that is model 2. These variables are theoretical variables proposed by structural approach and examined by the previous studies such as stock return, market capitalization, equity volatility to control for what stock market perceives about firm as well as income/asset ratio to control for profitability of each firm. The first three rely on market-based information and the last one on accounting-based information. The estimated coefficient of market debt leverage decreases to 0.062 and the estimated of non-market debt leverage decreases to 0.033. Both coefficients are statistically significant at 1 percent level and their signs are still positive as expected. A 1 percentage point increase in market debt leverage in a current quarter corresponds to 0.06 percentage point increase in CDS spread.

In regards to the estimated coefficients of control variables in column [2] of Table V, they all have the expected sign from the theoretical perspective at 1 percent statistical confidence level except for the 10 percent confidence level for stock return. The higher the return, the lower CDS spread as Merton Model (1974) and many other following studies have proposed and documented. In regards to market capitalization, we have a negative estimated coefficient showing that firms with higher market value have a lower CDS spread next quarter, since they are further away from the default point. Their higher market value of equity is an appropriate measure for their asset value according to Merton Model (1974). Column [2] also shows a negative relationship between income/asset ratio and next quarter's CDS spread, since firms with more profits have higher tendency to increase their asset value by keeping their profits inside the firm, for instance, as retained earnings. Markets consider profitability as a sign of being less credit risky. On the other hand, equity volatility is the only control variable that has a positive estimated coefficient. A 1 percentage increase in equity volatility increases the next quarter's CDS spread by 0.05 percentage point. Once we also interpret other control variables' coefficients economically, all coefficients can be interpreted in percentage points except the one for the market capitalization. A 1 percentage point increase in market cap leads to 0.196 basis point increase in CDS spread since market capitalization as a proxy for equity value is calculated in logarithmic term. Adding control variables raises the adjusted R-square to 55%.

We run the regression according to model 3 in column [3], where we employ only firm fixed effects. The estimated coefficient of market debt leverage is 0.062 at 1 percent statistical confidence level, twice of the coefficient of non-market debt leverage that is 0.031. A 1 percentage point increase in market debt leverage in quarter $t-1$ implies 0.06 percentage points increase in CDS spread in quarter t. The control variables still have their estimated coefficient with the expected signs from the theory at 1 percent confidence level. We can see that adding firm-fixed effect raises in absolute terms the coefficient of every control variables except equity volatility. After utilizing firm fixed effects, the statistical significance of variable stock return improve to 1 percent level from 10 percent level. Stock return, market capitalization, and income/asset ratio all have negative effect on CDS spread next quarter, whereas equity volatility influences CDS spread positively in the next quarter. We have a substantial change in the adjusted R-square in this column. Adding firm fixed effects increases the adjusted R-square from 55.3 % in model 2 to 76 % in model 3.

The Table V-column [4] presents the estimates for the regression that has both firm and time fixed effects according to model 4. The coefficient of market debt leverage is estimated 0.051 at 1 percent confidence level. It decreases by 0.011 compared the earlier column, but it is still circa twice of the coefficient of non-market debt leverage that is 0.023 and statistically significant at 1 percent confidence level. A 1 percentage point increase in market debt leverage leads to 0.05 percentage points increase in CDS spread next quarter. The coefficients for the control variables are all statistically significant at 1 percent confidence level and have the theoretically expected signs. For every control variable's coefficient even including the coefficient of equity volatility, we observe the increase in absolute terms in their magnitude economically. Furthermore, adding time fixed effects increases the adjusted R-square slightly from 76 % in model 3 to 78 % in this model.

The final column in Table V indicates that the estimated coefficient of interest is still statistically significant at 1 percent confidence level when industry-by-quarter fixed effect is added to the regression specification according to equation 5. In column [5], the estimated coefficient of market debt leverage is 0.050, almost the same as the previous specification's result. One percentage point increase in market debt leverage in quarter $t-1$ suggests 0.05 percentage points increase in CDS spread in quarter t. The coefficient of non-market debt leverage ratio is 0.021 and is still less than the coefficient of market debt leverage ratio. The trend about the difference between two coefficients continues in this column too and even market leverage ratio's is more than twice of the non-market debt leverage ratio's coefficient. We interpret this as evidence for CDS market reacting to firms' indebtedness from the financial markets substantially more than to other types of debt. The estimated coefficients of all control variables remain statistically significant at 1% confidence level with predicted signs at similar magnitudes in comparison to the previous specification. The adjusted R-square increases up to 80 % in this model, model 5, where we employ all three types of fixed effects.

Table V
Regressions of CDS Spread on Market Debt Leverage

The regressions in this table examine the impact of market debt on CDS spread. The dependent variable in these regressions is CDS spread that is the quarterly mean of daily CDS spreads. In all specifications, the dependent variable CDS spread has a lead of one period (quarter) with respect to all explanatory variables. The main independent variable, market debt leverage, is calculated by a ratio of market debt over market value of assets. Market debt consists of commercial papers, bonds, capital & finance lease obligations, federal loans, and other short-term & long-term borrowing derivatives. It is simply the sum of financial debts other than bank debts. The second independent variable, called "non-fin debt leverage", is calculated by total liabilities minus market debt over market value of assets. Return is quarterly mean value of daily logarithmic returns. Market capitalization (cap) is quarterly average of daily market capitalization that is *price* $\times$ *total number of outstanding shares*. Equity volatility is stock return volatility that is quarterly standard deviation of daily stock returns. Market leverage is the sum of book values of short-term and long term debts divided by market value of assets. Income/asset is the ratio of net income to total asset. All variables are trimmed at 0.05-percentiles from both ends. In all regressions, *t-statistics* are computed via robust standard errors which are clustered at company and quarter levels. They are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Market Debt Lev	0.105***	0.0620***	0.0618***	0.0509***	0.0503***
	(12.19)	(8.51)	(8.02)	(6.42)	(6.43)
Non-mrkt Debt Lev	0.0611***	0.0326***	0.0314***	0.0233***	0.0212***
	(7.37)	(5.13)	(4.32)	(3.40)	(3.01)
Return		-0.00125*	-0.00154***	-0.00167***	-0.00175***
		(-1.93)	(-4.10)	(-4.36)	(-3.58)
Market cap		-0.196***	-0.503***	-0.681***	-0.651***
		(-3.65)	(-3.84)	(-5.58)	(-5.10)
Equity volatility		0.0462***	0.0315***	0.0385***	0.0389***
		(8.13)	(6.63)	(9.92)	(9.75)
Income/Asset		-0.0393***	-0.0464***	-0.0479***	-0.0451***
		(-3.02)	(-5.91)	(-6.33)	(-5.34)
Adj. R-squared	0.412	0.553	0.760	0.782	0.796
Firm FE	-	-	Yes	Yes	Yes
Time FE	-	-	-	Yes	Yes
Industry x Time FE	-	-	-	-	Yes
N. of Firms	337	337	335	335	333
N. of Obs.	14517	14235	14233	14233	13943

Note: ***, ** and * depict 1%, 5% and 10% statistical significance levels respectively.

Bank Debt Leverage Ratio:

We analyze the leverage stemming from firm indebtedness to the banks as a second leverage ratio component. Table VI depicts the results of all five models in analyzing the effect of bank debt leverage ratio on CDS spread. Each column in the table reveals the regression result for one of our five models. In column [1], we see the estimated coefficient of bank debt leverage and non-bank debt leverage ratios which are 0.155 and 0.075 respectively. Both coefficients are statistically significant at 1 percent confidence level in this basic model that has neither control variables nor any fixed effects. Once we add the control variables to the regression specification as seen in column [2], the estimated coefficient of interest drops to 0.103 but it keeps its 1 percent statistical significance level. The coefficient of its counter leverage, non-bank leverage, shares the same trend: it decreases to 0.039 but it is also still statistically significant at 1 percent level. One percentage point increase in bank debt leverage suggests 0.10 percentage points increase in CDS spread next quarter. Adding control variables to the specification increases the adjusted R-square from 41% to 56%. The coefficient estimates of all control variables have the hypothesized sign and they are statistically significant at 1 percent level except variable return's coefficient which has 10 percent statistical confidence level.

Starting with model 3 as seem in Table VI column [3], we add fixed effects to our analysis one by one. Employing firm-fixed effect makes the estimated coefficient of bank debt leverage to decrease to 0.074 but keeps its statistical significance at 1 percent level. On the other hand, the estimated coefficient of non-bank debt leverage increases a little bit up to 0.049 and it is still statistically significant at 1 %. Adding firm-fixed effects does not change the hypothesized signs of the estimated coefficient of control variables. The coefficients' economic magnitudes do not have dramatic change compared to column [2], however, the statistical significance of variable stock return improves to 1 percent statistical significance level in column [3]. Utilizing firm fixed effects raises in absolute terms the coefficients of all control variables except equity volatility. As a final remark, once we add firm-fixed effects in this column, the adjusted R-square increases up to 76%.

The regression outputs are reported in column [4] of Table VI when time fixed effects are also included. The coefficient of bank debt leverage decreases somewhat to 0.061 compared to the previous specification but it is statistically significant at 1 percent. Moreover, it is still higher (circa 1.6 times bigger) than the estimated coefficient of non-bank debt leverage (0.039) that is also statistically significant at 1 percent level. The coefficient indicates that there is a positive relationship between bank debt leverage and CDS spread. Economically, one percentage increase in bank debt leverage ratio in quarter $t-1$ leads to 0.06 percentage points increase in CDS spread in quarter t. Using both firm and time fixed effects does not change the signs and statistical significance of the estimates of control variables. On the other hand, the magnitudes of all control variables' estimates increase in absolute terms in column [4] unlike the estimates of bank debt leverage and its counter leverage ratio.

Finally, the column [5] of Table VI presents the coefficients once we use model 5 that contains all fixed effects including industry-by-quarter fixed effects. Bank debt leverage ratio has an estimated coefficient of 0.066 at 1% statistical significance level. It is slightly higher than the previous column's corresponding coefficient. Bank debt leverage influences the next quarter's CDS spread more than non-bank debt leverage ratio. A 1 percentage point increase in bank debt leverage ratio leads to 0.07 percentage points raise in CDS spreads next quarter. Once we review the estimated coefficients of control variables, their signs and statistical significance levels are the same as previous columns. In addition, there is not a dramatic change in the economic magnitudes of their estimated coefficients. As seen in Table VI column [5], this last specification yields an adjusted R-square of 80%.

Table VI
Regressions of CDS Spread on Bank Debt Leverage

The regressions in this table investigate the impact of bank debt leverage regarding CDS spread. The dependent variable in these regressions, CDS spread, is the quarterly mean of daily CDS spreads. In all specifications, the dependent variable CDS spread has a lead of one period (quarter) compared to all independent variables. The main independent variable, bank debt leverage, is calculated by a ratio of total bank debt over market value of assets. The second independent variable, called "non-bank debt leverage", is calculated by total liabilities minus bank debt over market value of assets. Return is quarterly mean value of daily logarithmic returns. Market capitalization (cap) is quarterly average of daily market capitalization that is *price* $\times$ *total number of outstanding shares*. Equity volatility is stock return volatility that is quarterly standard deviation of daily stock returns. Income/asset is the ratio of net income to total asset. All variables are trimmed at the upper and lower 0.05-percentiles. In all regressions, *t-statistics* are computed using robust standard errors that are clustered at company and quarter levels. They are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Bank Debt Lev	0.155***	0.103***	0.0738***	0.0607***	0.0661***
	(9.72)	(7.44)	(5.33)	(4.76)	(5.43)
Non-bank Debt Lev	0.0746***	0.0393***	0.0485***	0.0389***	0.0383***
	(10.57)	(7.39)	(8.26)	(6.84)	(6.56)
Return		-0.00136**	-0.00141***	-0.00153***	-0.00158***
		(-2.18)	(-3.89)	(-4.01)	(-3.27)
Market cap		-0.232***	-0.443***	-0.633***	-0.573***
		(-4.47)	(-3.40)	(-5.16)	(-4.51)
Equity volatility		0.0451***	0.0310***	0.0382***	0.0386***
		(7.96)	(6.45)	(9.98)	(9.74)
Income/Asset		-0.0435***	-0.0482***	-0.0495***	-0.0441***
		(-3.17)	(-5.89)	(-6.43)	(-5.33)
Adj. R-squared	0.414	0.558	0.760	0.782	0.796
Firm FE	-	-	Yes	Yes	Yes
Time FE	-	-	-	Yes	Yes
Industry x Time FE	-	-	-	-	Yes
N. of Firms	337	337	335	335	333
N. of Obs.	14517	14235	14233	14233	13943

Note: ***, ** and * stand for 1%, 5% and 10% statistical significance levels respectively.

Trade Credit Leverage Ratio:

Another component of leverage ratio that we examine is trade credit leverage ratio. Table VII shows the estimates from each regression model in each column. Column [1] presents the basic model specification where trade credit leverage ratio and non-trade credit leverage ratio are the only regressors without any control variables as well as any fixed effects. The estimated coefficient of trade credit leverage is 0.043 and statistically significant at 1 percent confidence level. However, this coefficient is almost twice less than the estimated coefficient of non-trade credit leverage in magnitude, which is 0.087 and statistically significant at 1 percent confidence level. Both estimates have the expected sign. The higher each of these leverages, the higher the CDS spread in the next quarter. We note that in the previous leverage ratio components' analyses, the estimated coefficient of variable of interest is always greater than the coefficient of the counter leverage ratio. In fact, once we add the control variables to the regression as seen in column [2], the picture changes: The estimated coefficient of trade credit leverage is 0.011 and it has the expected positive sign theoretically, but it is not statistically significant anymore. On the other hand, non-trade credit leverage ratio's estimate decreases to 0.048 but it keeps its 1 percent level statistical significance. The control variables have their hypothesized signs: The variables of return, market capitalization, and income/asset ratio have negative relationship with next quarter's CDS spread, whereas equity volatility has a negative relationship with CDS spread in the next quarter as the structural models suggest.

As we do in the analyses of other component ratios earlier, we include firm fixed effects in the regression specification in column [3], then time fixed effects in column [4], and finally industry-by-quarter fixed effects in column [5]. The estimated coefficients of trade credit leverage ratio are all positive as we expect theoretically. However, these coefficients never become statistically significant although other regressors remain statistically significant in all these models: Model 3, model 4, and model 5. The counter leverage ratio of trade credit leverage, non-trade credit leverage, is always positive and statistically significant at 1 percent confidence level. The higher leverage other than the trade credit leverage, the higher the CDS spread in the next quarter. For instance, a 1 percentage point increase in non-trade credit leverage in quarter $t-1$ leads to 0.04 percentage points increase in CDS spread in quarter t according to model 5 in column [5] in Table VII.

Table VII
Regressions of CDS Spread on Trade Credit Leverage

The regressions examine the impact of trade credit leverage ratio on the CDS spread that proxies credit risk. The dependent variable of these regressions is CDS spread that is the quarterly mean of daily CDS spreads. In all specifications, the dependent variable CDS spread has one period (quarter) lead with respect to all independent variables. The main explanatory variable, trade credit leverage, is measured by the ratio of trade payable over market value of assets. The second independent variable, called "non-trade credit leverage", is calculated by total liabilities minus trade payable over market value of assets. Return is quarterly mean value of daily logarithmic returns. Market capitalization (cap) is quarterly average of daily market capitalization that is *price* $\times$ *total number of outstanding shares*. Equity volatility is stock return volatility that is daily stock returns' quarterly standard deviation. Income/asset is the ratio of net income to total asset. All variables are trimmed at the lower and upper 0.05-percentiles. In all regressions, *t-statistics* are calculated using robust standard errors that are clustered at company and quarter levels. They are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Trade Credit Lev	0.0426***	0.0105	0.0212	0.00750	0.0100
	(4.25)	(1.21)	(1.33)	(0.48)	(0.59)
Non-trade Credit Lev	0.0870***	0.0484***	0.0541***	0.0445***	0.0442***
	(11.83)	(8.74)	(9.37)	(7.98)	(7.59)
Return		-0.00138**	-0.00144***	-0.00154***	-0.00160***
		(-2.15)	(-3.80)	(-4.03)	(-3.23)
Market cap		-0.258***	-0.423***	-0.617***	-0.566***
		(-4.97)	(-3.21)	(-4.99)	(-4.36)
Equity volatility		0.0449***	0.0310***	0.0380***	0.0386***
		(7.92)	(6.45)	(10.06)	(9.72)
Income/Asset		-0.0410***	-0.0476***	-0.0487***	-0.0447***
		(-3.08)	(-6.02)	(-6.44)	(-5.26)
Adj. R-squared	0.408	0.555	0.761	0.783	0.796
Firm FE	-	-	Yes	Yes	Yes
Time FE	-	-	-	Yes	Yes
Industry x Time FE	-	-	-	-	Yes
N. of Firms	337	337	335	335	333
N. of Obs.	14427	14145	14143	14143	13853

Note: ***, ** and * stand for 1%, 5% and 10% statistical significance levels respectively.

Combined Analysis of All Components:

We further conduct an analysis in which we use all leverage component ratios as regressors in each model from model 1 to model 5 explained in Section 5. Table VIII documents the results of the regressions for this combined analysis. In the 1st column, we only regress leverage ratio components as well as "other leverage ratio" that is the ratio of the remaining debt in the liabilities of a firm divided by the book value of total liabilities and the equity market value. The estimated coefficients of all leverage ratios are statistically significant at 1 percent confidence level and, as we expect theoretically, positive. The higher each of these leverage ratios, the higher the next quarter's CDS spread. All four variables explain CDS spread with an adjusted R-square of 42%. According to column [1], bank debt leverage ratio has the highest estimated coefficient in terms of economic magnitude, 0.123.

As usual, in column [2], we include the control variables to the regression specification. Adding control variables causes the adjusted R-square to increase to 56%. The estimates of market debt leverage, bank leverage and other leverage ratios are still positive and significant at 1 percent statistical significance level. However, trade credit leverage ratio's estimated coefficient loses its statistical significance, although its sign is still positive. Bank debt leverage ratio still has the highest estimated coefficient compared to other three ratios, 0.087. The control variables also have the statistical significance at 1 percent level (except variable return with its significance at 5 percent level) and hypothesized signs.

As seen in Table VIII column [3], once we use firm fixed effects, market debt leverage ratio's estimated coefficient (0.057) ranks as the highest coefficient rather than bank debt leverage ratio's estimated coefficient (0.046). The former one is significant at 1 percent, the latter one at 5 percent level. Trade credit leverage ratio is statistically insignificant. On the other hand, other leverage ratio is positive and statistically significant at 1%. In this regression specification according model 3, the control variables have the theoretically expected signs and 1 percent statistical significance level all together. The adjusted R-square increases to 76% with adding firm fixed effects.

We continue the analysis by adding time fixed effects to the regression specification as shown in column [4] of Table VIII. The estimated coefficient of market debt leverage is 0.047, the highest one at 1 percent statistical significance level. It is followed by bank debt leverage and other leverage ratios. However, trade credit leverage is still statistically insignificant.

Furthermore, the statistical significance level of other leverage ratio becomes 5 percent in this specification. Both bank debt leverage and other leverage ratios have the hypothesized positive signs as market debt leverage has. All the control factors remain significant at 1 percent statistical significance level with their expected sign in this column too.

Finally, in column [5], we add industry-by-quarter fixed effect additional to other two fixed effects. The rank of leverage ratio components' estimated coefficients does not change in this column. Market debt leverage has the highest coefficient at 1 percent statistical significance level. A 1 percentage point rise in market debt leverage leads to 0.05 percentage points rise in CDS spread in the next quarter. Both bank debt leverage and other leverage ratios have positive and significant at 5 percent level estimated coefficients. Every control variable has the expected sign. They are all statistically significant at 1 percent level. As a last point, the adjusted R-square in the most advanced model, model 5, becomes 80% as seen in Table VIII.

Table VIII
Regressions of CDS Spread on Market Debt, Bank Debt, and Trade Credit Leverage Ratios

The regressions examine the impacts of market debt leverage, bank debt leverage and trade credit leverage on the CDS spread. The response variable in these regressions is CDS spread with a lead of one quarter ahead of other variables. The independent variables of interest (market debt, bank debt, and trade credit leverage ratios) are calculated by a ratio of each of these debt to market value of assets respectively. The independent variable, called "other leverage", depicts the remaining debt in the total liabilities of each firm. It is calculated by total liabilities minus account payable, bank debt and market debt over market value of assets. The remaining control variables are calculated in the same manner as in the previous regression tables. All variables are trimmed at the upper and lower 0.05-percentiles. In all regressions, *t-statistics* are calculated using robust standard errors that are clustered at company and quarter levels. They are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Market Debt Lev	0.0940***	0.0511***	0.0571***	0.0467***	0.0458***
	(9.42)	(6.22)	(6.50)	(5.30)	(5.38)
Bank Debt Lev	0.123***	0.0868***	0.0460**	0.0357**	0.0375**
	(5.23)	(4.67)	(2.31)	(2.02)	(2.35)
Trade Credit Lev	0.0448***	0.0135	0.0133	-0.000404	-0.00110
	(4.49)	(1.56)	(0.81)	(-0.02)	(-0.06)
Other Leverage	0.0658***	0.0365***	0.0278***	0.0203**	0.0178**
	(6.64)	(4.99)	(3.06)	(2.45)	(2.09)
Return		-0.00136**	-0.00169***	-0.00184***	-0.00192***
		(-2.20)	(-4.47)	(-4.52)	(-3.75)
Market cap		-0.219***	-0.579***	-0.753***	-0.733***
		(-4.15)	(-3.86)	(-5.41)	(-4.94)
Equity volatility		0.0455***	0.0316***	0.0386***	0.0390***
		(8.14)	(6.50)	(9.96)	(9.72)
Income/Asset		-0.0411***	-0.0472***	-0.0490***	-0.0461***
		(-3.07)	(-5.85)	(-6.36)	(-5.53)
Adj. R-squared	0.420	0.562	0.760	0.782	0.796
Firm FE	-	-	Yes	Yes	Yes
Time FE	-	-	-	Yes	Yes
Industry x Time FE	-	-	-	-	Yes
N. of Firms	337	337	335	335	333
N. of Obs.	14427	14145	14143	14143	13853

Note: ***, ** and * stand for 1%, 5% and 10% statistical significance levels respectively.

7 FURTHER ANALYSIS

The Relationship between Trade Receivable and CDS Spread:

One of the findings that we have found in the previous section is that trade credit leverage ratio has a statistically insignificant estimate when we regress CDS spread on one quarter lagged trade credit leverage ratio and control variables. We understand that CDS spread do not response changes in debt of the firm to its suppliers in its product market both economically and statistically as seen in from column [2] to column [5] in Table IX. At this point, we also consider analyzing the effect of the relationship of firm with its customers on its CDS spread. We want to figure out whether CDS spread is also not responsive to the changes in trade receivables as it is to trade payable.

In evaluating financial risk and indebtedness of a firm, practitioners such as bank supervisors often assess the account of trade receivable together with the account of trade payable in their financial analysis of firm since these two balance sheet accounts give information about both sides of the trade relations that the firm has. From now on, I will name these accounts as account receivable and account payable as the accounting field do. It is a fact that uncollected account receivables from a specific customer or customers and receivables whose due dates pass long time ago are the factors contributing to the credit riskiness of a firm. In turn, if a firm is heavily indebted to a specific supplier of it, this is also another risk for the firm since this supplier may enforce some difficulties for the firm due to concentrated trade relation. Another possibility might be that the firm cannot pay its debt to this supplier on time. In short, information about concentration and due dates of account receivables and account payables is substantially essential in analyzing the credit riskiness of the firm from its trade relations. At this point, we have a caveat that it would be better if we had a larger data set showing the maturities of the sub-accounts that make up account receivable and account payable as well as the classification of these two general accounts according to customers and suppliers. By having this detail information, analysis of credit riskiness of the firm stemming from its trade relations would be more complete. Nevertheless, we examine the effects of account receivable on CDS spread using the account receivable's overall balance data.

In order to perform the analysis, we first calculate a ratio where we divide account receivable by the total asset's market value. We do the same standardization while calculating leverage ratio components. In calculating the market value of total asset, we sum the market value of equity and the book value of total liabilities. We name this new variable as "trade receivable/asset ratio". We hypothesize that the larger the trade receivable/asset ratio, the higher the CDS spread next period, since account receivable is a part of firm asset value. According to the Merton Model (1974), a higher asset value signals being further away from the default point for a firm, which is translated into a lower credit risk and thereby, a lower CDS spread. While we regress CDS spread on trade receivable/asset ratio, we prefer to control for the indebtedness of the firm by employing the total leverage ratio whose definition is provided in Table I.

We investigate the effect of trade receivable/asset ratio on CDS spread. Table IX reports the results of the regressions with the main explanatory variable is trade receivable/asset ratio. In column [1], we regress this main explanatory variable only with total leverage ratio. The estimate of the coefficient for trade receivable/asset ratio is -0.045 and statistically significant at 1 percent level. The sign is negative as we hypothesize. In this basic model specification, a one percentage point increase in trade receivable/asset ratio leads to 0.045 percentage point decrease in CDS spread next quarter. The higher the trade receivable/asset ratio, the lower the CDS spread next quarter. On the other hand, the estimated coefficient of total leverage ratio is 0.085 and also statistically significant at 1 percent level. The higher the total leverage ratio, the higher the CDS spread next quarter. The adjusted R-square in this basic model is 40%.

We add the control variables in column [2] of Table IX, the coefficient of trade receivable/asset ratio become -0.056, economically more significant in magnitude and still keeps it statistical significance at 1 percent level. In turn, the economic magnitude of total leverage ratio decreases to 0.046, although it is still significant at 1 percent level. In regards to the control variables, stock return affects the next quarter's CDS spread negatively and statistically significant at 5 percent level. We can see the same negative effects on the next quarter's CDS spread of the variables of market capitalization and income/asset ratio. Both variables have estimates which have statistical significance at 1 percent level. On the other hand, colum [2] shows that the bigger the equity volatility, the higher the next quarter's CDS spread, implying a positive relationship which is significant at 1 percent level between stock return volatility and CDS spread. It is noteworthy that the effects of control variables do not change in terms of sign and statistical significance when the main explanatory variable is trade receiable/asset ratio compared the regression results in Section 6. As a final comment about column [2], using control variables in the regression specification increases the adjusted R-square to 56%.

As usual according to our empirical methodology in Section 5, we employ firm fixed effects in column [3] of Table IX, then we add time fixed effects besides firm fixed effects in column [4], and finally we use all three fixed effects including industry-by-quarter in column [5]. In column [3], the estimated coefficient of trade receivable/asset ratio increases in absolute terms and it becomes -0.073, economically more significant. In terms of statistical significance, it is still significant at 1 percent level. This same trend between column [2] and [3] is also valid for total leverage ratio. Its estimated coefficient economic magnitude also increases from 0.046 to 0.053 and it is statistically significant at the same level. The magnitude increase in absolute terms also happens for the control variables except equity volatility. Its coefficient drops from 0.045 to 0.031. However, all control variables preserve their expected signs and statistical significance in their coefficients once we add firm fixed effects. Even, the statistical significance of stock return improves to 1 percent level from 5 percent level. Moreover, we can see the effect of using firm fixed effect in the adjusted R-square: It increases to 76% from 56% in the previous column.

In column [4] of Table IX, after adding time fixed effects, the estimated coefficient of trade/receivable increases a little bit in economic magnitude. It is -0.076 and statistically significant at 1 percent level. On the other hand, total leverage ratio's coefficient loses its economic magnitude and it becomes 0.043 at 1 percent statistical significance. The coefficients of control variables increases in economic magnitude slightly compared to their values in column [3]. They are all significant at 1 percent level statistically. Finally, column [5] employs industry-by-quarter fixed effects besides other two effects. All estimated coefficients are significant at 1 percent level in this column too. In addition, they all keep their economic magnitude almost at the same level in comparison to the values in column [4]. The last regression specification provides us with a coefficient of -0.076 for trade receivable/asset ratio. As seen in column [5] of Table IX, this implies that a 1 percentage point rise in trade receivable/asset ratio leads to circa 0.08 percentage points decrease in CDS spread next quarter. It is noteworthy that this coefficient is greater than the estimated coefficient of total leverage ratio in absolute terms, almost twice of it. This gives us an intuition that CDS spread is substantially responsive to account receivables of a firm. This finding is understandable, because a higher balance of account receivable gives a signal that the firm has the potential to maintain its cash flow stream in the future once it collects these receivables from its customers. However, this interpretation is valid as long as if we assume that the quality of these receivables are high on average meaning that the percentage of uncollectible account receivable is low and/or if we assume that no material level of concentration from a specific customer among these receivables exists.

Table IX
Regressions of CDS Spread on Trade Receivable/Asset Ratio

These regressions analyze the effect of trade (account) receivable on the CDS spread. The dependent variable in these regressions is CDS spread that is the quarterly mean of daily CDS spreads. In all specifications, the dependent variable CDS spread has a lead of one period (quarter). The main independent variable, trade receivable/total asset, is computed by a ratio of trade receivable to market value of assets. The second independent variable, called "total leverage", is calculated by total liabilities over market value of assets. The other control variables are calculated in the same manner as in the previous tables. All variables are trimmed at the upper and lower 0.05-percentiles. In all regressions, *t-statistics* are calculated using robust standard errors that are clustered at company and quarter levels. They are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
Trade Receivable/Asset	-0.0450***	-0.0560***	-0.0730***	-0.0756***	-0.0755***
	(-3.29)	(-4.85)	(-3.53)	(-3.85)	(-3.98)
Total Leverage	0.0853***	0.0462***	0.0527***	0.0434***	0.0438***
	(11.46)	(8.67)	(8.77)	(7.44)	(7.57)
Return		-0.00152**	-0.00164***	-0.00171***	-0.00173***
		(-2.47)	(-4.30)	(-4.24)	(-3.47)
Market Cap		-0.304***	-0.501***	-0.687***	-0.639***
		(-5.68)	(-3.37)	(-4.93)	(-4.49)
Equity Volatility		0.0450***	0.0312***	0.0370***	0.0373***
		(8.02)	(6.50)	(9.42)	(9.08)
Income/Asset		-0.0426***	-0.0455***	-0.0474***	-0.0434***
		(-3.20)	(-5.70)	(-6.09)	(-4.96)
Adj. R-squared	0.398	0.556	0.763	0.785	0.801
Firm FE	-	-	Yes	Yes	Yes
Time FE	-	-	-	Yes	Yes
Industry x Time FE	-	-	-	-	Yes
N. of Firms	336	336	334	334	332
N. of Obs.	14186	13911	13909	13909	13577

Note: ***, ** and * show significance at the 1%, 5% and 10% levels respectively.

8 CONCLUSION

We investigate how different components of leverage ratio affect CDS spreads while controlling for theoretical determinants of CDS spreads from structural models and accounting-based credit risk models. We believe that leverage deserves more attention as a crucial determinant of credit risk and, accordingly, of CDS spread, because it is a factor proposed by both Merton-type structural models and credit risk models relying on accounting measures such as Altman's Z-score model. To date, this study is the first to analyze the effects of different components of leverage ratio on CDS spread.

Firms have different types of debt in their liabilities depending on to whom they are indebted. We discretize the leverage ratio into different components according to account type. The first component that we examine is market debt leverage ratio measuring a firm's indebtedness from commercial papers, bonds, and other debt to the financial markets. The second component is bank debt leverage ratio showing what part of leverage stems from bank loans. The third component is trade credit leverage ratio measuring how much firms owe to their suppliers. Finally, we structure a leverage ratio of the remaining debt that we cannot classify due to the lack of data and call it other leverage ratio.

First, we show that market debt leverage and bank debt leverage have statistically and economically significant positive effect on next quarter's CDS spread, whereas trade credit leverage ratio is insignificant in explaining the CDS spread. Second, we also answer the question of which component influences the CDS spread more. We document that market debt leverage ratio has the highest estimated positive coefficient when we regress the CDS spread on all leverage ratio components. All these findings are obtained while we control for theoretical determinants of CDS spread (e.g., stock return, market capitalization, equity volatility) as well as income/asset ratio as a proxy for firm profitability. The adjusted R-square for the regression using all leverage ratio components together with control variables is 80% in the most sophisticated econometrics model that we employ.

Statistically insignificant relationship between CDS spread and trade credit leverage ratio has led us to examine the impact of the other side of the trade relations on CDS spread. We document that a higher balance of trade receivables imply a lower CDS spread in the next quarter.

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10 APPENDIX

10.1 Figures: Bivariate Plots of Control Variables with CDS Spread

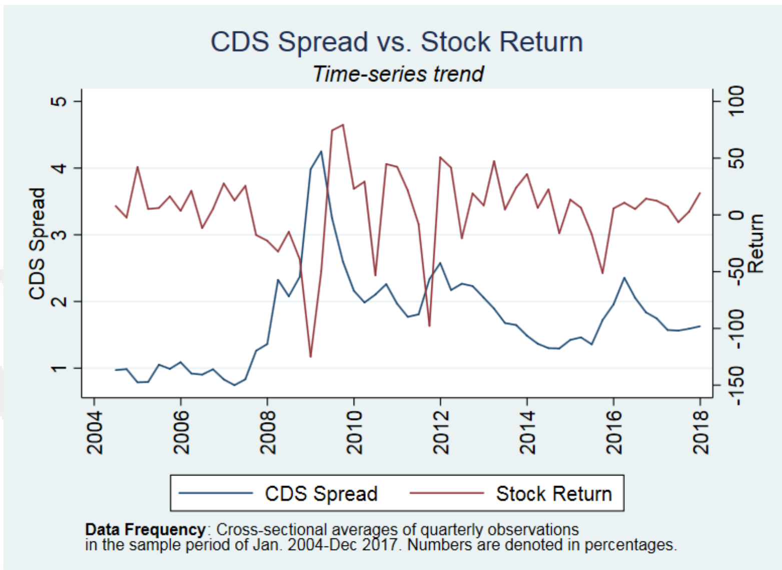

Figure 5: A Time Series Analysis of CDS Spread and Stock Return

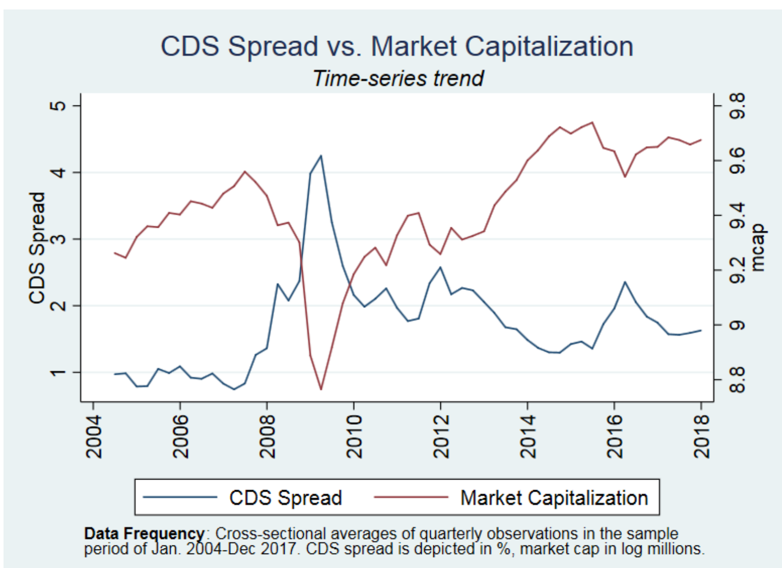

Figure 6: A Time Series Analysis of CDS Spread and Stock Market Capitalization

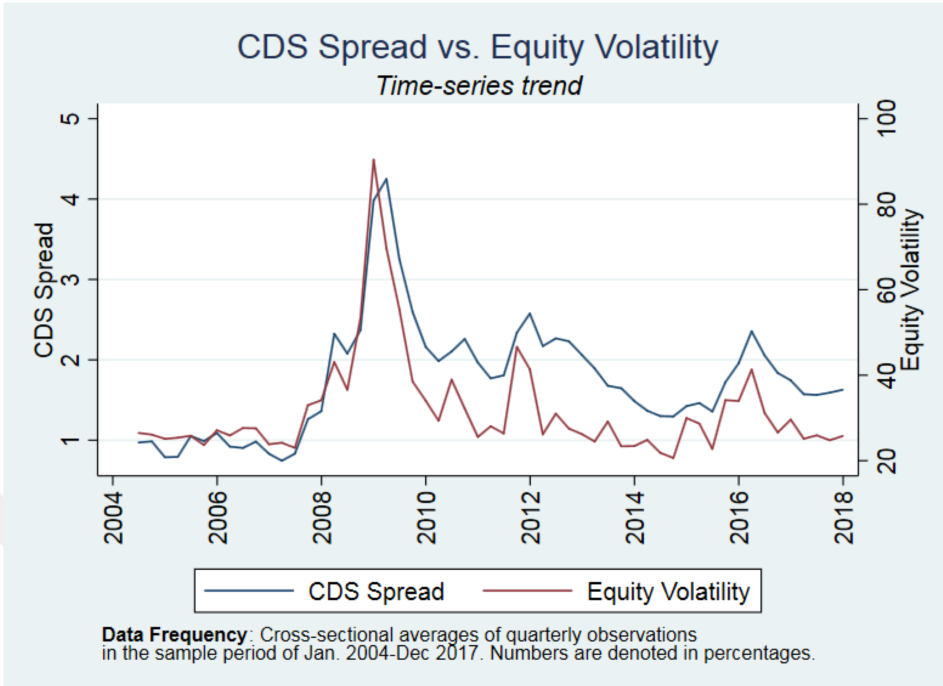

Figure 7: A Time Series Analysis of CDS Spread and Equity Volatility

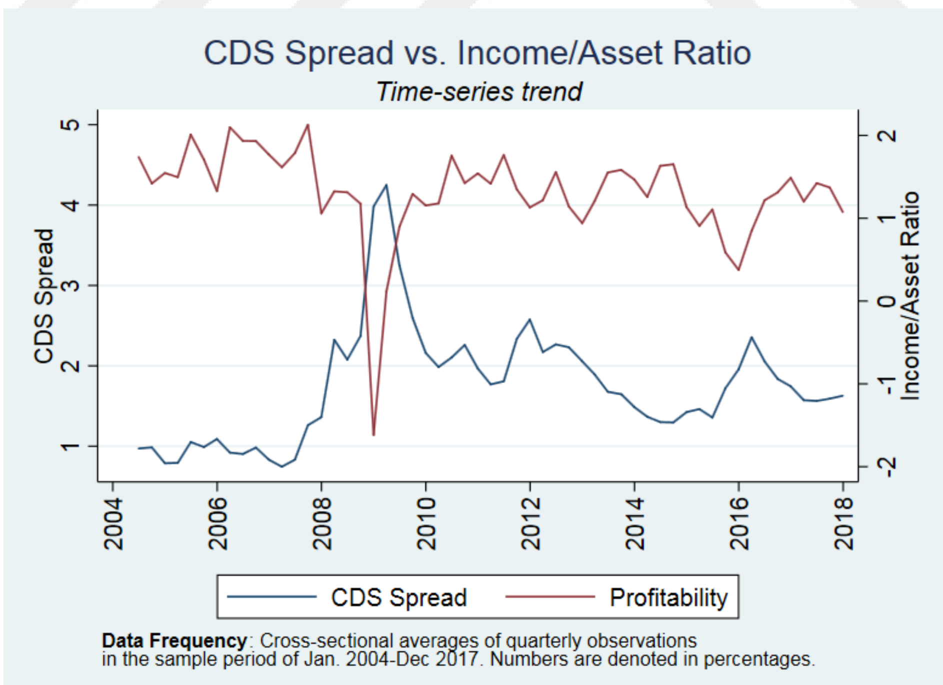

Figure 8: A Time Series Analysis of CDS Spread and Profitability

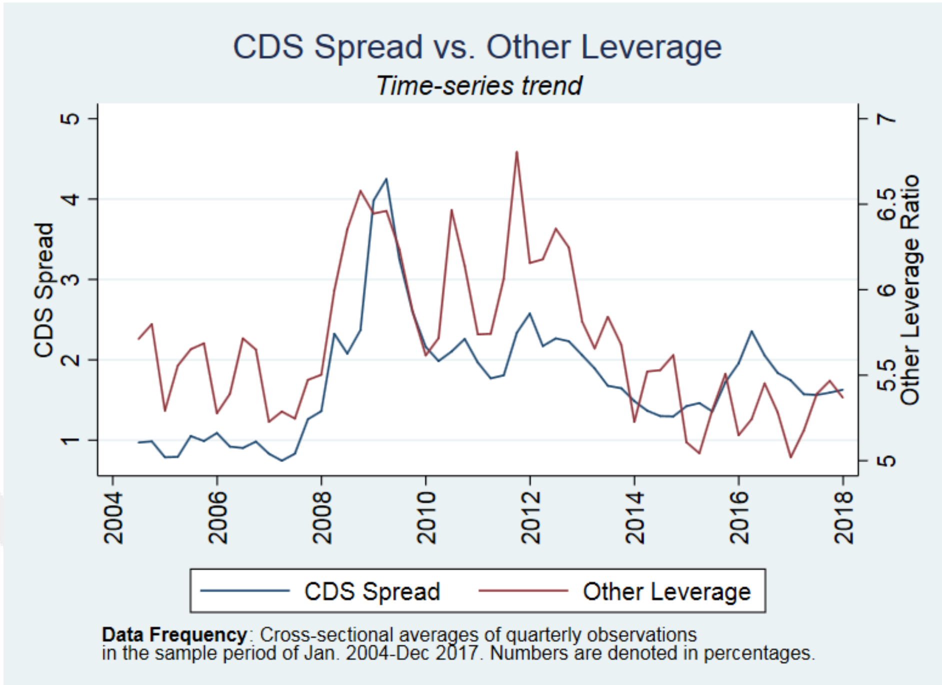

Figure 9: A Time Series Analysis of CDS Spread and Other (Remaining) Leverage